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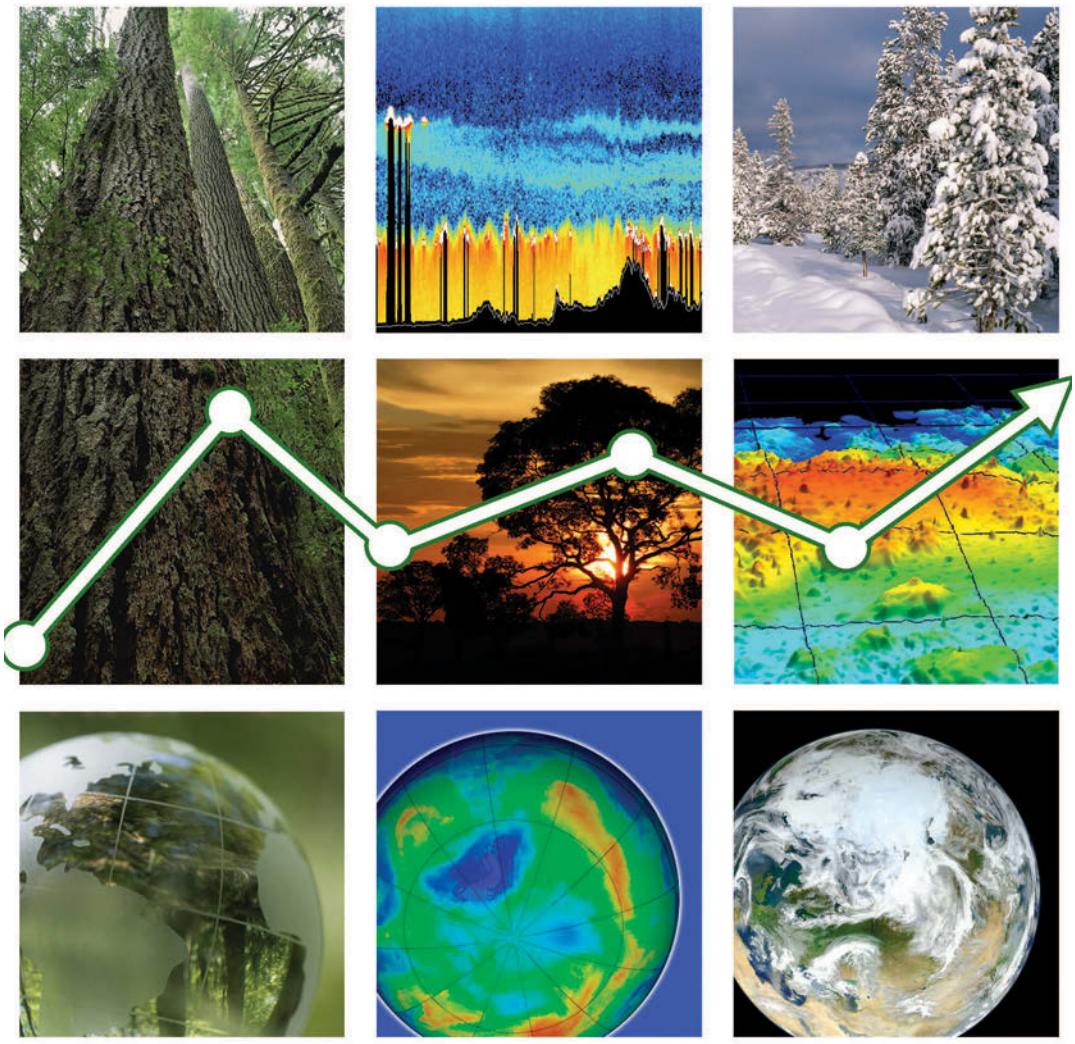
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Forest
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**Northern
Research Station**

**General Technical
Report NRS-P-105**

Moving from Status to Trends: Forest Inventory and Analysis (FIA) Symposium 2012



Abstract

These proceedings report invited presentations and contributions to the 2012 biennial Forest Inventory and Analysis (FIA) Symposium, which was hosted by the Research and Development branch of the U.S. Forest Service. As the only comprehensive and continuous census of the forests in the United States, FIA provides strategic information needed to evaluate sustainability of current forest management practices across all ownerships. Papers and abstracts included in the publication have been sorted into topic areas that match the sessions presented during the meeting. Symposium papers cover high priority and timely issue-based topics including climate change, wildlife, fire, bioenergy, geo-spatial extensions, monitoring over time, integrating remote sensing and GIS applications, statistical and related quantitative solutions to emerging needs, and many others.

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Moving from Status to Trends: Forest Inventory and Analysis (FIA) Symposium 2012

December 4-6, 2012

Baltimore, MD

Compiled by

Randall S. Morin

Greg C. Liknes

United States Department of Agriculture

Northern Research Station

General Technical Report NRS-P-105

November 2012

PREFACE

The eleventh biennial Forest Inventory and Analysis Symposium was held December 4-6, 2012, in Baltimore, MD. The symposium featured 128 presentations by scientists from across the United States and 10 foreign countries. In addition, the trend for participation by scientists from outside the formal Forest Inventory and Analysis Program continues to increase. The symposium organizers thank all participants and presenters and convey special thanks to those who submitted their papers for these proceedings.

Randall S. Morin

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FOREST PRODUCTS INDUSTRY STATUS AND TRENDS: NATIONAL AND REGIONAL PERSPECTIVES

EFFECTS OF THE "GREAT RECESSION" ON THE FOREST PRODUCTS SECTOR IN THE NORTHERN REGION OF THE UNITED STATES

Christopher W. Woodall, William G. Luppold, Peter J. Ince, Ronald J. Piva, and Kenneth E. Skog[1]

Abstract.—The forest industry within the northern region of the United States has demonstrated a notable decline in terms of employment, number of mills, wood consumption, and forest harvests since 2000—a downturn exacerbated by the "Great Recession" of 2007-2009. Longer term industrial decline (since 2000) has been evidenced by reductions in secondary product (e.g., furniture) and print paper manufacturing, which can be attributed to the lack of global competitiveness of U.S. wages and ascent of electronic media. In contrast, more recent (since 2008), yet sharper declines can be found in industries such as composite panel production that service the housing industry. Despite a decade of decline, future prospects for this region's forest industry may be viewed as positive. The region's forests are predominantly within private ownership and represent some of the world's most valuable sawtimber. Coupled with the natural resource is a present but underutilized industry with spare capacity and a highly skilled work force.

INTRODUCTION

The northern region, which for the purposes of this paper broadly includes New England, upper mid-Atlantic, Great Lakes, central hardwood, and eastern Plains states, supports 27 percent of the Nation's timber volume and 46 percent of its hardwood resource (Smith et al. 2009). These hardwood-dominated forests contain over two-thirds (FIA 2012) of the Nation's high-valued select hardwoods (e.g., select white oaks, select red oaks, hard maple, ash, and black walnut) and accounted for approximately 18 percent of the Nation's hardwood removals in 2006 (Smith et al. 2009). These hardwood removals supply a large share (48 percent; Smith et al. 2009) of U.S. hardwood lumber production and this region is the principle source of high grade hardwood lumber, plywood, and veneer production. These products, in turn, are used by secondary manufacturers (e.g., kitchen cabinet, millwork, and furniture manufacturers) domestically and internationally.

Following the same trends as found across the United States (Woodall et al. 2012a), the northern region had declines in numerous forest products industries beginning in 2000 followed by a precipitous drop in the wake of the housing construction downturn (~2006) and recession of 2007 to 2009 (Woodall et al. 2012b).

Declines in production have been accompanied by declines in the number of mills and wood consumption for saw, pulp, and composite panel mills within the north central subregion (IL, IN, IA, KS, MI, MN, MO, NE, ND, SD, WI) of the region and reflect recent trends in these industries both nationally and regionally (Figs. 1 and 2). Mill numbers and wood consumption have generally fallen since 2000 for both pulp and composite panel sectors, with steep declines starting in 2005 (Fig. 1). By 2009 there were 25 percent fewer pulp mills processing 13 percent less

[1] Research Forester (CWW), U.S. Forest Service, Northern Research Station, 1992 Folwell Ave., St. Paul, MN 55108; Economist (WGL) and Forester (RJP), U.S. Forest Service, Northern Research Station; Research Forester (PJI) and Supervisory Research Forester (KES), U.S. Forest Service, Forest Products Lab. CWW is corresponding author: to contact, call 651-649-5141 or email at cwoodall@fs.fed.us.

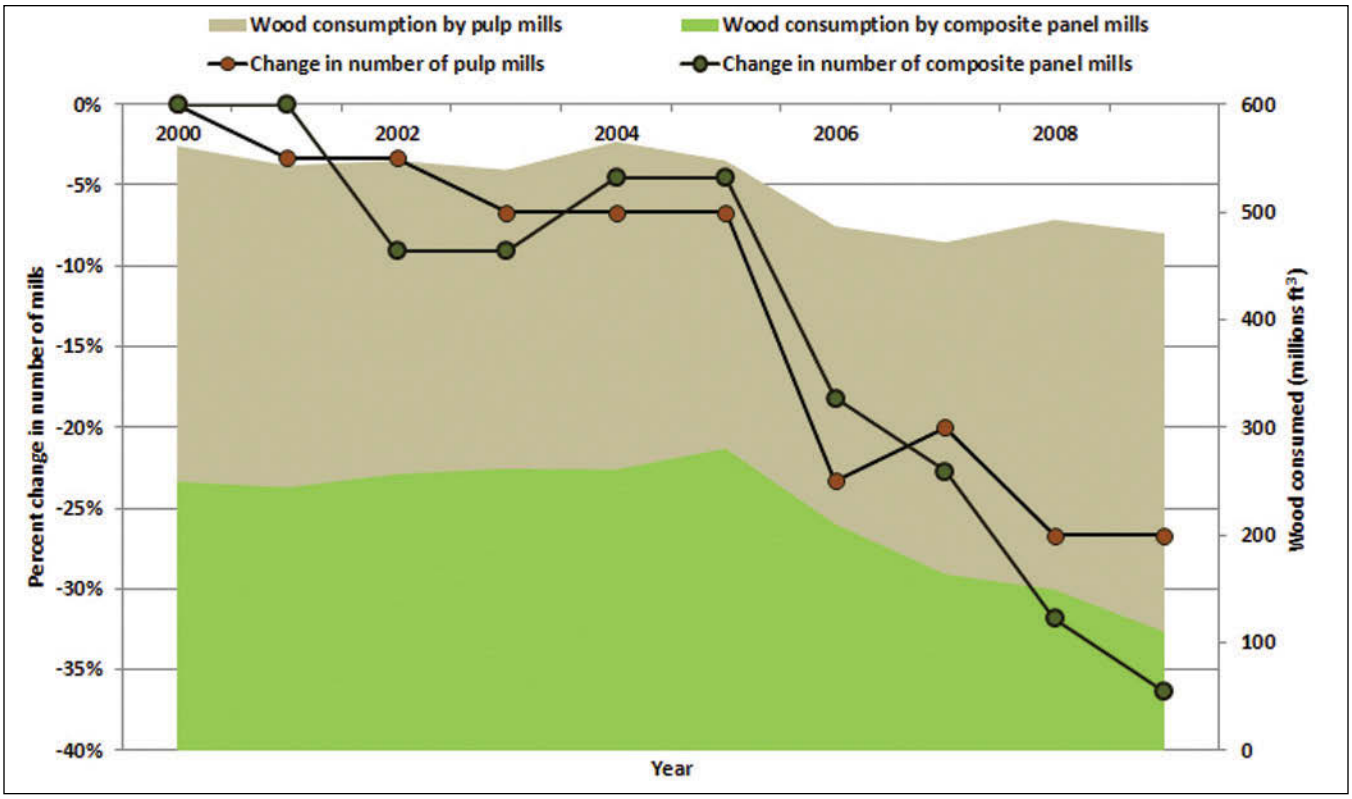


Figure 1.—Change (percent) in number of pulp and composite wood panel mills since 2000 and wood consumed by pulp and composite panel mills, 2000-2009, north-central states (IL, IN, IA, KS, MI, MN, MO, NE, ND, SD, WI).

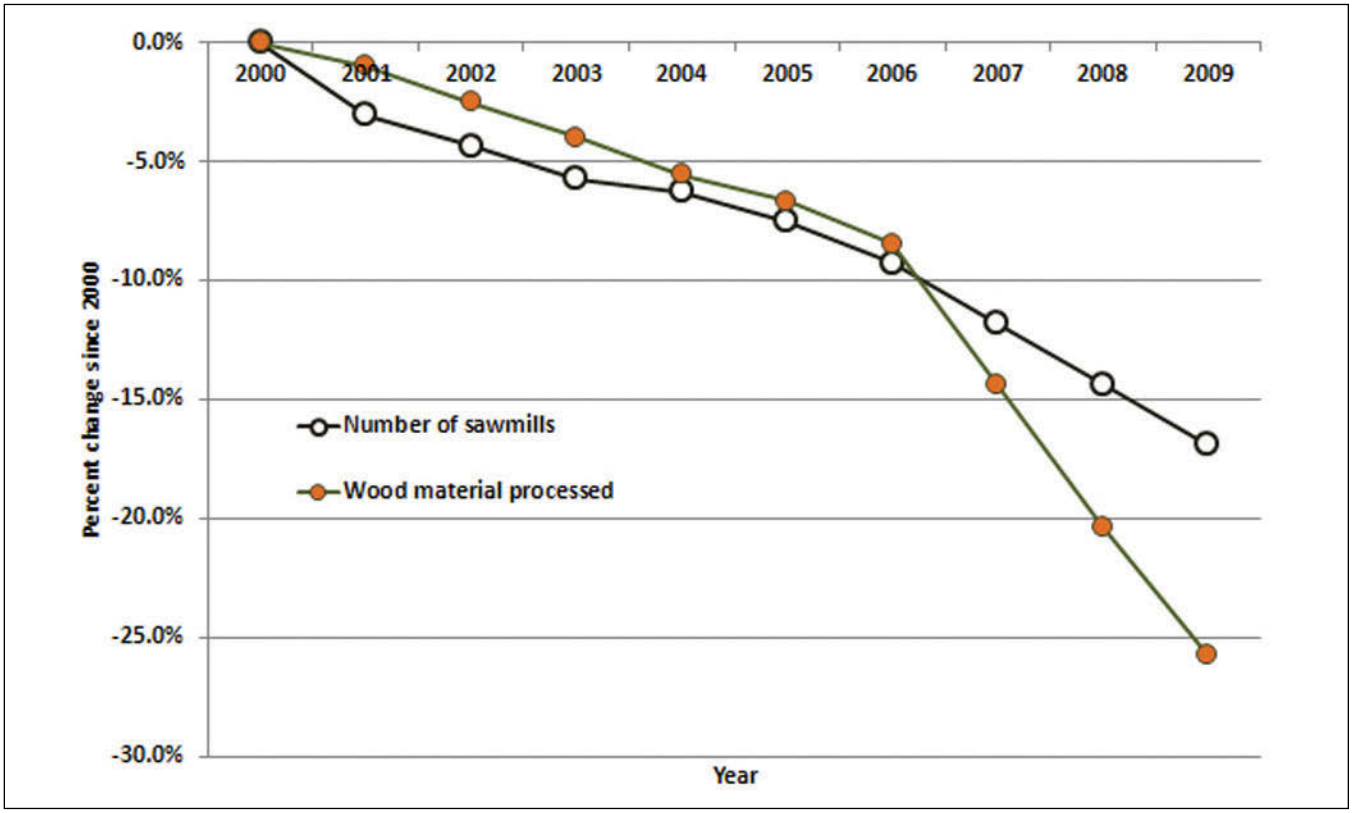


Figure 2.—Percentage change in number of sawmills and quantity of processed wood since 2000, 2000-2009, north-central states (IL, IN, IA, KS, MI, MN, MO, NE, ND, SD, WI).

pulpwood. These disproportional declines (percentage decline in mill number exceeds percentage decline in feedstock use) suggest a shift in productive capacity to larger and potentially more efficient mills despite the economic downturn. In contrast, 36 percent fewer composite panel mills in 2009 processed 56 percent less wood than peak production in 2005, a direct consequence of the fall of the housing market. Trends in the sawmill sector mirror those of the composite panel sector and are linked to the plight of the housing market (Fig. 2). From 2000 to 2006, sawmill numbers and wood consumption demonstrated similar percentages of decline. After 2006, the amount of wood consumed decreased faster than the decline in mill counts. This trend resulted in 17 percent fewer sawmills processing 26 percent less wood by 2009—an indicator that the remaining sawmills are running at less than full capacity.

Despite a decade of decline, future prospects for this region's forest industry may be viewed as positive. The region's forests are predominantly within private ownership and represent tremendous volumes of some of the world's most valuable sawtimber. The forest landowners of the northern region have been diligently managing their forests for generations as evidenced by the ever-increasing volumes for decades (USDA 2011). Coupled with this natural resource is a present but underutilized industry with spare capacity and a highly skilled work force. The continued development of competitive secondary industries in the United States to receive this region's high quality select hardwoods (e.g., walnut and select oaks) might increase regional employment while maintaining critical positive international trade balances. The export of hardwood saw logs may provide a positive trade balance today but also represents the offshoring and loss of skilled U.S. labor into the future. In total, the highly abundant forest resource, mill capacity, and secondary product workforce skills in the northern region provide an economic opportunity to foster increased competitiveness and evolve beyond the downturn precipitated by the housing crash and years of offshoring the Nation's forest products industry.

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IMPACT OF THE GREAT RECESSION ON THE FOREST PRODUCTS INDUSTRY IN THE WESTERN UNITED STATES

Charles E. Keegan, Colin B. Sorenson, Todd A. Morgan, Jean M. Daniels, and Steven W. Hayes[1]

Abstract.—Wood product prices and production fell dramatically in 2009 as a severe recession and massive decline in U.S. housing led to a global financial crisis. In 2009 and 2010, virtually every major western mill suffered curtailments and 30 large mills closed permanently. Sales value of wood and paper products in the West dropped from $49 billion in 2005 to $34 billion in 2009. Employment declined by 71,000 workers and lumber production fell by almost 50 percent from 2005 to 2009. Capacity utilization at sawmills and other timber-using facilities in the West fell from more than 80 percent in 2005 to just over 50 percent in 2009 and 2010. With the exception of exports and some paper markets, U.S. wood products markets have improved little since the recession officially ended in 2009. Modest improvements are expected in domestic markets in the short term, but substantial improvements are unlikely until 2014 or later, as U.S. home building recovers and global demand increases. Much of the West retains the bulk of its pre-recession (2006) capacity and mills could respond quickly to increased demand spurred by economic recovery.

NOTE: A longer version of this paper with additional tables, figures, and a full Literature Cited section was published in the Forest Products Journal, Vol. 61, No. 8, in July 2012.

INTRODUCTION

The first decade of the 21st century proved tumultuous for the global and U.S. economies and the western forest products industry. Following a relatively mild recession in 2001, a booming economy, low interest rates, easy access to credit, and real estate speculation fostered more than 2 million U.S. housing starts in 2005 and record lumber consumption from 2003 to 2005 (Western Wood Products Association 2010).

The falloff in U.S. housing markets beginning in 2006 abruptly ended the credit-fueled growth that had been based on the rapid increase in home prices up to that point. This period was followed by an official recession from December 2007 through June 2009 (National Bureau of Economic Research 2010), a massive decline in home values and housing-related financial instruments, and ultimately a global financial crisis in the last quarter of 2008. Tightening credit, an oversupply of foreclosed homes, and a collapse in speculative housing investment made 2009 through 2011 the worst years for home building and wood products markets since the Great Depression. Housing starts hit a 50-year record low of 554,000 in 2009, with only slight increases during 2010 and 2011. Wood product prices and production fell dramatically during the recession and have remained quite low throughout the post-recession "recovery."

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IMPACTS ON THE FOREST PRODUCTS INDUSTRY IN THE WEST

The Great Recession and housing collapse had large-scale impacts on the western forest products industry. Value of industry outputs fell 31 percent from $49 billion in 2006 to $34 billion (fob the producing mill) in 2009 (U.S. Census Bureau 2010). Employment dropped 29 percent from 249,000 workers in 2005 to 177,000 in 2009 (Table 1) and further to 170,000 in 2010, while earnings of workers fell almost 22 percent from $12.9 billion in 2005 to $10.1 in 2009 and 2010 (Fig. 1).

Every sector of the western forest products industry was negatively impacted by the economic downturn. The wood products sectors, which are more heavily dependent on housing and construction than paper products, experienced the largest impacts. Sales value of wood products fell from $28 billion in 2005 to $14 billion in 2009, while the primary and secondary pulp and paper industry was virtually unchanged at $21 billion (in current year dollars) over the same period.

LUMBER PRODUCTION AND TIMBER HARVEST

For at least 50 years before the recent housing collapse, the West was the major softwood lumber producing region in the country. Softwood lumber was the largest single component of the industry in the West, accounting for approximately $8 billion per year or almost 40 percent of total value from the primary industry in 2004 and 2005. As U.S. housing starts fell by 75 percent and the U.S. consumption of softwood lumber dropped by half, lumber production in the West fell from more than 19 billion board feet (BBF) lumber tally (48 percent of U.S. production) in 2005 to an estimated 10.4 and 11.1 BBF in 2009 and 2010, respectively (less than 45 percent of U.S. production). In 2007, output of softwood lumber from the South exceeded output from the West for the first time since at least 1955. In 2009, lumber production in the West was at its lowest level in more than 50 years (Fig. 2). Because of the substantial decline in both prices and production, the value of lumber produced by western sawmills fell by more than 60 percent (in current year dollars) from nearly $8 billion in 2004 and 2005 to less than $3 billion in 2009 and 2010 (U.S. Census Bureau 2010).

Table 1.—Western states forest products industry employment, 2005 vs. 2009

	2005	2009	Net change	% Change
Pacific Coast states				
Alaska	1,805	1,465	(340)	-19
California	79,513	56,630	(22,883)	-29
Hawaii	1,091	984	(107)	-10
Oregon	58,858	42,578	(16,280)	-28
Washington	44,416	32,612	(11,803)	-27
Pacific Coast subtotal	185,683	134,269	(51,414)	-28
Interior West states				
Arizona	14,222	7,160	(7,062)	-50
Colorado	9,521	7,293	(2,228)	-23
Idaho	14,116	10,028	(4,088)	-29
Montana	9,783	7,464	(2,319)	-24
Nevada	3,358	2,003	(1,355)	-40
New Mexico	3,715	2,623	(1,092)	-29
Utah	7,282	5,941	(1,341)	-18
Wyoming	1,148	629	(519)	-45
Interior West subtotal	63,145	43,141	(20,004)	-32
Grand Total	**248,827**	**177,410**	**(71,418)**	**-29**

Sources: U.S. Department of Commerce 2012; U.S. Department of Labor 2012; Forest Industries Data Collection System 2012.

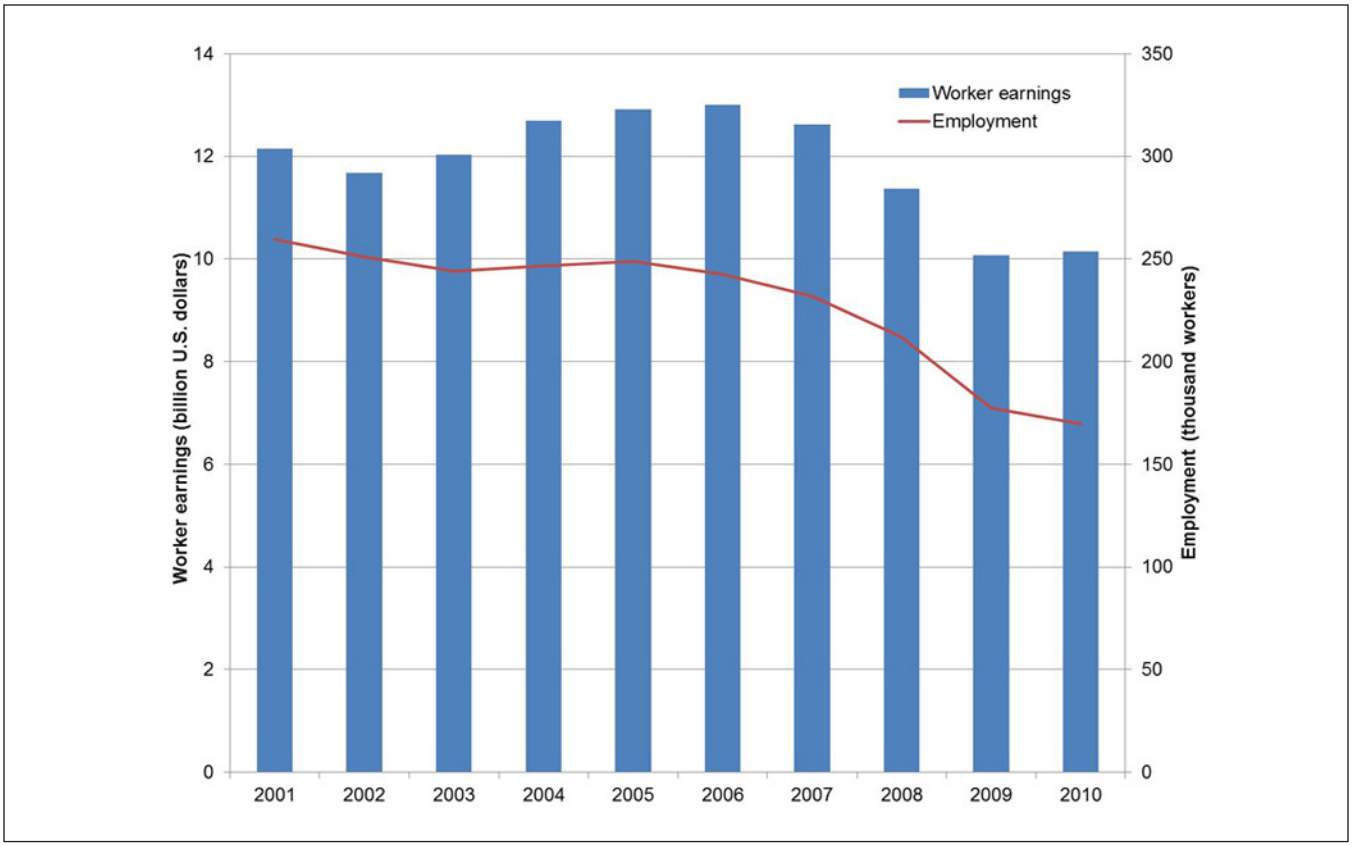


Figure 1.—Forest products industry worker earnings and employment in the West, 2001-2010.

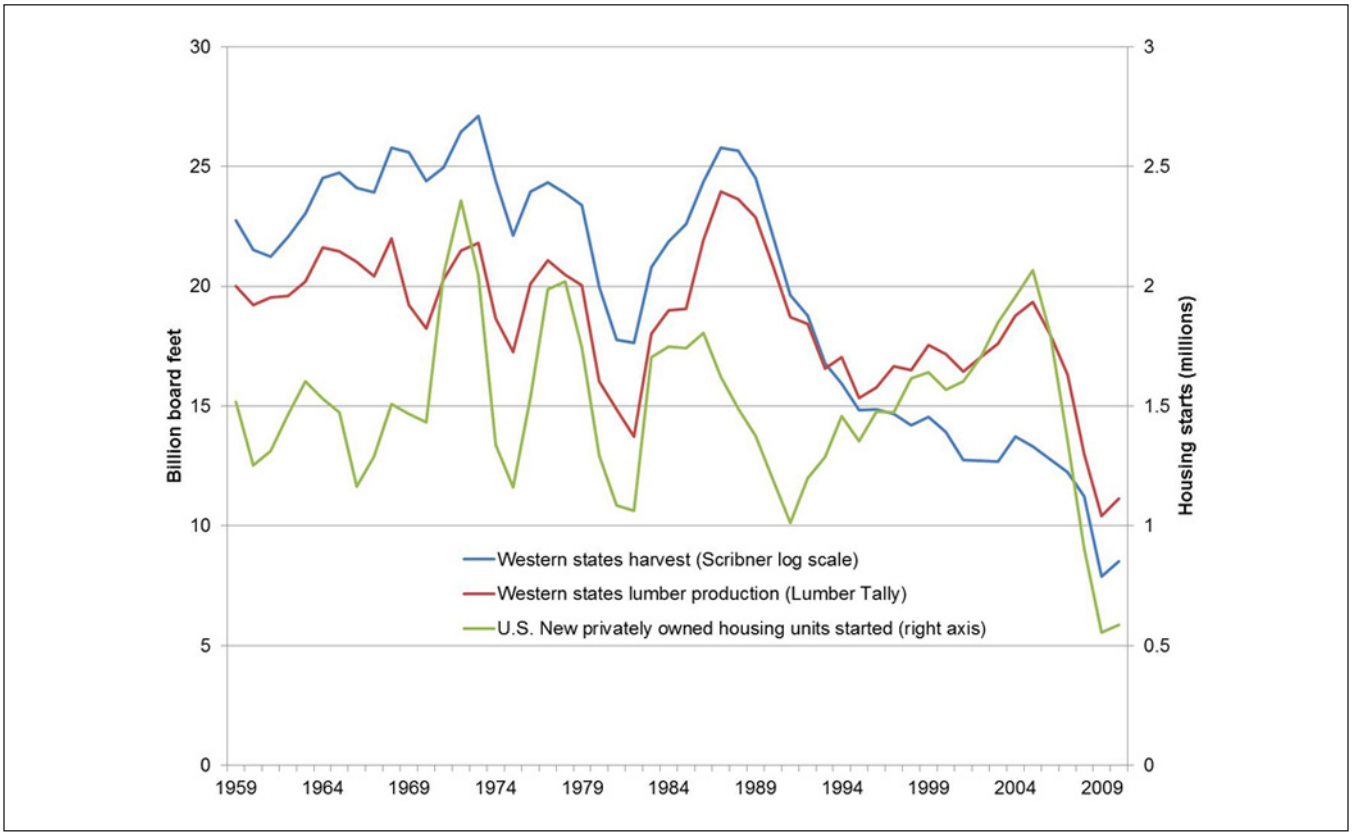


Figure 2.—New U.S. home construction and western states timber harvest and lumber production, 1959-2010.

Timber harvest volume in the West also fell dramatically during the downturn, from more than 13 BBF Scribner in 2004 and 2005, of which more than 70 percent was used to produce lumber, to 7.9 BBF in 2009 (Fig. 2). During 2009 and 2010, West-wide harvest and lumber output were at the lowest levels since the late 1940s. These extremely low timber harvest and lumber production figures are particularly notable when considering U.S. population in the late 1940s was less than half of the 2011 population of 311 million people. Timber harvest fell by just over 40 percent in both the Pacific Coast and Interior West regions from 2005 to 2009, while lumber production fell more than 45 percent.

LOSSES IN INDUSTRY INFRASTRUCTURE: TIMBER PROCESSING CAPACITY

At the start of the Great Recession in 2007, annual capacity to process timber in the West was an estimated 14.4 BBF, and by 2010, capacity had declined by 10 percent to an estimated 13 BBF. Capacity utilization, however, declined much more precipitously from around 80 percent during the 2003 to 2006 period to 64 percent in 2008 and 56 percent in 2010 (Forest Industries Data Collection System 2012, Smith and Hiserote 2010).

EXPORTS

From 2000 to 2009, log exports from the West remained relatively consistent, and Japan was the dominant destination (Fig. 3). This trend began to change in 2009 when the proportion of log exports going to China began to rise. By 2011, the volume of logs shipped to China had jumped by almost 600 percent to reach 1.2 BBF Scribner, equivalent to 14 percent of the West-wide harvest in 2010. This log export trend is likely to persist until domestic demand for wood products returns, Chinese demand decreases, or policy changes impact log exports.

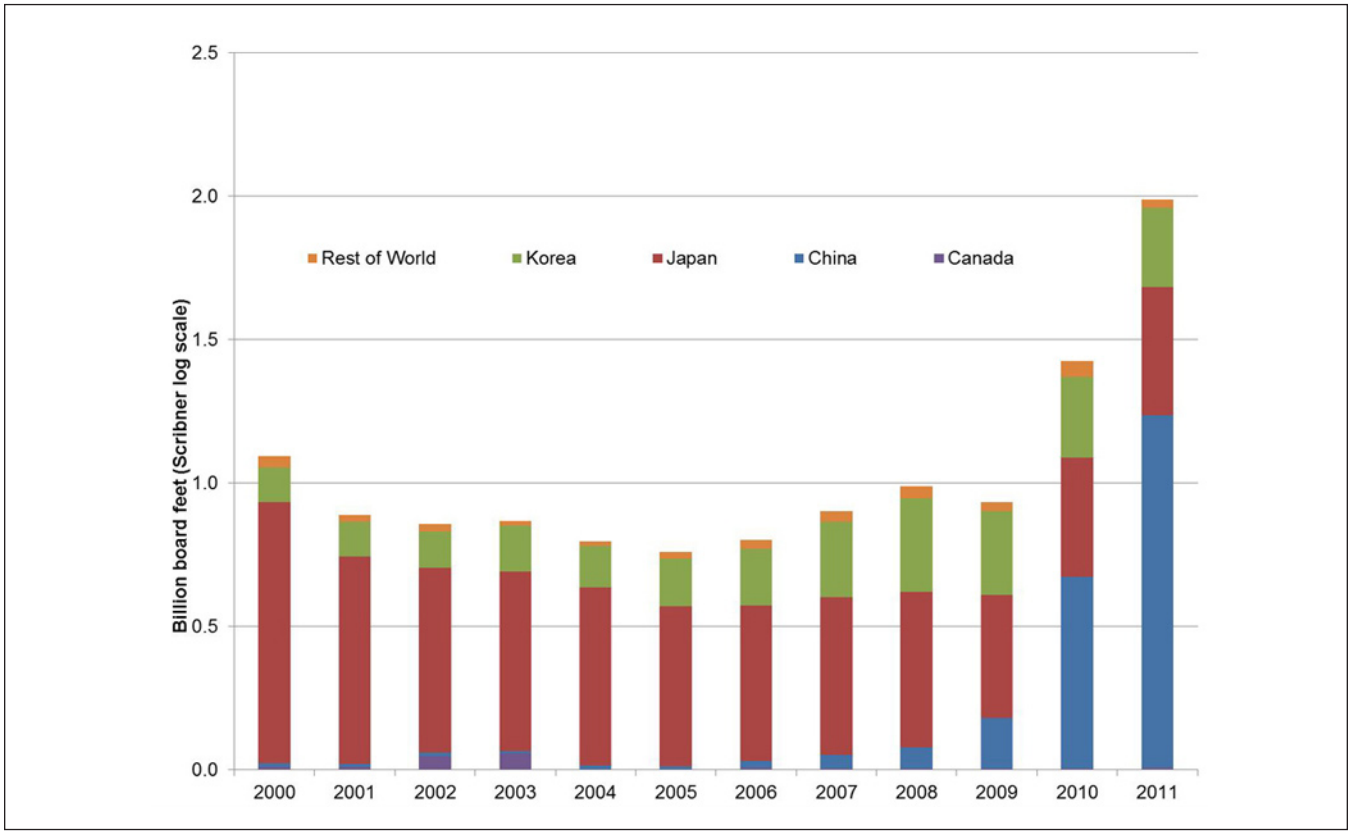


Figure 3.—Volume of softwood logs exported from western customs districts, 2000 to 2011.

FUTURE OUTLOOK

In 2012, U.S. lumber and wood products markets have shown little improvement. Modest improvements are expected in domestic wood products markets in 2013, with substantial improvements not predicted until 2014 or beyond, contingent upon recovery in U.S. home building and continued increases in global demand.

Low capacity utilization rates in the West suggest the possibility of additional mill closures, but because much of the reduced output is due to curtailments rather than permanent closures, the industry retains the ability to quickly increase production at existing mills when market conditions improve.

ACKNOWLEDGMENTS

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RESULTS AND ISSUES ENCOUNTERED WHILE INVESTIGATING SOUTHERN FOREST INDUSTRY AND MARKET RESPONSES TO CHANGING ECONOMIC CONDITIONS

Andrew J. Hartsell, Thomas J. Brandeis, James W. Bentley, Consuelo Brandeis, and Donald Hodges[1]

Abstract.—Recent Forest Inventory and Analysis (FIA) studies revealed the impact that the recent economic downturn had on southern forest industries, markets, and forests. We used FIA data, timber product output (TPO) surveys, and IMpact analysis for PLANing (IMPLAN) output to quantify these impacts. This analysis involves comparing recent changes to the pre-downturn trend. IMPLAN analysis suggests that the total jobs associated with the wood products industry (direct, indirect, and induced employment) fell from 1.2 million jobs to 0.97 million jobs between 2004 and 2009. TPO results indicate that total softwood output declined 22 percent between 2005 and 2009, while hardwood total product output fell 30 percent over the same time period. Data collected from FIA Phase 2 plots suggests that landowners are performing less final harvests and more thinnings and other silvicultural treatments. Issues pertaining to correlating annual TPO data with moving average FIA inventory data will be discussed.

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SOCIAL DIMENSIONS OF FOREST INVENTORY

ASSESSING FOREST OWNERSHIP DYNAMICS IN THE UNITED STATES: METHODS AND CHALLENGES

Brett J. Butler, Brenton J. Dickinson, and Jaketon H. Hewes[1]

Abstract.—The National Woodland Owner Survey (NWOS) is conducted by the U.S. Forest Service, Forest Inventory & Analysis (FIA) Program as the social complement to its biophysical inventory. The NWOS is aimed at understanding who owns the forests of the United States, why they own it, what they have done with it in the past, and what they plan to do with it in the future. On a recurring basis, self-administered surveys are sent to randomly selected private forest owners from across the U.S. The sample points correspond with plot center of the FIA Phase 2 field plots. For the first time, in 2011, the NWOS began to resample points that were sampled between 2002 and 2006. If the same owner still owned the sample point, they were resurveyed and if there was a new ownership, they were surveyed for the first time. These results will provide the most comprehensive examination of forest ownership dynamics in the U.S. to date. Topics that will be explored include parcellation and changes in forest owners' attitudes, behaviors, and demographics. This information should prove useful to state forestry agencies, policy makers, nongovernmental organizations, forest industry, educators, researchers, forest landowner organizations, and anyone who is interested in understanding forest owners and/or interacting with them.

INTRODUCTION

There are 751 million acres of forest land in the United States and 56 percent of this land is owned by 11 million families, individuals, corporations, and other private groups (Butler 2008). The collective decisions of these owners will have profound effects on the future forest resources. If the forestry community is interested in understanding the factors affecting the sustainability of forests and designing effective policies, programs, and services that foster this sustainability, then it is imperative to understand forest ownerships and forest ownership dynamics.

The U.S. Forest Service, Forest Inventory and Analysis (FIA) Program conducts inventories of the biophysical forest resource in order to answer questions related to the composition, extent, health, and trends in this resource. As a complement to this biophysical inventory, FIA conducts the National Woodland Owner Survey to answer the following questions:

- Who owns the forests of the United States?
- Why do they own forests?
- How have they used their forests in the past?
- How do they plan to use their forests in the future?

This information is used by policy analysts, researchers, nongovernmental organizations, forest industry, and others in order to create policies, programs, and services that more effectively and more efficiently aid private forest owners.

The objectives of this paper are to provide some background on the National Woodland Owner Survey, present some of the current challenges, and discuss some things being done to overcome these challenges.

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BACKGROUND

The National Woodland Owner Survey has been conducted on a periodic basis for many decades. The first national data on private forest ownerships comes from Josephson and McGuire (1958). This simply provided numbers of private forest ownerships and area of private forest ownership by size of forest holdings by region. The next iteration of a national survey was conducted by Birch, Lewis, and Kaiser (1982). Here more detailed information was collected including demographics and methods of land acquisition along with size of forest holdings. The finest resolution was again regions.

Birch (1996c) greatly expanded on the previous efforts by providing state-level summaries (Birch 1996a, 1996b, 1996d) and information on ownership objectives, management practices, size of forest holdings, and other topics. The National Woodland Owner Survey switched from a periodic to an annual basis in 2002 (Butler 2008). The most recently completed cycle, completed between 2002 and 2006, contained many of the same elements as Birch (1996c) and added some additional elements. Like Birch (1996a, 1996b, 1996d), Butler (2008) also provided state-level summaries.

The most current iteration of the National Woodland Owner Survey was initiated in 2011. One major advance is that for the first time, the same points on the ground are being included, i.e., point-to-point remeasurement will be feasible. If the same ownership still owns the ground on which the point is located, then that ownership is resurveyed, otherwise the new ownership is surveyed.

METHODS

The National Woodland Owner Survey, beginning with Birch (1996c), is coupled with the national FIA sample design. The FIA sample design (Bechtold and Patterson 2005) consists of dividing the United States into hexagons (approximately 6,000 ac/hexagon) and randomly locating a sample point within each hexagon. These sample points correspond to plot center of the FIA Phase 2 field plots. Twenty to fourteen percent of the sample points in the East and 10 percent of the sample points in the West are visited each year resulting in 5 to 7- and 10-year inventory cycles, respectively. For those sample points that are determined to be forested and privately owned, the landowner is invited to participate in the National Woodland Owner Survey. The ownerships of record are determined through county and municipal property tax records.

The National Woodland Owner Survey is a mail-based survey that follows the procedures outlined by Dillman (2009). Following an introductory postcard, each potential respondent receives a questionnaire, cover letter, and business reply envelope. The next mailing is a reminder/thank you postcard followed by, for those who have not responded, another questionnaire, cover letter, and business reply envelope. For those who still have not responded, a random subset is contacted via telephone in order to facilitate a nonresponse bias assessment. The cooperation rate to the National Woodland Owner Survey between 2002 and 2006 was 51 percent.

CURRENT CHALLENGES

A primary objective of the National Woodland Owner Survey is to monitor trends in forest ownership over time. Therefore, consistency over time is paramount. Changes are periodically made to the survey and estimation procedures, but only when deemed necessary and when the benefits sufficiently outweigh the costs.

Recent work has shown that there was an error in the underlying estimation algorithm for calculating numbers of owners (Metcalf 2010). While the impact of this error on estimates is minimal, the estimation algorithms are being reworked. Once this is completed, data from the 2002-2006 and the newer, 2011 and future, surveys will be (re)calculated using the adjusted procedures.

A challenge with presenting results from the National Woodland Owner Survey is how to clearly and precisely report different units, i.e., ownerships versus acres. The units can have profound impacts on the interpretation of the results (e.g., Fig. 1). In addition to reporting statistics in terms of ownerships and acres, the latest iteration will, for the first time, allow for estimates of the number of owners—an ownership is a legal entity and can, and often does, consist of more than one owner.

The ability to analyze remeasured data is a large opportunity and a great challenge. How does one know when an ownership has changed? A seemingly simple question that quickly becomes complicated. When a sample point is remeasured, the new and old owners are recorded in the database. If the names and mailing addresses are the same, it is the same owner. If the names and mailing addresses are completely different, they are different owners. But often, the differences are more subtle (e.g., Bob Smith to Bob and Sue Smith). Therefore, it will be necessary to quantify change on a sliding scale from definitely the same owner to definitely different owners, and thus be able to quantify and analyze the subtle differences.

NEXT STEPS

Next steps will include continued honing of the National Woodland Owner Survey estimation procedures with special emphasis on quantifying change over time. This will allow unprecedented examination of forest ownership dynamics.

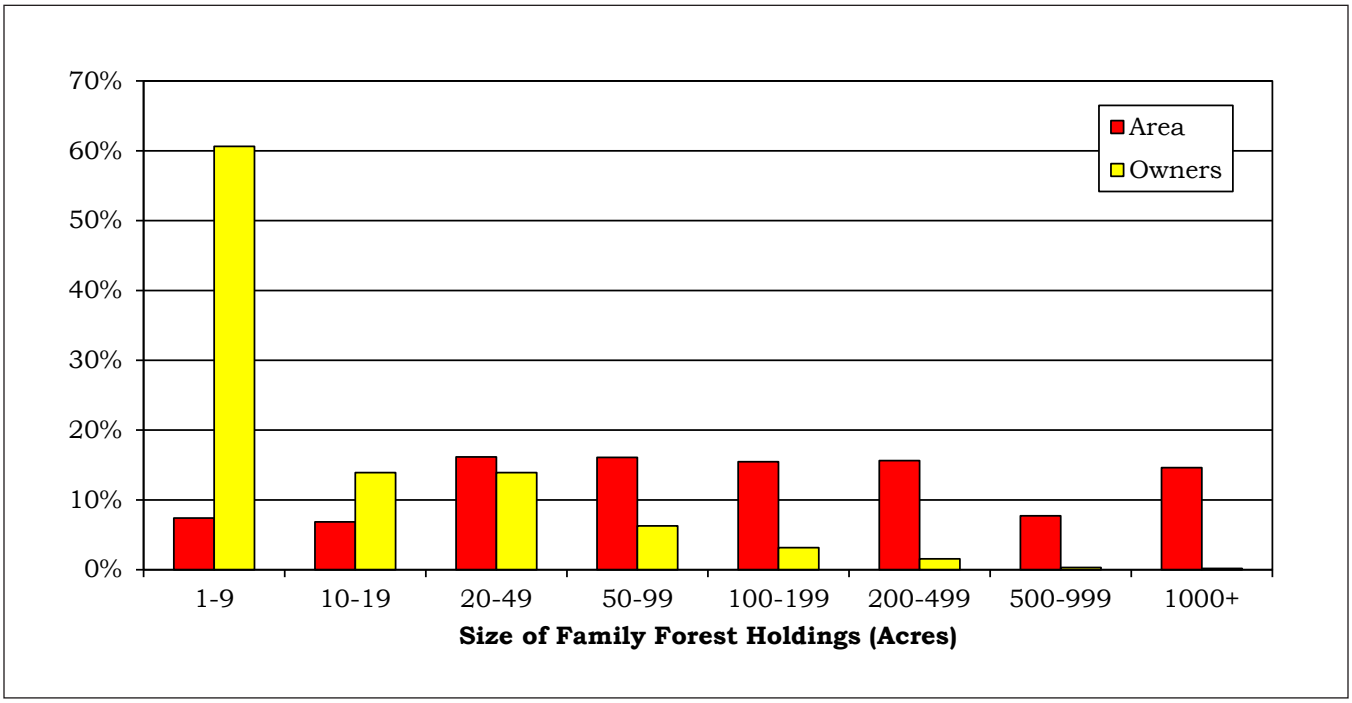


Figure 1.—Percentage of family forest acres and family forest owners by size of forest holdings (Butler 2008).

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USING MULTIPLE RESEARCH METHODS TO UNDERSTAND FAMILY FOREST OWNERS

John Schelhas[1]

Abstract.—Applied research on family forest owners ensures that we understand who they are, what they do, and why they do it. This information enables us to develop policy, management, and outreach approaches that can optimize the social, economic, cultural, and environmental benefits of private forests at the landowner, community, and national levels. The three principal scientific sources of information are National Woodland Owner Survey (NWOS) data, Forest Inventory and Analysis (FIA) data, and individual research efforts focused on specific geographical areas. NWOS and FIA data aim to be geographically comprehensive and are collected in intervals to provide time series data but are also less responsive to change in order to provide time series data. Individual research studies are tailored to specific questions, but their place specificity makes generalization difficult. We need to identify key management questions, use multiple research methods and data sources, and work collaboratively to maximize the effectiveness of our research.

INTRODUCTION

Family forests (sometimes called Nonindustrial Private Forest, or NIPF, owners) represent 40 percent of the forested acres in the United States and are particularly prevalent in the Eastern United States, where 83 percent of the forest is in private ownership (Butler and Leatherberry 2004). In the South, family forests represent about 95 percent of the private forest owners and 63 percent of the private forest land (Birch 1996). Family forests provide many important private and public benefits. Family forest owners benefit from their forest lands through economic returns from sales of timber and other forest products, returns on investments, harvesting of products for home or farm use, enjoyment of recreation opportunities, appreciation of aesthetics and wildlife, and perpetuation of family legacy. Family forest lands also provide public goods related to land ownership, timber and pulpwood supplies, economic development, biomass for energy, forest health, watersheds, biodiversity, and global climate change. Research on and outreach to family forest owners can enhance these benefits, and private forests have long been a key target of public policy and outreach (Best and Wayburn 2001).

The study of relationships between people and forests is complex. First, family forests are subject to myriad social, economic, cultural, political, and biophysical factors and changes. These influences include: (a) the ways that people value forests, (b) markets for forest products, (c) government policies and programs that provide assistance to forest owners and restrictions on their actions, (d) market-based governance mechanisms such as certification programs, (e) long- and short-term environmental changes, and (f) changing population and residence patterns. Second, private forests can be studied at various scales, including the individual family forest holding; smaller social or biophysical areas such as watersheds or communities; and larger political units such as states, regions, and the nation. Finally, people and forests are studied by many academic disciplines, including human dimensions of natural resources, anthropology, geography, rural sociology, economics, and political science.

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FAMILY FOREST RESEARCH

Studies of family forest owners have described their social and economic characteristics (Birch 1996, Hartsell and Brown 2002), attitudes and values (Bliss and Martin 1989, Schelhas and Pfeffer 2009), forest management practices in response to policies (Brockett and Gebhard 1999, Zobrist and Lippke 2003), and use of government and professional assistance (Zhang et al. 1998). Other research has examined social relationships among forest owners, the dynamics between communities and forests, and institutions and governance affecting people's interactions with forests (Gibson et al. 2000, Lee and Field 2005).

As a result of these studies, we know that family forest owners are diverse in terms of demographics, ownership objectives, and amount and type of forest owned (Best and Wayburn 2001). Families own forests for many reasons, such as aesthetics, wildlife, recreation, income, and investment, but non-commercial reasons tend to predominate (Koontz 2001). Timber harvest is rarely the main reason for owning forests, although most owners do harvest and sell timber (Koontz 2001). Only a small percentage of forest owners make use of professional forestry assistance and/or have written management plans (Butler and Leatherberry 2004). Most have only a limited knowledge of professional forestry, and many forest landholdings receive little systematic management attention (Birch 1996). Recent research has examined differences by owner type and parcel characteristics (Koontz 2001) and used cluster analysis to group forest owners by similarities (Majumdar et al. 2008). Research in the United States on social relationships, communities, and governance has lagged behind international research in these areas (Schelhas et al. 2003).

The body of research on family forests helps us to develop conceptual models that link people to forests, with a critical nexus being human behavior and forest conditions. We know that human forest-related behavior is determined by complex mixes of economics, values, social characteristics and relationships, institutions, and policies across scales. Environmental conditions that limit or enable various types of forest management and uses at particular places are also important in determining what people do. Complex people-environment interactions over time—and forests have a long-term temporal dimension—ultimately produce specific environmental conditions (habitat and biodiversity, biomass and carbon sequestration, watersheds) and human conditions (well-being of individuals and communities, economic and rural development). The practical value of research is learning about these broad relationships in a way that helps us to make educational, management, and policy interventions that steer human-forest relationships toward more environmentally and socially beneficial outcomes or identify tradeoffs.

HOW DO WE LEARN AND KNOW?

Ultimately, the science of people-forest relationships is cumulative—we are able to develop the knowledge we need only through multiple studies of different natures that draw on the full range of data types. It is important for us to step back occasionally and reflect on the goals of our research, the data we are collecting, and how we can most effectively move our knowledge forward. For family forest owners, we have three major data sources, each of which has different strengths and weaknesses.

National Woodland Owner Survey (NWOS) Data

Today's NWOS builds on earlier periodic surveys of forest owners (e.g., Birch 1996) and is now an annual survey of forest owners in 5- and 10-year cycles (Butler and Leatherberry 2004). The NWOS represents our only comprehensive effort to understand family forest owners over time. Its value to forestry is similar to the value of the U.S. Census of Agriculture in understanding farmers (Schelhas et al. 2003). The NWOS is the fundamental source of information about the characteristics and practices of family

forest owners, and how these change over time. It has limitations that include the following: (a) questions change slowly to enable longitudinal studies, but limit tailoring to new issues, (b) it has historically focused primarily on owner characteristics and practices, and not social relationships and governance, (c) both the general and forest owner population are suffering from survey fatigue, reducing response rates and forcing researchers to limit questionnaire length.

Forest Inventory and Analysis (FIA) Data

FIA data provide a systematic sampling of a fixed set of plots, measuring topography, site conditions, and forest characteristics (Majumdar et al. 2009). When linked to NWOS or other survey data, FIA data add the important dimension of environmental data and forest characteristics. These data are limited to the standard FIA measurements, and linking to other data is hindered by non-response rates in surveys and the NWOS and by the low density of FIA plots in the case of more geographically focused surveys.

Individual Research Projects

Researchers at universities and Federal agencies conduct question-driven research projects. These projects at times use data from systematic monitoring efforts like NWOS and FIA to answer specific questions, but often collect original data. The many forest owner surveys with econometric analysis (Beach et al. 2005) show relationships among different social and economic variables and are important in understanding forest and people relationships. Qualitative research provides more nuanced understanding of values and behaviors (Bliss and Martin 1989). Projects focusing on policies and institutions may use combinations of ethnographies, interviews, and text analysis (Gibson et al. 2000). What these individually focused projects gain in depth and focus, they lose in breadth; they generally cover single sites or a few selected comparison sites, thereby hindering generalizability.

FORMULATING POLICY- AND MANAGEMENT-RELEVANT QUESTIONS

The goal of applied research on family forest owners is to formulate questions relevant to policy and management and to draw on the full range of research methods and data types to answer them. Two examples highlight research projects that drew on diverse data sets to answer complex and important policy questions.

Kaetzel (2011) used both NWOS and FIA data from Alabama, Georgia, and South Carolina to conduct an analysis of timber availability that adjusted the standing timber according to forest owners' willingness to harvest timber. By taking into account the diverse values, objectives, and practices of forest owners along with their timber inventory, Kaetzel obtained a more refined and useful measurement of timber supply.

Schelhas and Pfeffer (2009) combined qualitative interviewing and a survey to develop a conceptual model of the formation of forest owner values from both global environmental messages and local conditions, and how these values interact with livelihood needs to determine behavioral outcomes. The results provide guidance to programs that encourage family forest owners to manage forests for environmental benefits in buffer zones and corridors.

CONCLUSION

Forestry and social science researchers are asking critical questions and collecting a great deal of relevant data. There are many advantages to using multiple methods. Combining both survey and qualitative research can lead to nuanced understanding that can be used to develop better questionnaires; statistical analysis of quantitative data obtained from these questionnaires can then be used to support qualitative findings (Schelhas and Pfeffer 2009). Adding forest and site data adds an important environmental component. Yet many research efforts are

compartmentalized by institutional, disciplinary, and data boundaries. We can learn more if we endeavor to identify key management and policy questions, draw on multiple sources of data, and work collaboratively in our research.

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FOREST VALUES AND THE IMPACT OF THE FEDERAL ESTATE TAX ON FAMILY FORESTS

Brenton J. Dickinson, Brett J. Butler, Michael A. Kilgore, Paul Catanzaro, John Greene, Jaketon H. Hewes, David Kittredge, and Mary Tyrrell[1]

Abstract.—Previous research has suggested that heirs to family forest land may sell timber and/or land in order to pay state and/or federal estate taxes, which could result in land use conversion or other adverse ecological impacts. We estimated the number of Minnesota family forest landowners and the associated acreage that could be subject to estate taxes at various exemption levels. Using 2011 Minnesota forest land sale transactional data we calculated the minimum acreage that would trigger the federal estate tax at different hypothetical tax exemption levels and estate compositions (percent of gross estate whose value is comprised of forest land). Using the U.S. Forest Service's National Woodland Owner Survey data for Minnesota and population mortality rates, we estimated the number of family forest ownerships and acres potentially affected under various scenarios.

INTRODUCTION

Of the United States' estimated 751 million acres of forested land, 35 percent is owned by families and individuals (Butler 2008). Family forests, sometimes referred to as non-industrial private forests, are owned by individuals, married couples, trusts, and other unincorporated entities.

The federal government has taxed the intergenerational transference of estates through various laws since 1916 (Jacobson et al. 2007). Some 20 states and the District of Columbia also currently impose estate and/or inheritance taxes; 12 impose estate taxes and six impose inheritance taxes. Two impose both (Michael 2011). The legal environment surrounding the estate tax has been particularly dynamic and uncertain over the past decade (Greene et al. in press).

From the perspective of large landowners in particular, the worst case scenario for estate tax law is that Congress allows the 2010 Tax Relief Act to sunset, causing the estate tax exemption and rate to revert to 2001 levels (Public Law 111-312, 124 Stat. 3296). That would mean that owners of estates worth more than $1 million ($2 million for couples) would have to pay a rate of 55 percent on estate value over that threshold. If Congress extends the current exemption and rate, owners of estates worth more than $5 million for individuals and $10 million for couples (plus inflation since 2001) will pay a rate of 35 percent.

The U.S. Forest Service expects that fully one-sixth of family forest land will be transferred over the next 5 years (USDA Forest Service 2012). This conclusion is derived in part by the fact that 19 percent of family forest owners fall within the ages 65-74 and an

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additional 15 percent are 75 or older. Collectively, this group of retirement-aged individuals owns 44 percent of family forests (Butler 2008). Some estates have had to sell parcels of land or timber to pay the estate tax (Greene et al. 2006). Given the area of land expected to be transferred in the near future, this raises two questions: How many owners and acres of forest land will be affected?; and Will affected landowners sell timber and/or land as a result?

The objective of this study was a) to estimate the number of owners and associated acres that could be affected by the federal estate tax; and b) estimate the degree to which timber and land might be sold as a result under various tax law scenarios within five states.

BACKGROUND

Greene et al. (2006) attempted to quantify the effects of the federal estate tax on land ownership patterns among family forest owners. The authors surveyed about 1,400 members of two forest owner groups: the National Woodland Owner Association and the American Tree Farm System. With a 33 percent response rate, they found that 9 percent of family forest owners were involved in an estate transfer between 1987 and 1997, during which there was a constant $600,000 exemption. Extrapolating, they estimated that 77,200 such transfers take place each year in the United States. Using average acreage owned by family forest owners, Greene et al. estimated the corresponding acreage to be 79.1 million per year.

Extrapolating from average acreage of timber in their sample that was sold to pay the estate tax, Greene et al. estimated that each year 4,900 estates sell timber to pay the estate tax, amounting to 2.4 million acres. The authors similarly estimated that 3,300 family forest owners sell on the order of 1.3 million acres annually to meet their tax liability. Since 29 percent of those sold parcels were developed, the authors estimated that about 400,000 acres of family forest are lost to development each year in such a fashion.

While the estimates made by Greene et al. (2006) need to be viewed with suspicion due to likely sample selection bias and other issues, they suggest that the estate tax has significant implications for the fate of family forests. No subsequent study has tried to reproduce or broaden their results. In this uncertain legal environment, there is a need for thorough understanding of how various permutations of estate tax law affect family forests.

METHODS

The degree to which forest land is affected by the estate tax depends in part on the forest land owners' estate compositions. Only forest estates worth more than $1 and $5 million would be affected by "worst case" and "status quo" tax scenarios, respectively. Assuming a worst-case tax scenario, an extreme case of "all-forest" estate composition, and using our estimated median per-acre price for Minnesota parcels greater than 100 acres ($975), only plots in excess of 730 acres would be affected by the estate tax. National Woodland Owner Survey (NWOS) data from 2006 suggest that an estimated 1,000 landowners in Minnesota own such parcels.

The extreme case of "all-forest" estate composition seems highly unlikely. We must take into account nonforest components of the estate: housing, investments, savings, and other assets. But we are faced with a near absence of data. We can only examine the affected owners and acres under differing assumptions of estate composition.

We began with a pilot study estimating forest land values in Minnesota. We obtained a sample of 489 forest land sales transactions in Minnesota that include the town, county, size of plot, and sales price.[2] These sales transactions occurred in 2009 and 2010 and represent only unimproved (no buildings) forested tracts, 20 acres or greater in size. We excluded tracts with improvements because we did not want to

[2] Source: Michael Kilgore, University of Minnesota

conflate forest land value with the value of buildings. We limited our sample to parcels of 20 acres or more.

We calculated hypothetical minimum acreage thresholds, assuming a variety of per-acre forest land values, estate compositions (percent of total estate that is forest by value), and estate tax exemption levels. Put another way, we constructed a set of simplifying assumptions about the population of forest land owners and then calculated the minimum number of acres a landowner would have to own to be affected by the estate tax given those assumptions. The 489 forest land sales transactions informed the range of per-acre price assumptions and the possible tax law scenarios informed the range of tax exemption level assumptions. We then used 2006 NWOS data from Minnesota landowners to estimate the number of landowners and associated forested acreage meeting specified acreage thresholds.

An estimated 1,700 family forest owners could be affected by the estate tax at a $1 million dollar tax exemption level, assuming estates are 50 percent forest and given a $975 per-acre price (Fig. 1). At a $5 million exemption level, the number of potentially affected ownerships drops to less than 50. The number of affected acres increases similarly for higher per-acre prices, estates with lower percent forest (by value), and lower tax exemption levels (Fig. 2). It is important to realize that these graphs indicate estimated owners and acres who *might* be affected by the estate tax, but not all of these landowners are expected to die (and therefore face the tax) every year. Nor does this information suggest how the families will react to the tax (e.g., sell land, sell timber, or some other action).

We can cautiously draw several conclusions. Under current estate tax law, it is mainly landowners who are relatively cash-rich and land-poor who will face the estate tax. That is because there are very few (if any) privately owned tracts of forest land valued near $5 million. If, on the other hand, the estate tax law is not continued at the status quo and instead reverts back to 2001 levels, many more landowners are expected to face the tax, including the relatively land-rich and cash-poor.

NEXT STEPS

To obtain reasonable estimates of the number of forest land owners who might face the estate tax, we need more details about forest land owners' estate compositions. Specifically, we need to know what percentage of their total estates are composed of forest land. We are currently surveying Minnesota landowners to request information on, among other things, the value of their total estate and what percentage of that estate value is forest land. With this information, we can assign a more realistic range of estate compositions to the analysis behind Figures 1 and 2.

We also will expand the analysis to four other states—California, Michigan, North Carolina, and Washington—following similar procedures. There appears to be at least some high quality forest land sales transaction data from Michigan, but the types of data we seek may not be available in all states. In that case we will alter our analytical approach and/or select different states.

Indeed, a preliminary search for forest land sales transaction data suggests a near total lack of availability. This highlights the need to develop a nationally consistent periodic assessment of forest land values across the United States, something we will explore further upon completion of this analysis.

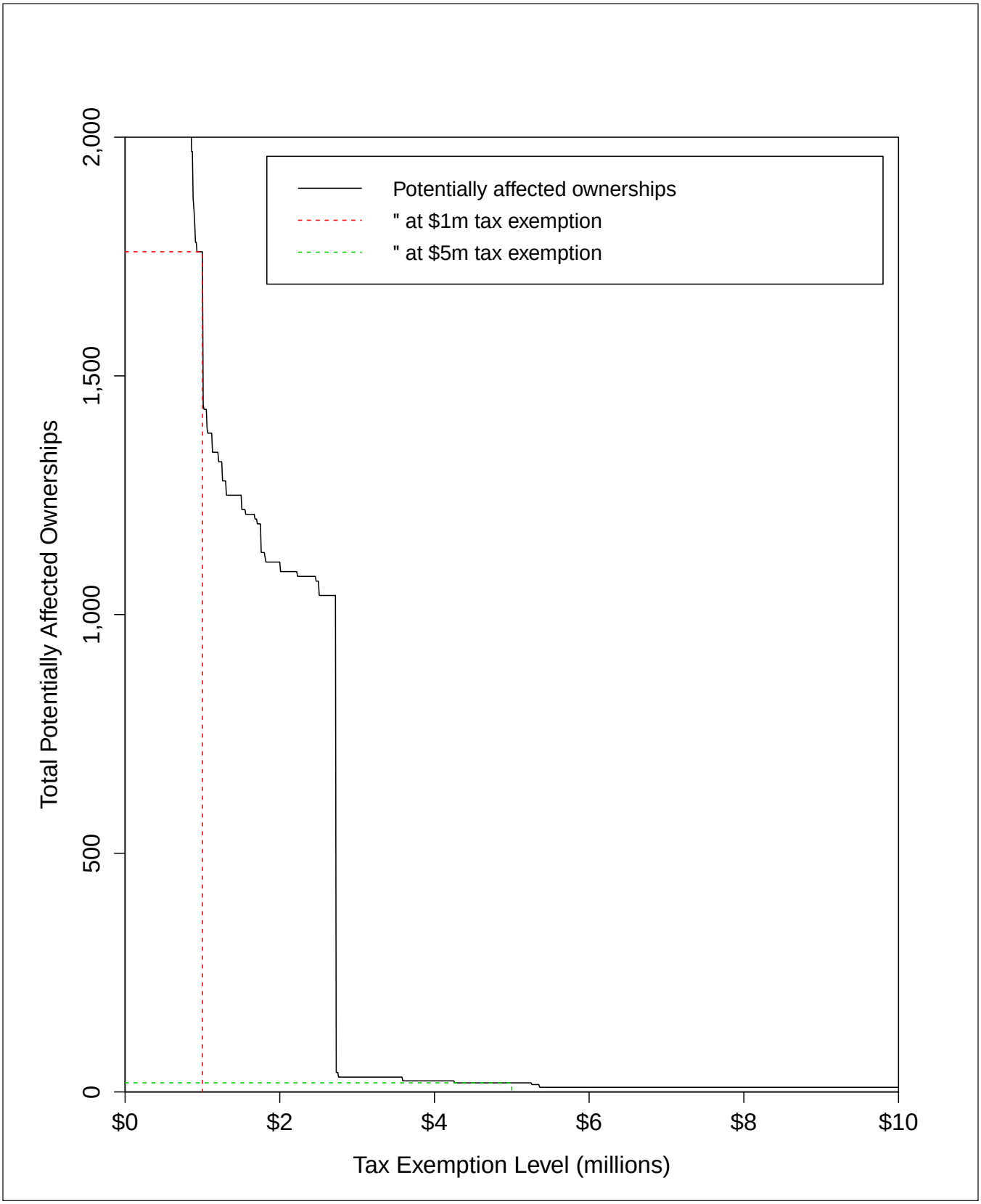


Figure 1.—Numbers of forest land owners potentially affected by the estate tax at varying tax exemption levels with estate = 50 percent forest and per-acre price = $975.

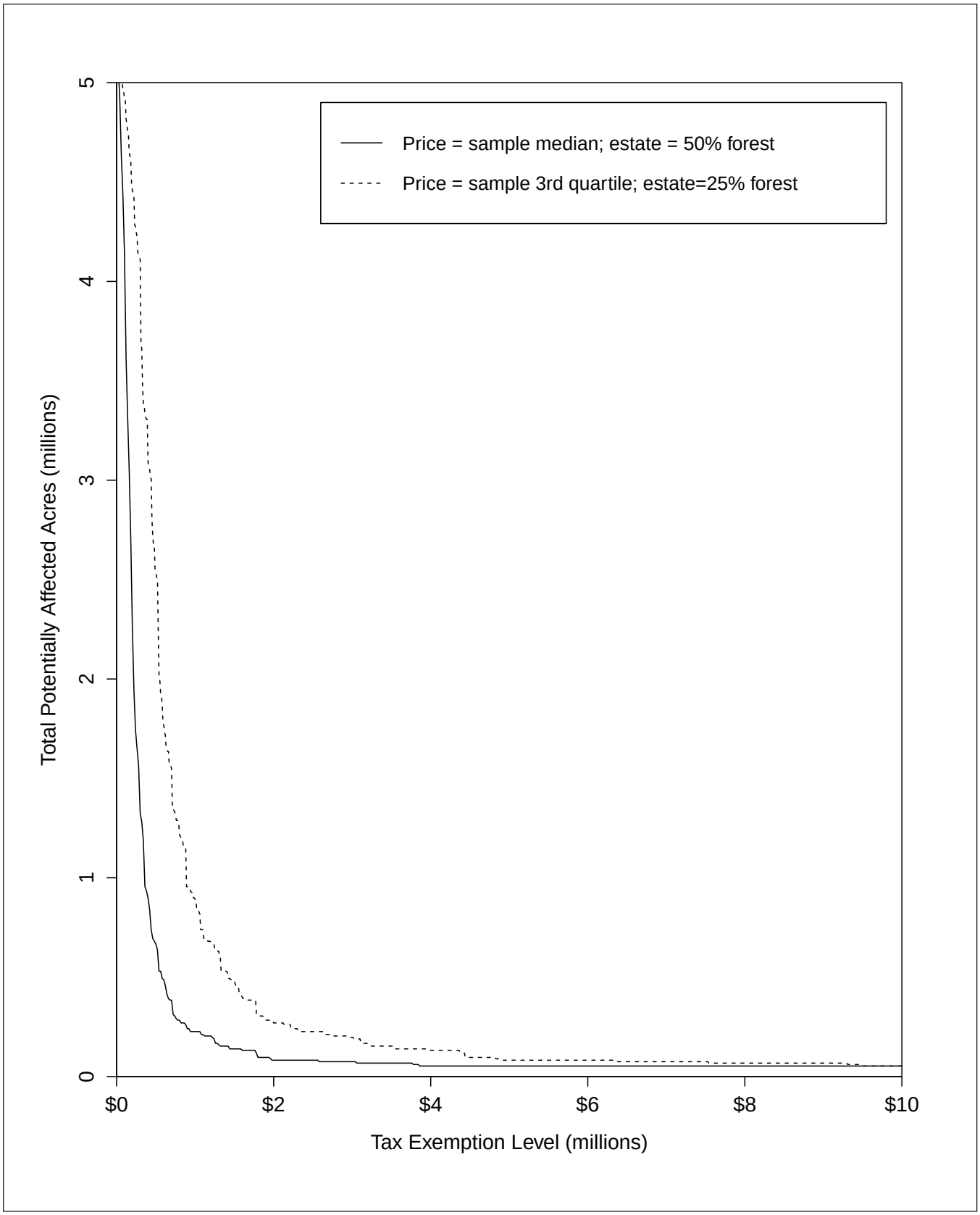


Figure 2.—Acres of forest potentially affected by the estate tax at varying estate values with varying estate composition and per-acre price.

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NONTIMBER FOREST PRODUCT HARVESTING ON FAMILY FORESTS: RESULTS FROM THE NATIONAL WOODLAND OWNER SURVEY

Marla R. Emery, Zhao Ma, Stephanie Snyder, and Brett J. Butler[1]

Abstract.—The 2002-2006 National Woodland Owner Survey asked a series of three questions about nontimber forest products (NTFPs) to assess the current status of their use on family forests. We report on responses to those questions. Logit models showed positive relationships between NTFP use and other forms of active engagement with family forests. Higher age and lower levels of educational attainment correlated negatively with likelihood of gathering, although not strongly. A history of gathering was the best predictor of future plans to do so.

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ASSESSING AND MITIGATING DENIED ACCESS ON FIA PLOTS

Brett J. Butler and Andrew Hill[1]

Abstract.—Nationally, field crews are denied access to approximately 11 percent of Forest Inventory and Analysis (FIA) forested plots that are privately owned. The denied access rate varies from less than 1 percent in Alabama, Georgia, Louisiana, Maine, South Carolina, and Virginia to more than 30 percent in Arizona, California, Colorado, Montana, New Jersey, Rhode Island, and Texas. The large disparity is due, in part, to state laws that govern access. We hypothesize that there are also significant differences in the socio-demographics of the private owners that are influencing access rates. The first part of this presentation will focus on the current patterns of denied access rates across the United States and present a model to help explain some of its causes. There is a rich body of literature, primarily related to surveys, that has theoretically and empirically examined ways for maximizing response rates. This literature deals with topics such as personalization of communications, financial and nonfinancial incentives, modes of contacts, and timing of contacts to name but a few. We believe these findings may be very useful for minimizing FIA denied access rates. The second part of our presentation will focus on a literature synthesis and experiment that we are conducting to identify best practices for minimizing denied access rates.

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METHODS FOR MEASURING AND ASSESSING LANDSCAPE CHANGE

COMPARISON OF FOREST AREA DATA IN THE CHESAPEAKE BAY WATERSHED

Tonya W. Lister and Andrew J. Lister[1]

Abstract.—The Chesapeake Bay, the largest estuary in the United States, has been designated by executive order as a national treasure. There is much interest in monitoring the status and trends in forest area within the bay, especially since maintaining forest cover is key to bay restoration efforts. The Chesapeake Bay Land Cover Data Series (CBLCD), a Landsat-based, multi-temporal change detection raster geographic information system (GIS) product was developed by the U.S. Geological Service (USGS) to monitor land cover change in the bay. The objective of this study was to assess relationships between the CBLCD dataset and Forest Inventory and Analysis (FIA) estimates of land use in order to provide a better understanding of the nature of the CBLCD and its potential for use in assessing forest cover dynamics. Data were summarized at different geographic scales, and differences between datasets were highlighted with the goal of providing information that will help users of the CBLCD interpret findings. Our analyses suggest there is a strong, positive relationship between the CBLCD forest information and that from the FIA data. Misclassifications can be explained by analyses created by integrating the CBLCD data with the FIA data and standard FIA reporting tools.

INTRODUCTION

The Chesapeake Bay Watershed, which includes parts of Maryland, Delaware, Pennsylvania, New York, Virginia and West Virginia, contains the largest estuary in the United States and provides habitat for thousands of species of plants and animals. The forests in this area provide many ecological services including protecting drinking water, serving as buffers against sedimentation and nutrient enrichment for estuarine species, and providing economic and other benefits for humans. However, the forests in the Chesapeake Bay Watershed have experienced a 2 percent net loss of forest land since the 1980s (Lister and Perdue 2011). Claggett et al. (2004) predict significant perturbations of the bay region's forests in the coming decades, due largely to development pressures.

In recognition of the importance of and current and future threats to the bay's natural resources, Congress and several of the states containing parts of the watershed established the Chesapeake Bay Program partnership in the early 1980s. This partnership was based in part on an agreement to protect and restore the Bay's ecosystems and has since been reaffirmed and updated. One component of the agreement is that the signatories will work to establish a system to monitor the status of and trends in forest cover.

The Chesapeake Bay Land Cover Data Series (CBLCD) was developed to help with these efforts to track and monitor forest land in the bay (Irani and Claggett 2010). The CBLCD is a 30-m Landsat-based, multi-temporal geographic information system (GIS) change detection dataset produced by the U.S. Geological Survey (USGS 2006). The data series was created by merging the National Land Cover Dataset (NLCD) from the USGS (Homer et al. 2007) with land cover data from the National Oceanic and

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Atmospheric Administration's (NOAA) Coastal Change Analysis Program (C-CAP) (NOAA 2007) and improving the classification of urban and agricultural land. The CBLCD can be used to characterize land cover conversions for several dates between 1984 and 2006. It is not clear, however, how the land cover classification system used by the CBLCD, which is based on that of Anderson et al. 1976, agrees with that used by other agencies, such as the U.S. Forest Service's Forest Inventory and Analysis (FIA) Program. The FIA Program uses a network of ground plots to characterize land use on all lands along with tree and site information associated with forest land.

The goal of the current study was to assess relationships between the CBLCD dataset and FIA estimates of land use in order to provide a better understanding of the nature of the CBLCD and its potential for use in assessing forest cover dynamics.

MATERIALS AND METHODS

The original classification system used for the 2006 CBLCD image (USGS 2006) was reclassified into eight categories: open water/perennial ice and snow, developed open space, developed low-high intensity, barren land, forest including woody wetlands, shrub/scrub, grassland/herbaceous, pasture/hay/cultivated crops, and emergent herbaceous wetlands.

A GIS was used to intersect the U.S. Census Bureau's Tiger Line 2010 GIS county boundary files with a GIS file of the outline of the Chesapeake Bay Watershed. Within each of the counties that were completely within the watershed, areas of each of the eight reclassified CBLCD land cover classes were tabulated. Within these same counties, the area of forest land use was calculated from the FIA data using the PC EVALIDator tool, and a linear regression analysis with accompanying R2 values was calculated to assess relationships. Next, the individual FIA plots were used to characterize the CBLCD. Locations of the 4,784 FIA plots within the watershed (Fig. 1) were used to generate 43-m radius circular buffers which were then intersected with the CBLCD. The reclassified CBLCD class with maximum area within the buffer was assigned to each FIA plot location. This new attribute was then incorporated into the PC EVALIDator reporting tool and was used as a categorical variable for conducting cross tabulations of FIA data (Miles 2009). Cross tabulations included estimates of forest area by combinations of CBLCD class and FIA major land use, stocking, stand size, and physiographic classes (Woudenberg et al. 2010). In addition, a land use matrix from the PC EVALIDator tool that compares FIA major land use (forest, nonforest, and water) with the equivalent classes from the CBLCD was generated.

RESULTS AND DISCUSSION

An assessment of the relationship between the county FIA forest use and the CBLCD forest cover area estimates is shown in Figure 2. Summary statistics that describe the fit of the linear relationship indicate a strong, positive, nearly 1:1 linear relationship between the two attributes for all counties in each of the states, with R^2 values greater than 0.80 in all cases. This suggests that there is no spatial trend in the strength of the relationship, or spatial variation in the CBLCD product. The land class matrix that was created to compare forest, nonforest, and water classes on FIA-sampled land with the equivalent classes from the CBLCD (Table 1) also indicates strong agreement, with 87 percent agreement between the FIA and CBLCD estimates. This is further evidence that there is a strong correspondence between forest information from the CBLCD and the land use information associated with the FIA data. The strength of the relationship is somewhat surprising given the differences in the definitions of the attributes. For example, FIA defines forest land using a combination of stocking, aerial extent and shape of the land cover patch, and an assessment of the ability of the land to provide forest regeneration. The CBLCD definition of forest land is based on that of the USGS National Land Cover Dataset (NLCD) (Homer et al. 2007) and includes tree canopy cover thresholds instead of

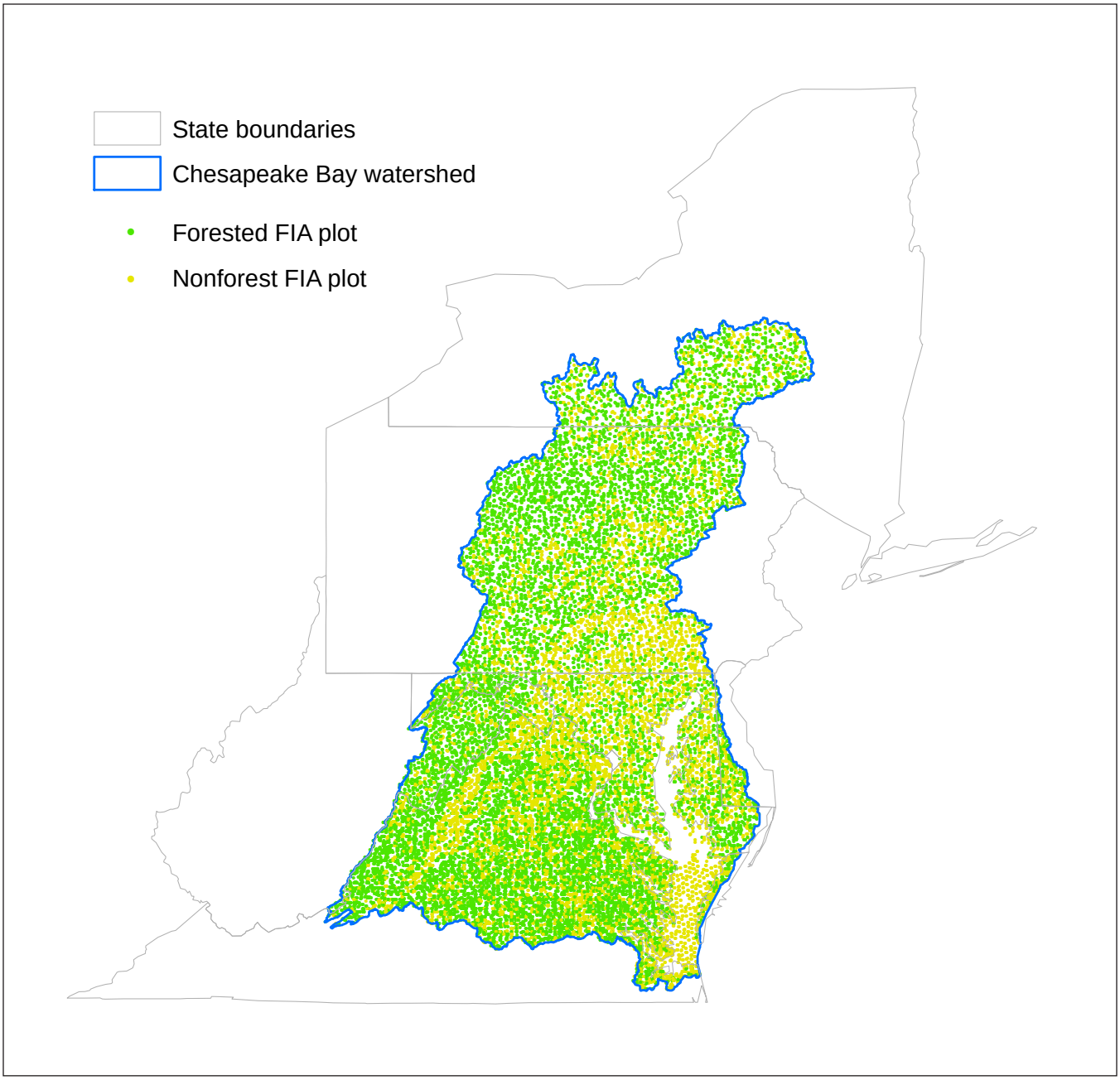


Figure 1.—Distribution of FIA plots within the Chesapeake Bay. Plot locations are approximate.

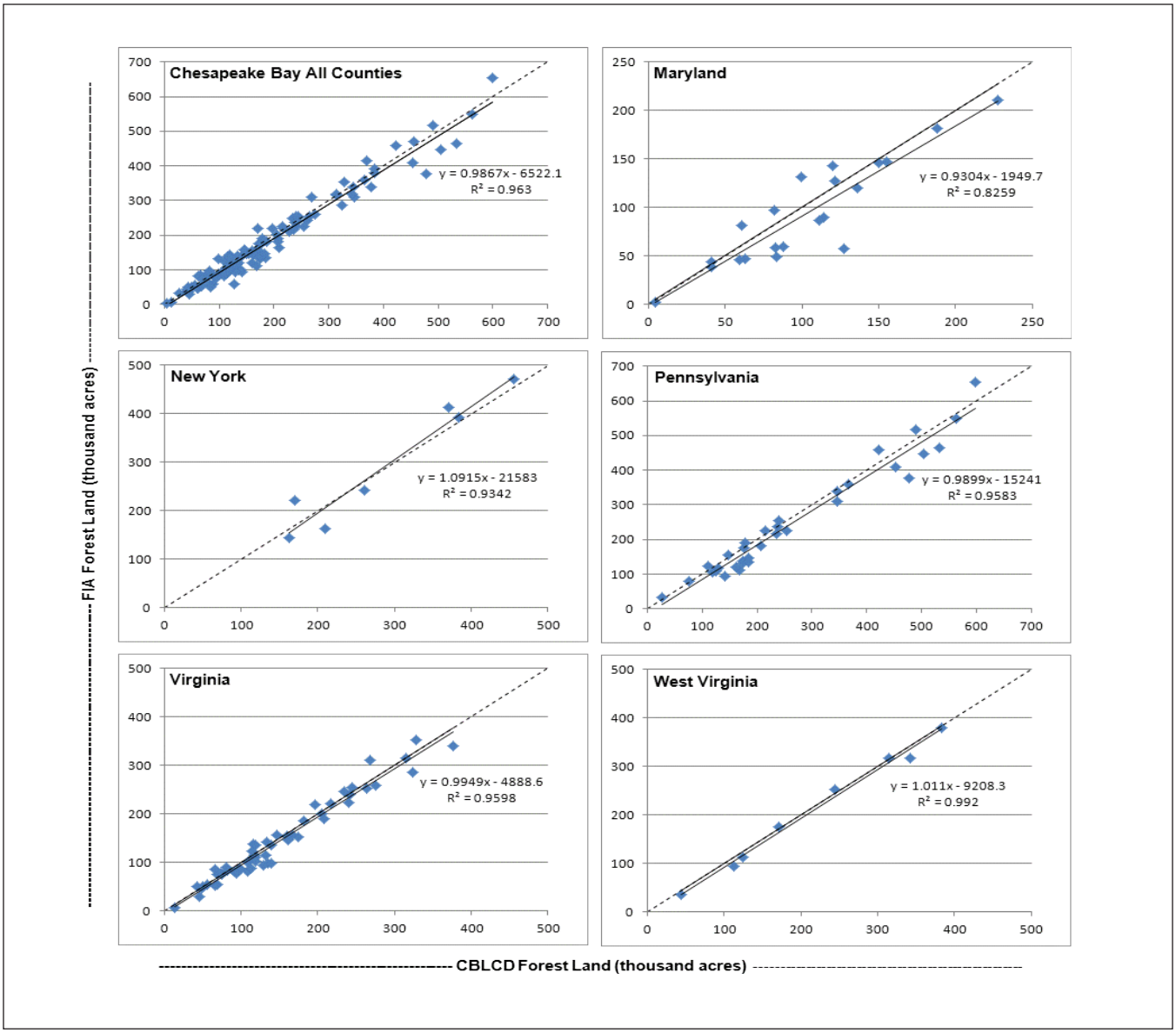


Figure 2.—Comparison of county-level FIA forest land estimates with county-level CBLCD within the Chesapeake Bay Watershed. Dashed line represents a 1:1 linear relationship.

Table 1.—Land use matrix comparing FIA to collapsed Chesapeake Bay Land Cover Data series (CBLCD) cover class data in the Chesapeake Bay Watershed

	CBLCD (acres)			
FIA (acres)	**Forest**	**Nonforest**	**Water**	**Total**
Forest	21,636,051	1,948,338	21,198	23,605,587
Nonforest	2,981,308	13,679,780	60,660	16,721,748
Water	202,872	97,682	457,811	758,365
Total	24,820,231	15,725,800	539,669	41,085,700

stocking and different aerial extent requirements for inclusion in the forest class. Although the distinction between land cover and land use can sometimes be stark (e.g., a clearcut with no trees can still be a forest land use), it is clear that in the case of the CBLCD and the FIA data, the majority of the land cover, as detected by the satellite, is also forest land use as detected by a ground observer on an FIA plot. Generally, it must be assumed that forest cover maps like the CBLCD are surrogates for forest land use maps, since forest land use maps are challenging to produce and are not widely available.

The area of forest land from the CBLCD classes assigned to the FIA plots was 5 percent higher than that derived from the FIA forest classes from the same plots (Table 1). This is an expected result given that the CBLCD estimates forest cover and FIA estimates are land use based. For example, the CBLCD may assign a forest cover class to treed areas where the underlying use is not forest, but rather a treed, low density residential development. Accuracy statistics from the NLCD 2001 dataset in Massachusetts and Rhode Island show a similar (almost 8 percent) overestimate of forest, with most misclassifications occurring where the NLCD forest class was actually developed for agricultural land use (Hollister et al. 2004).

Ninety-two percent of the land FIA plots classified as forest is also classified as forest by the CBLCD (Table 1). The majority of the remaining 8 percent is classified as agricultural and shrubland (Fig. 3). These types of differences may be due to the presence of marginal agricultural lands at various stages of succession in the area. It is likely that the CBLCD classification procedures had difficulty distinguishing old or fallow fields from forest. We had expected to see this hypothesis reinforced by an analysis of the areas of CBLCD classes within areas classified as FIA forest, partitioned by stocking class and stand diameter class (Fig. 4) since one might expect areas

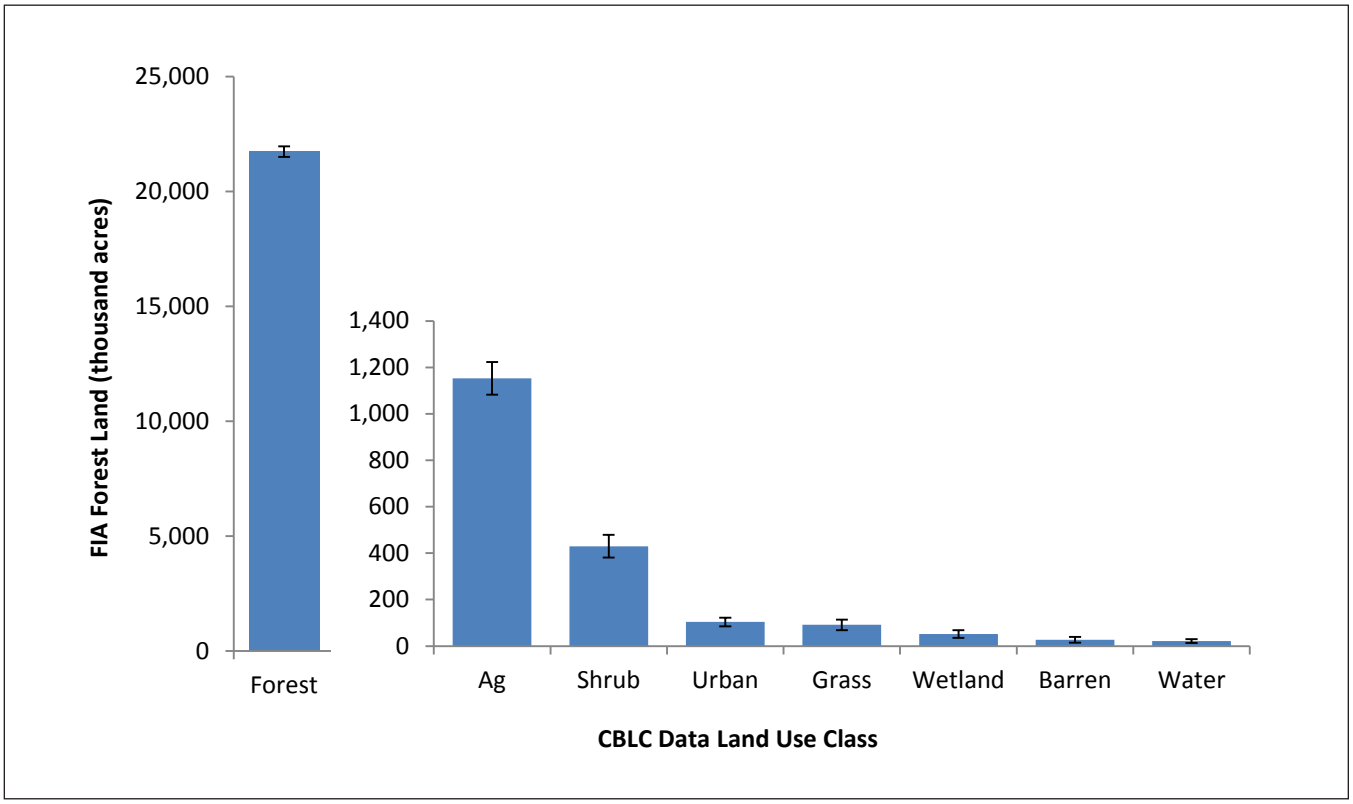


Figure 3.—Composition of the FIA forest land estimate by corresponding CBLCD land use class. Error bars represent 68 percent confidence intervals.

with a higher stocking class or larger trees to generate more of a "forest signal" in the CBLCD classification procedure. Although the data do not suggest that forested plots with low stocking classes are more likely to be misclassified, the data do suggest that there is generally a large proportion of medium and higher stocked plots in the forest class. Two notable exceptions to this pattern, however, are the barren and the grassland CBLCD classes, which also show relatively high areas of medium and higher stocked

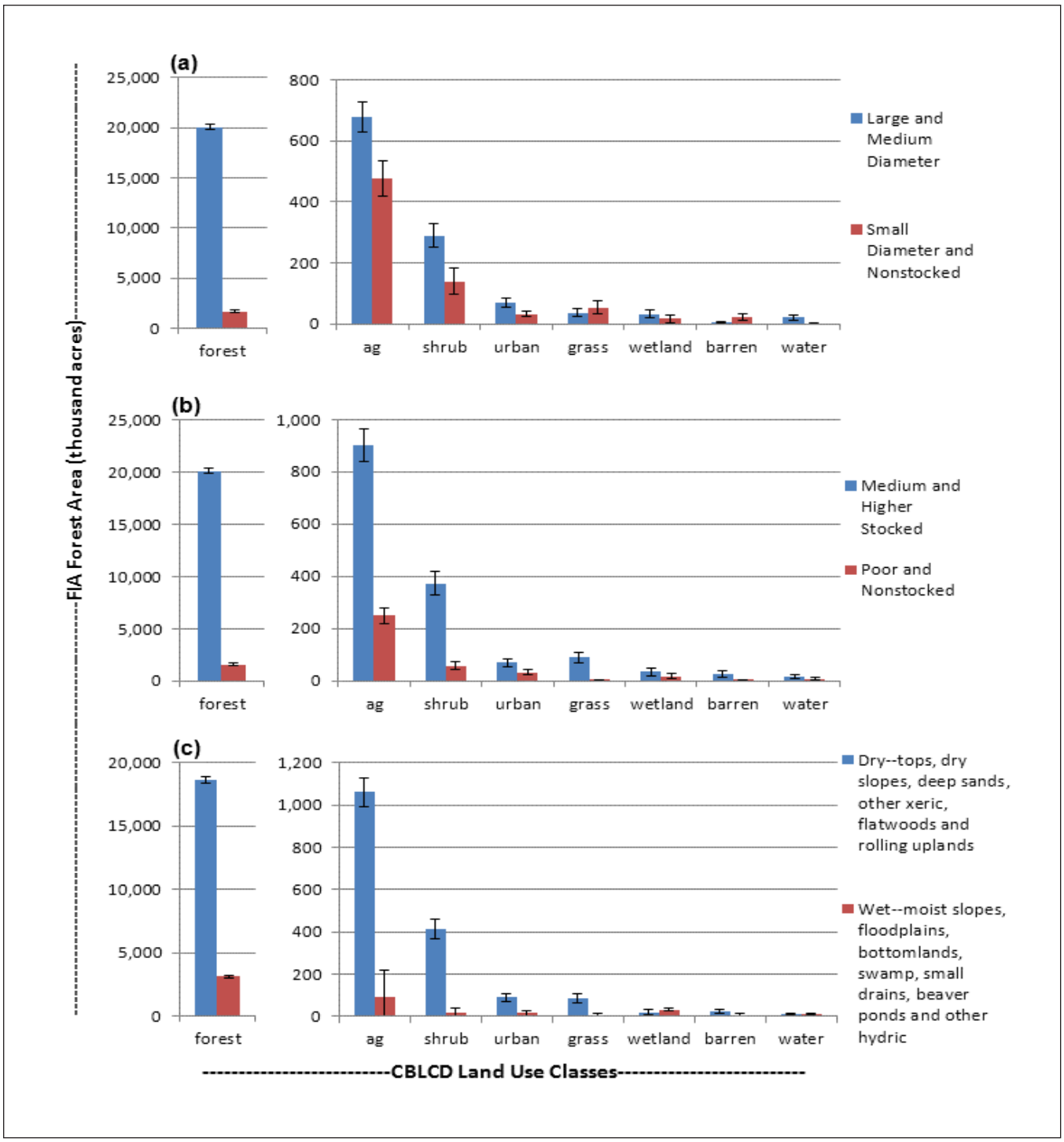


Figure 4.—Forest land area of select FIA forest class variables including stocking class (a), stand size class (b), and physiographic class (c), within each CBLCD land use class. Error bars represent 68 percent confidence intervals.

stands. This could be explained by the relatively large areas of small diameter stands within these classes (Fig. 4b), suggesting that the high stocking values are due to large numbers of small trees or seedlings. These areas may confuse the classification algorithm as they may resemble barren sites or grasslands.

Another interesting finding from our comparisons is the amount of FIA forest land area misclassified as water by the CBLCD (Fig. 3). While this is a fairly serious misclassification, Figure 4c suggests that the physiographic classes associated with these misclassified areas tend to be wetter (coves, floodplains, bottomlands, swamps, ponds) than areas associated with other types of misclassifications. In these areas, the signal imparted by these wet sites likely led to the confusion of the classification algorithm.

Our main conclusion from this study is that, assuming FIA data are representative of the forest attributes that Chesapeake Bay land managers want to monitor, the strong relationship between CBLCD and FIA data indicates that the CBLCD can be a valuable tool for characterizing land cover in the Chesapeake Bay Watershed. Our analyses suggest that in aggregate (at the county scale) there is a strong, positive relationship between the CBLCD forest information and that from the FIA data. Misclassifications that occurred can be explained by analyses created by integrating the CBLCD data with the FIA data and standard FIA reporting tools. Results of this study shed light on the relationship between the two land classification systems and will provide managers with information that can be used to not only interpret land class changes in the Chesapeake Bay Watershed, but also to help improve future versions of the CBLCD product. Future work will involve looking at species assemblage data and their effects on relationships between CBLCD and FIA data, as well as the relationship between other land cover products and FIA data in this important region.

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ASSESSMENT OF LAND USE CHANGE IN THE COTERMINOUS UNITED STATES AND ALASKA FOR GLOBAL ASSESSMENT OF FOREST LOSS CONDUCTED BY THE FOOD AND AGRICULTURAL ORGANIZATION OF THE UNITED NATIONS

Tanushree Biswas, Mike Walterman, Paul Maus, Kevin A. Megown, Sean P. Healey, and C. Kenneth Brewer[1]

Abstract.—The Food and Agricultural Organization (FAO) of the United Nations conducted a global assessment for forest change in 2010 using satellite imagery from 1990, 2000, and 2005. The U.S. Forest Service was responsible for assessing forest change in the United States. A polygon-based, stratified sampling design developed by FAO was used to assess change in forest area within 10 km by 10 km tiles at every 1° from 1990, 2000, and 2006 using Landsat TM and ETM+ data. The assessment included: 1) mapping land cover (tree and non-tree) and land use (forest and nonforest) within these tiles for each time period; 2) a segment-based analysis of land use transition between 1990 and 2000, and 2000 and 2005; 3) reporting forest change (area) by FAO ecoregions; and 4) comparing the estimates from segment-based analysis of land cover and land use change in the coterminous United States between the study periods. The current paper summarizes the estimates of land use change by FAO ecoregions in the United States between 1990 and 2000, and 2000 and 2006 based on the survey and compares land cover and land use change estimates for the coterminous United States. Our analysis shows that most forested and nonforested areas remained unchanged during each time period. Overall rate of forest loss was higher between 1990 and 2000 than between 2000 and 2006. Net forest loss in the United States for the entire study period was 0.79 percent. The ecoregion stratum subtropical humid forest showed the highest net forest loss, followed by temperate continental forest and temperate mountain system. Net forest and tree cover change was higher in 1990-2000 than 2000-2006 in the coterminous United States and confirmed that land cover change does not necessarily indicate land use change.

INTRODUCTION

The Remote Sensing Application Center conducted a survey of land cover and land use change in the United States (including Alaska) using a forest sampling design developed by the Food and Agricultural Organization (FAO) of the United Nations (Ridder 2007) for global assessment of forest loss. The survey included a segment-based assessment of land use and land cover types within 10 km by 10 km grids at every 1° interval for 1990, 2000, and 2006 (Fig.1). Land cover (tree, woodland, other, and water) and land use (agriculture, bare, built-up, forest, natural herb, other wooded land, wetland, and water) were mapped within these grids (Fig.1). For simplicity of analysis the land cover types were merged into two broad classes "Tree" and "NonTree" while the land use types were merged into "Forest" and "NonForest"' classes to assess change and meet FAO's goal of global assessment of forest loss (Table 1). Woodland and other wooded land were included in "NonTree" and "NonForest,"

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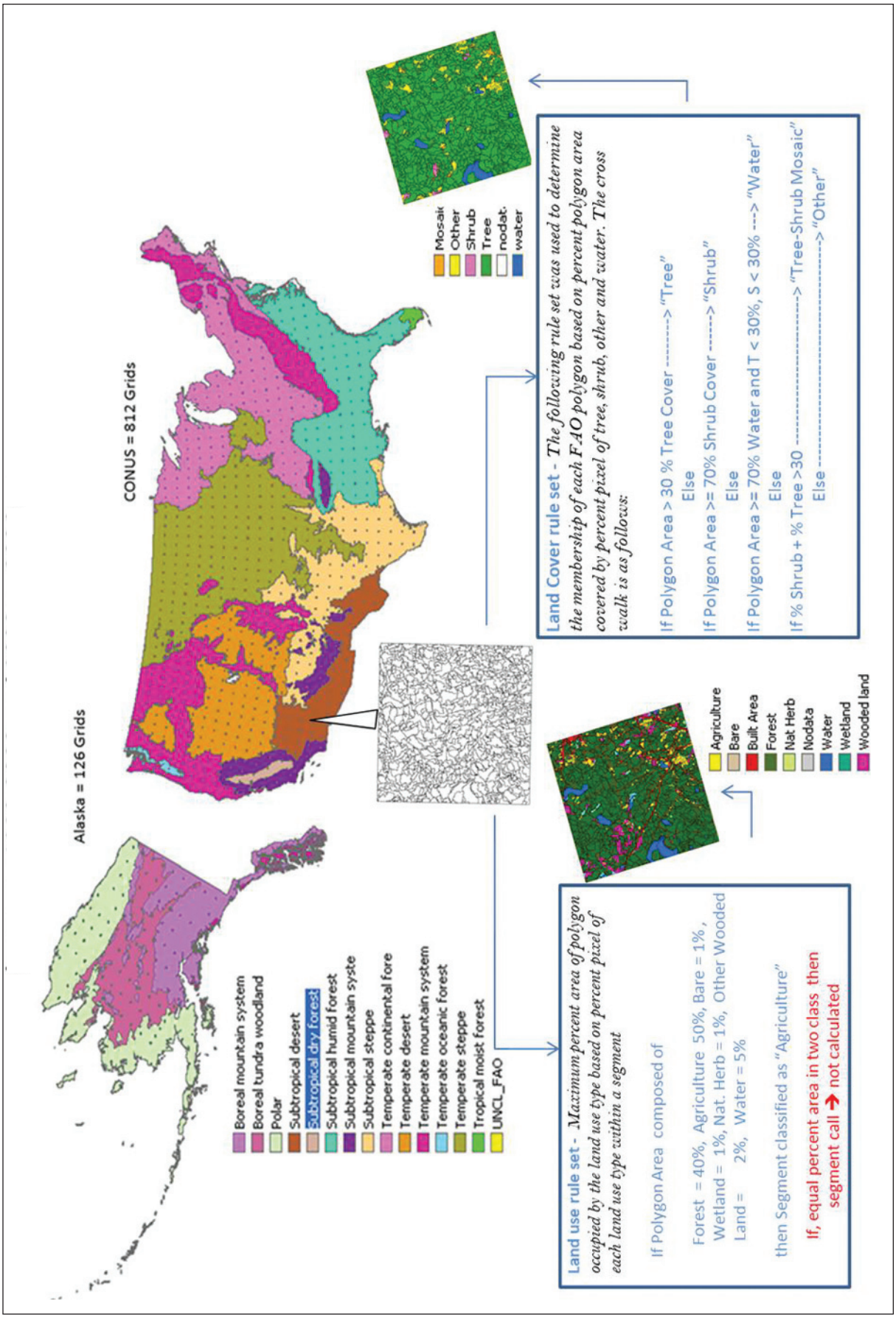


Figure 1.—Distribution of the 10 km x km study grids and the rule set used to classify the segments within the grids into land cover and land use types based on the corresponding NLCD data for assessing land use and land cover changes within the United States between 1990, 2000, and 2006. These rule sets were only used to classify the segments within the survey grids within CONUS based on pixel (30 m resolution) information available from NLCD data cross walked to corresponding land use and land cover product for each time period.

Table 1. Cross walk between NLCD land cover types and FAO land use and land cover types

NLCD Class (1990, 2000, 2006)	FAO Classes-Level I		FAO Classes-Level II	
	Land Use	Land Cover	Land Use	Land Cover
Deciduous Forest	Forest	Tree	Forest	Tree
Evergreen Forest	Forest	Tree	Forest	Tree
Mixed Forest	Forest	Tree	Forest	Tree
High Intensity Residential	Built-Up	Other	NonForest	NonTree
Low Intensity Residential	Built-Up	Other	NonForest	NonTree
Commercial Industrial	Built-Up	Other	NonForest	NonTree
Open Water	Water	Water	NonForest	NonTree
Orchard/Vineyards	Agriculture	Other	NonForest	NonTree
BareRock/Sand/Fallow/Barren	Bare	Other	NonForest	NonTree
Pasture/Hay	Natural Herb	Other	NonForest	NonTree
Grassland/Herbaceous	Natural Herb	Other	NonForest	NonTree
Emergent Herbaceous Wetlands	Wetlands	Other	NonForest	NonTree
Row Crop/Small Grain	Agriculture	Other	NonForest	NonTree
Shrubland	Woodland	Shrub	NonForest	NonTree
Transitional	Woodland	Shrub	NonForest	NonTree
Urban	Built-Up	Other	NonForest	NonTree
Woody Wetland	Other Wooded Land	Other	NonForest	NonTree
Quarry, Mine	Bare	Other	NonForest	NonTree
Perennial Ice/Snow	Bare	Other	NonForest	NonTree
Dwarf Scrub	Other Wooded Land	Shrub	NonForest	NonTree

respectively (Table 1). Changes in land use and land cover within these grids were summarized by different ecoregions (Commission for Environment Cooperation 2006) in the United States between 1990 and 2000, and 2000 and 2006. The current paper provides an overview of the methods and assessment of land use change conducted in the United States.

METHODS

We assessed forest loss in the entire United States based on 938 grids provided by FAO (Fig.1). The following section discusses the methods used for mapping, change detection, and validation of change in the coterminous United States (CONUS) (812 grids) and Alaska (126 grids).

Mapping

(i) Coterminous United States. The National Land Cover Database (NLCD) product (30-m resolution raster, available from the corresponding time period [1990, 2001, and 2006]) was used for the assessment in the coterminous United States (Fry et al. 2011, Homer et al. 2007, Vogelmann et al. 2001). The NLCD land cover types corresponded closely to FAO's land cover and land use classes of interest by FAO (Table 1). The segments within the grids (n=812) were classified based on pixel (30-m resolution) using information available from NLCD-derived land use and land cover product for each time period (Fig. 1).

(ii) Alaska. Absence of NLCD product for Alaska from all study periods led to independent unsupervised classification of Landsat TM imagery of 126 grids into forest and nonforest classes for each time period. Zonal majority of area under forest and nonforest within each segment was eventually used to classify the segments to the dominant land use type.

Change Detection

(i) Land Use. The land use types from each time period from CONUS were merged to forest and

nonforest classes (Table 1) to assess change in the United States across four transition types: forest to nonforest (forest loss), nonforest to forest (forest gain), forest to forest (no change forest) and nonforest to nonforest (no change nonforest). Change in area (ha) under each transition type was summarized by each ecoregion for 1990 to 2000, and 2000 to 2006. A latitude correction factor was used to account for the variation in area of each segment in the study area based on location relative to the equator (Equation 1). The correction factor was applied to all the segments prior to assessing area under different land use transitions.

$$\text{Latitude Correction Factor} = 2*pi*R*\cos(lat) / (2*pi*R*\cos(lat0)) = \cos(lat)/\cos(lat0) \quad \text{Eq (1)}$$

(ii) Land Cover. Land cover change was conducted only for the coterminous United States across four transition types: tree to non-tree, non-tree to tree, no change tree, and no change non-tree. The latitude correction factor was used to summarize the area estimates of land cover change within the four transition types.

Validation

The validation exercise was conducted only for land use change to meet FAO's goal of estimate of forest loss. A stratified random sampling approach was used to photo interpret (PI) a minimum of 20 random points within each land use transition in each FAO region for each time period. Google Earth™, National Agricultural Imagery Program imagery from 2000 and 2006, and ground knowledge of the PI personnel were used to validate the land use transition of the segment that intersected with the random points. The agreement matrix for validation was enumerated from the weights of sampled points instead of actual count of points within each transition. The weight of each sampled point within each stratum was developed as a function of the area of the land use change stratum relative to the total area and total number of points within the stratum (Fig. 2). The proportion of agreement and disagreement in the land use transitions observed between the PI land use change call and NLCD results was used to develop a correction factor for the final estimate of area under each transition type in each FAO region.

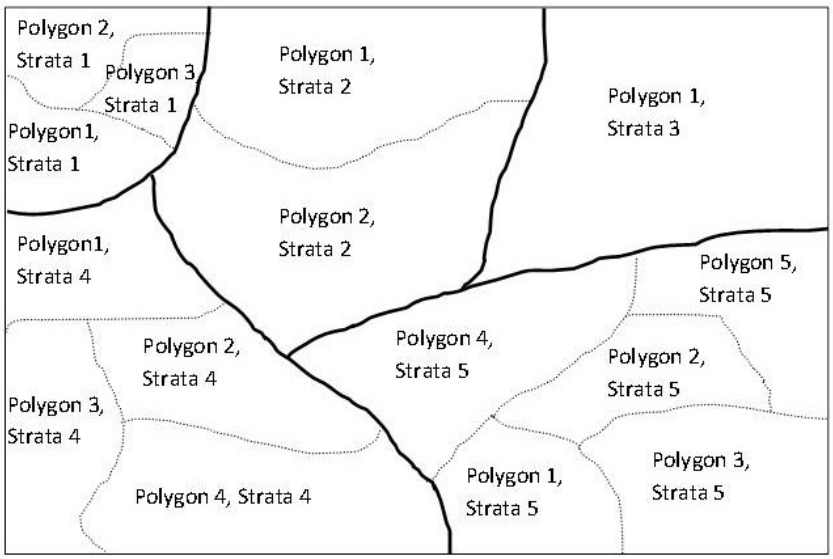
A total of 2,536 points were validated for observed land use transitions between 1990 and 2000 with 120 points in Alaska and the rest in CONUS. For the second time period 1,280 points were validated for all the land use transition types observed in each FAO region between 2000 and 2006. For the first time period sampling for validation was done within 64 land use transitions before merging the land use classes to forest and nonforest and without the knowledge of the FAO ecoregions. Using the weights of the sampled points instead of actual counts also accounted for the difference in sampled size under each land use transition between the study periods.

RESULTS

Land Use Change

Land use change (overall forest loss and forest gain) was assessed based on the original area of segment, area corrected by latitude, and latitude-corrected area post-validation and by different ecoregion (Fig. 3). These results suggest the importance of latitude correction and an accuracy assessment of change, and effect of location and relative size of the segments, on the overall estimate of forest loss. Segments from Alaska (Ecoregion - Polar and Boreal) after the latitude correction had considerable influence on the overall estimate and percent forest loss and forest gain. The final estimates used to report and summarize land use change during this study were derived from the latitude correction function and validation.

The results of the survey indicate more nonforested area than forested area, with most of the forest (28.8% in 1990-2000, 30.8% in 2000-2006) and nonforest (68.6% in 1990-2000, 68.2% in 2000-2006) area remaining stable (Table 2). Overall rate of loss of



To determine the weight each polygon contributes to accuracy we can use the chain rule to define a strategy for finding this probability of selection:

$$p(\text{strata} = i, \text{polygon} = j) = p(\text{polygon} = j \mid \text{strata} = i) * p(\text{strata} = i)$$
$$= (1/n_i) * p(\text{strata} = i) = p(\text{strata} = i) / n_i$$

where,

n_i is the number of samples within strata I

$p(\text{strata} = i)$ is area of strata _ i / Total Area of all strata

These probabilities are simply the proportion, by area, of each polygon. The points divide the strata into n_i equal areas (again, where i is the i'th strata).

E.g, The weight of 10 random points sampled within Forest-NonForest Transition can be computed by the following formula :

Area Forest-NonForest Transition/Total Study Area *1/10

Figure 2.—Calculating the weight of each sample point by land use change strata.

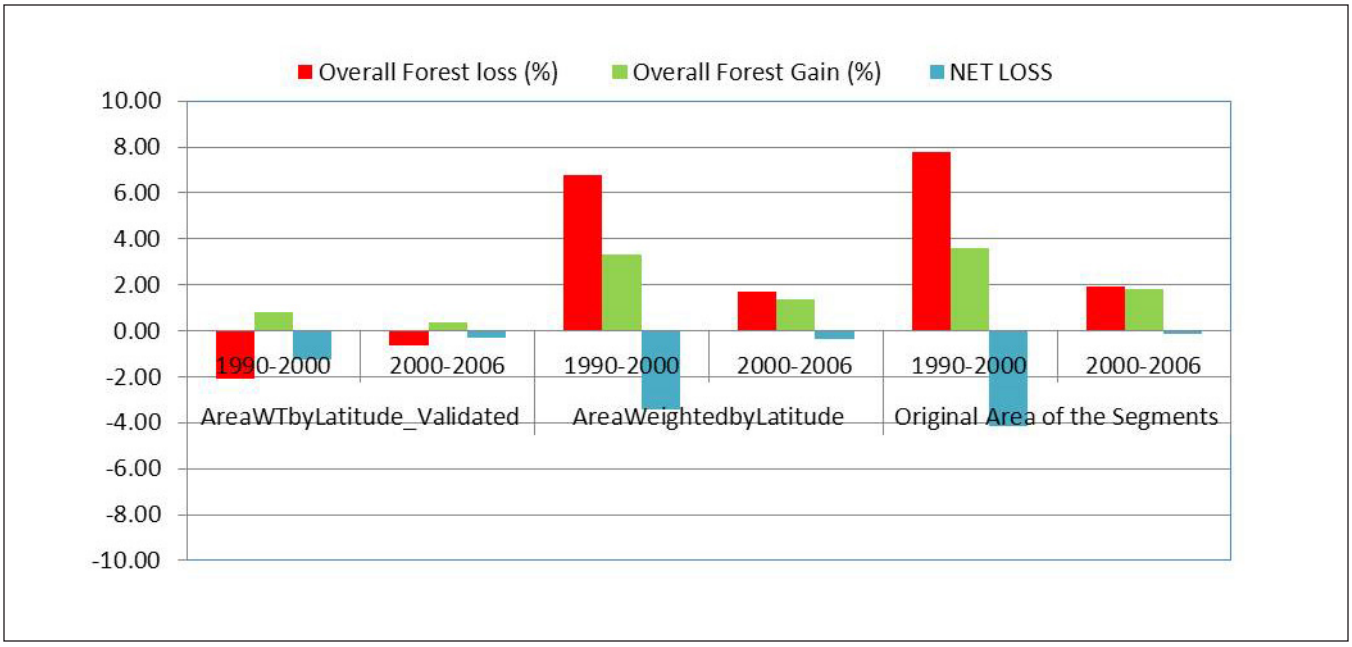


Figure 3.—Comparing differences in assessment of forest loss and forest gain, based on the original area of the segments, after the latitude correction function on the original segments (AreaWeightedby Latitude) and validation of the latitude corrected segments (AreaWTbyLatitude_Validated) within the coterminous United States.

Table 2.—Comparison of overall estimates of area (ha) (validated and weighted by latitude) under different land use transitions in the United States between 1990 and 2000, and 2000 and 2006, based on the survey grids

Land Use Change	1990-2000	2000-2006
Forest to nonforest	123,927.05 (1.8%)	43,133.15 (0.63%)
No change forest	1,968,040.55 (28.8%)	2,106,957.36 (30.86%)
No change nonforest	4,683,794.57 (68.6%)	4,653,012.52 (68.2%)
Nonforest to forest	51,730.53 (0.8%)	24,389.67 (0.36%)
Total Area	6,827,492.71	6,827,492.71

forest was higher between 1990 and 2000 (1.8%) than between 2000 and 2006 (0.63%). Rate of overall forest loss was higher than forest recovery during both the study periods. Overall rate of both forest loss and forest gain declined by 1.17 percent and 0.44 percent, respectively (Fig. 3, AreaWTbyLatitude_validated), reducing the overall net forest loss in the United States. Net loss of forest was less than 1 percent between 2000 and 2006. Given the large proportion of area under stable forest, the observed change in forest area was minimal.

Subtropical humid forest region underwent the highest net forest loss, followed by the Polar region, Subtropical steppe, and temperate mountain system. The pattern was consistent for both study periods (Fig. 4a). Net percent forest loss was higher between 2000 and 2006 than between 1990 and 2000 in most ecoregions except Boreal and Temperate steppe. Boreal tundra woodland and Temperate steppe showed net forest gain between 1990 and 2000 and net forest loss between 2000 and 2006, although the percent change was small. Percent forest gains in these ecoregions were higher than percent forest loss in 1990-2000. Percent forest gain in Polar, Subtropical humid forest, Temperate continental forest, and Temperate mountain system was lower than percent forest loss for each time period, resulting in net forest loss (Fig. 4a).

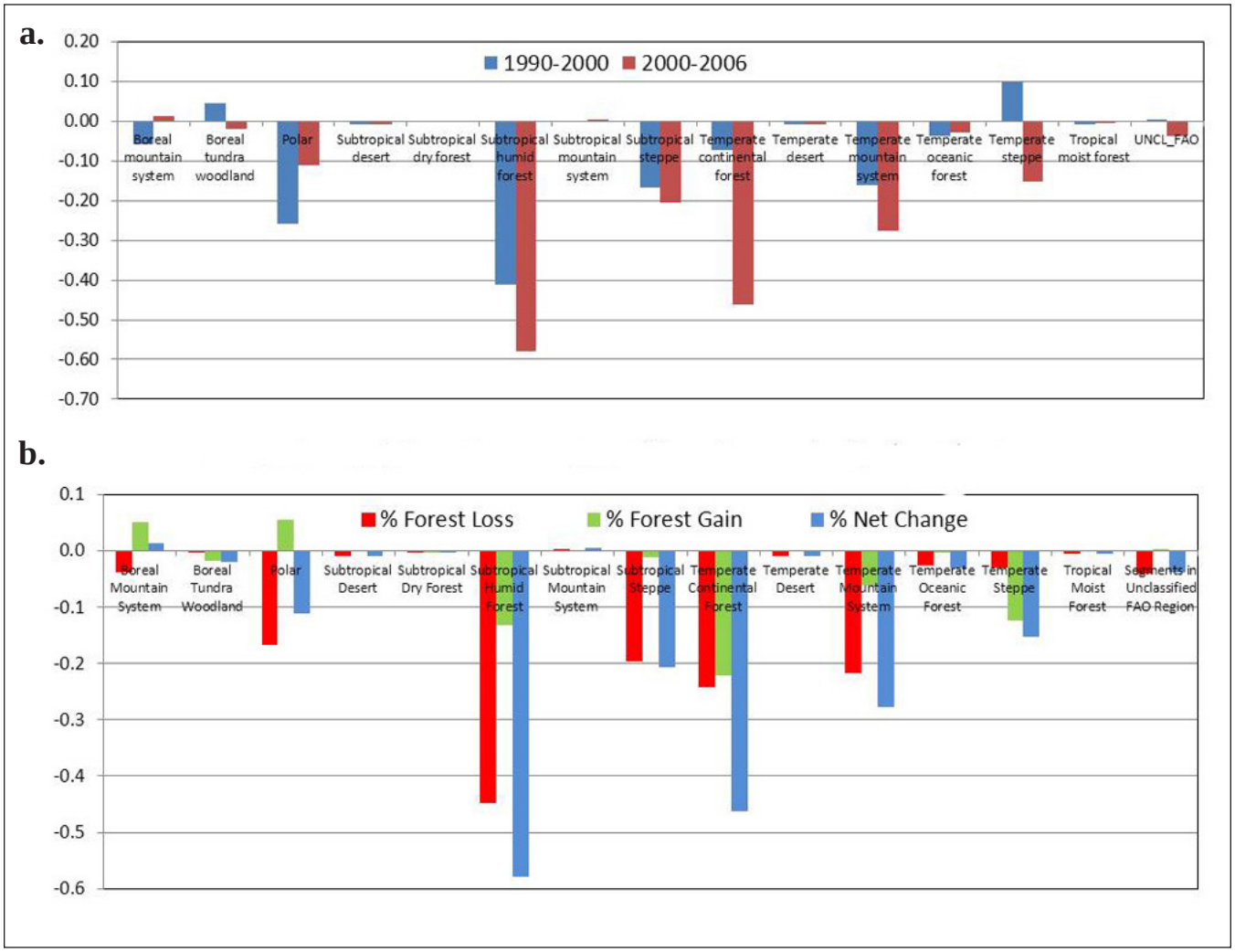


Figure 4.—(a) Comparing net percentage change in forest (Forest Gain – Forest Loss) between 1990-2000 and 2000-2006 by ecoregion; (b) Overall net change in forest area within the United states by FAO ecoregion for the entire study period.

Overall net forest loss in the United States was less than 2 percent (Fig. 4b). Net forest area increased the most in Boreal Tundra (4,965.4 ha, Table 3) and Boreal mountain system (495 ha, Table 3) for 1990-2000 and 2000-2006. Net forest loss was highest in Subtropical Humid Forest (36,255.6 ha, Table 3) and Temperate Continental Forest (32,782.9 ha, Table 3) followed by Temperate Mountain system (14,638.7 ha) and Subtropical Steppe (11,546.5 ha, Table 3) with net percent loss being less than 1 percent. Increased forest loss and reduced forest gain led to increased forest loss in these regions. A similar pattern was observed in other regions with net loss being less than 9,000 ha (1%, Fig. 4b). According to the recent Forest Inventory and Analysis report (Smith et al. 2009), forest land across the Nation has increased by 4 percent since 1987; it decreased 3 percent between 1953 and 1987. In the North region, forest area has increased by nearly 7 percent while it declined by 5 percent in the South region since 1953. In the Rocky Mountain region forest acreage rose by 6 percent whereas in the Pacific Coast region (including Alaska) forested acreage declined by 4 percent between 1953 and 2007. These trends seem to be consistent with the patterns observed during this survey (Fig. 4b).

Table 3.—Change in area (ha) under forest gain and forest loss between 1990 and 2000, and 2000 and 2006 in the United States by FAO region (estimates are based on the segments from the survey grids that were corrected for latitude and validated)

FAO Ecoregions	Forest to Nonforest	Nonforest to Forest	Net Change
Boreal Mountain System	-2078.4	2,527.8	449.4
Boreal Tundra Woodland	2,994.1	1,971.3	4,965.4
Polar	-10,908.2	3,316.2	-7,592.0
Subtropical Desert	0.0	8.9	8.9
Subtropical Dry Forest	-188.9	-0.6	-189.5
Subtropical Humid Forest	-11,229.2	-9,391.4	-36,255.6
Subtropical Mountain System	-17,845.7	67.0	248.2
Subtropical Steppe	-11,229.2	-317.3	-11,546.5
Temperate Continental Forest	-17,845.7	-14,937.2	-32,782.9
Temperate Desert	-935.0	8.4	-926.6
Temperate Mountain System	-11,199.7	-3,438.9	-14,638.7
Temperate Oceanic Forest	-1,193.0	-92.8	-1,285.8
Temperate Steppe	-1,242.6	-7,212.8	-8,455.4
Tropical Moist Forest	-368.3	0.0	-368.3
Segments in Unclassified FAO Region	84.2	150.6	234.8
Overall net change in forest area	-79,761.4	-31,387.0	-10,8134.8

Land Cover Change

Land cover change estimates from the coterminous United States showed higher estimates of net change in tree cover (3.2%, 201,761.4 ha in 1990-2000 and 0.6%, 40,126.4 ha in 2000-2006) than net forest change (2.2%, 139,067.3 in 1990-2000 and 0.8%, 53,267.8 in 2000-2006) (Fig.5). Both net forest and tree cover change was higher in 1990-2000 than 2000-2006. These estimates for the coterminous United States were calculated prior to the validation and hence cannot be used to report actual change. These patterns suggest, however, that estimates calculated from land cover change, as opposed to land use change, overestimate change. Area under forest loss included areas with gain in tree cover. Likewise area under forest gain included area with conversion of tree to non-tree (loss of tree cover). Stable non-forest area included 1.4% (58850.7 ha) gain in tree cover. Forest loss observed between 1990 and 2000, and 2000 and 2006, showed 82,203 ha and 29,736 ha of persistent tree cover, respectively, and included gain in tree cover as well (19.7 ha and 58.2 ha, respectively). These patterns primarily confirm that land cover change does not necessarily indicate land use change. Unless a forest segment has undergone a change in its use to a non-forest class, observed change in the land cover type is only a transitional state to the next successional or vegetation type.

CONCLUSION

Based on the survey conducted within the FAO grids, most of the forested area remained stable between 1990, 2000, and 2006. Overall forest gain and loss ranged from less than 1 percent to 2 percent during the study periods. Subtropical humid forest showed the highest net forest loss, followed by temperate oceanic forest. Overall rate of loss of forest was higher between 1990 and 2000 than between 2000 and 2006. Accounting for the latitude of the segments significantly altered the estimate of area under different land use change. Accuracy assessment of the land use change further reduced the estimated area under change. This study demonstrated the importance of a latitude correction and validation on actual estimates and indicated that most of the forest area within the surveyed grid in the United States remained stable after 2000.

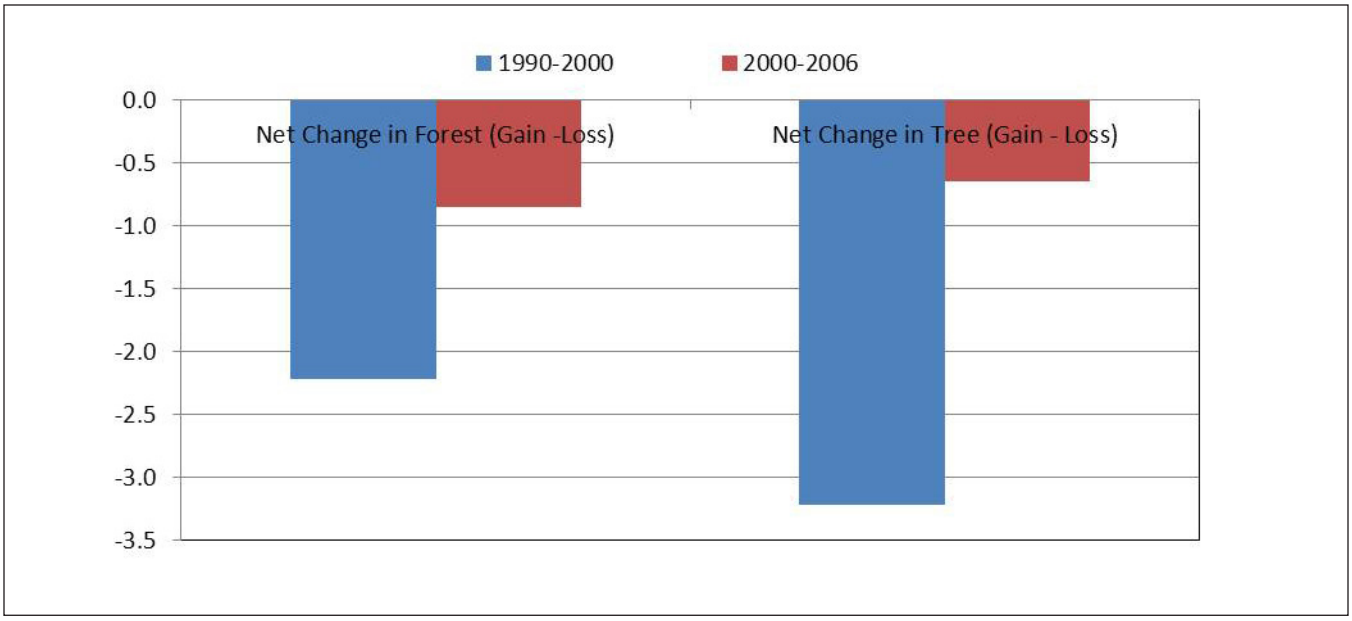


Figure 5.—Comparing net percent change in forest (NonForest to Foreste – Forest to NonForest) and tree (NonTree to Tree – Tree to NonTree) between 1999-2000 and 2000-2006 within the coterminous United States.

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IMAGE-BASED CHANGE ESTIMATION FOR LAND COVER AND LAND USE MONITORING

Jeremy Webb, C. Kenneth Brewer, Nicholas Daniels, Chris Maderia, Randy Hamilton, Mark Finco, Kevin A. Megown, and Andrew J. Lister[1]

Abstract.—The Image-based Change Estimation (ICE) project resulted from the need to provide estimates and information for land cover and land use change over large areas. The procedure uses Forest Inventory and Analysis (FIA) plot locations interpreted using two different dates of imagery from the National Agriculture Imagery Program (NAIP). In order to determine a suitable project workflow, interpretation methods and database options were explored. The results provide useful information for the change occurring between land cover and land use types across two prototype landscapes.

INTRODUCTION

Understanding changes in land use and land cover (LULC) over space and time provides a means to evaluate the complex interactions between human and biophysical systems, to project future conditions (absent policy changes), and to design mitigation and adaptive management strategies. Understanding and modeling LULC change is evolving into a foundational element of climate, environmental, and sustainability science. Land use and land cover data are core to applications including: carbon accounting, greenhouse gas emission reporting, biomass and bioenergy assessments, hydrologic function assessments, fire and fuels management, and forest and rangeland health assessments. The lack of comprehensive and spatially-explicit historical vegetation data for the entire United States challenges the ability of scientists and land managers to understand cumulative effects of natural disturbances and human activities. By extension, our ability to understand and model future scenarios is limited by a lack of information about the disturbance processes that shape land cover changes and land use decisions by private landowners and public land managers.

A recent resolution from the National Association of State Foresters (NASF) reflects both the importance of these data and the need to generate reliable estimates of land cover and land use change. The NASF resolution suggests an enhanced Forest Inventory and Analysis (FIA) program that prioritizes the "Use of remote imagery to track harvest intensity, land-use change, and land cover change" (NASF State Forester Resolution 2009-6). The FIA program and the Remote Sensing Applications Center (RSAC) were specifically identified as partners for accomplishing this. In 2011, RSAC initiated this Image-based Change Estimation (ICE) project in response to the NASF resolution. The specific objectives of the project were to: (1) develop an efficient, repeatable workflow that could be implemented nationwide in conjunction with the FIA program for assessing LULC change from imagery, and (2) test and demonstrate the workflow in two diverse pilot study areas.

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METHODS

The study areas for the ICE project were the states of Colorado and Georgia. They were selected to provide diverse and dissimilar landscapes where the effectiveness of photo-based data collection for identifying and classifying LULC change could be evaluated. LULC change was assessed in the two states by interpreting two dates of National Agriculture Imagery Program (NAIP) imagery within plots located on each state's base FIA grid (Bechtold 2005). The circular plots were 1.44 acres (144-foot radius) in size, which ensured full coverage of the FIA subplots. The total number of plots interpreted for the study was 17,222 with 10,815 in Colorado and 6,407 in Georgia.

Both Colorado and Georgia had full, state-wide coverage of NAIP imagery for 2005 that was used for the Time 1 (T1) dataset. The Time 2 (T2) dataset consisted of four band (red, green, blue, near-infrared) NAIP imagery acquired in 2009 for Colorado and 2010 for Georgia. The spatial resolution of the imagery was 1 meter for all datasets except the 2005 Georgia imagery, which was 2 meters. The temporal scale of approximately 5 years was chosen to align with the FIA panel system and the plot revisit times by FIA field personnel.

Classification Schemes

The LULC classes for this project were based on the FIA land cover and land use classes (USDA FS 2011) for defining condition class as well as those described by Anderson et al. (1976). The classification schemes, summarized in Table 1, allowed the newly photo-interpreted data to align with previously collected FIA plot data. Along with the LULC classes, an agent of change was recorded for any plots that had a change in LULC between T1 and T2. This provided additional information about the type of change that may not have been inferred from the LULC attributes. The agent of change classes included: reforestation/afforestation, partial tree harvest, clear cut harvest, fire, development, and other change.

Photo Interpretation and Data Entry Interface

Due to the large number of plots to be interpreted, it was important to use a data collection method that allowed for rapid image viewing, interpretation, and data entry. Two software applications were evaluated and compared for this purpose: ESRI ArcMap™ and Microsoft Access®. The ESRI ArcMap interface was set up using a feature dataset within a file geodatabase.

Table 1.—Primary and secondary classes for land cover and land use used in ICE project.

Land Cover	
Tree:	Deciduous Tree, Evergreen Tree, Uninterpretable Tree
Other Vegetation:	Shrub, Herbaceous, Nonvascular Vegetation, Uninterpretable Vegetation
Water and Ice:	Water, Ice and Snow
Barren:	Soil/Sand, Rock, Paved Surface, Building Rooftop, Other Barren Land
Uninterpretable	
Land Use	
Forest:	Forest, Tree Farm
Rangeland:	Rangeland
Natural/Semi-natural:	Wetland/Riparian, River, Lake, Other Natural/Seminatural
Agriculture:	Cropland/Pasture, Orchards/Groves/Vineyards/Nurseries, Confined Feeding Operations, Other Agriculture
Developed:	Residential, Recreational, Commercial/Services, Industrial, Transportation/Communications/Utilities, Strip Mines/Quarries/Gravel Pits, Mixed Urban/Built-up Land, Canals/Reservoirs, Other Developed
Uninterpretable	

The feature dataset contained the FIA plots and the fields to be attributed. The reference imagery used was provided by image services from the Forest Service's enterprise instance of ArcGIS® Image Server. Since the FIA plot data was already in an ESRI file format, setup was relatively quick. The main limitation of using this method was the inability to customize the interface without a programming skillset.

The Microsoft Access interface was a modification of prior work conducted by Andrew Lister of the Northern Research Station FIA program. The database consisted of a data entry form attached to a main table which stored the data. One of the greatest advantages of using an Access database was the ability to easily customize the form to meet the project needs. The layout of the ICE form allowed the user to view two timeframes of aerial imagery side-by-side and enter all pertinent information for an individual plot within a single form. The form layout consisted of the imagery and data entry fields for T1 on the left and the imagery and data entry fields for T2 on the right (Fig. 1). Additionally, by using buttons placed at the top of the images, the interpreters were able to toggle between varying image scales and band combinations. Buttons on the form also gave the interpreters quick access to supplementary imagery available on Bing™ and Google Maps™.

Another design objective for the Access form was to maintain data integrity throughout the course of the project. To support this, features such as predefined dropdown lists for land cover, land use, and agents of change were implemented. Other quality control (QC) features included a "no change" button to minimize data entry errors as well as checks for missing data that prevented the user from proceeding until the fields were attributed. Along with keeping data entry consistent, these built-in QC functionalities saved a considerable amount of time.

To test the efficiency of the two applications, a total of 1,000 non-FIA plots were randomly selected from the two states. Two interpreters used both methods to view and attribute the plots. The results of the study showed that the Access approach was 28 percent more time efficient than the ESRI ArcMap approach. This improved efficiency was attributed to faster image load time and the ability to customize tools to maximize the ease of data entry. As a result of its increased efficiency and availability, the Microsoft Access approach was selected for use in the project.

Interpretation Methodology

During the early development phase of this project, a study was conducted comparing the interpretation of land cover within polygons versus at a point (i.e., the plot center). The polygon method required the interpreter to evaluate the entire plot and mentally draw boundaries around the land cover types. Using FIA guidelines for minimum mapping units (MMU), polygons representing land cover types were identified (USDA FS 2011). The class corresponding to the land cover polygon located at the plot center was recorded by the interpreter. The point method had no associated MMU for specifying a land cover type. The plot center was visually assessed by the interpreter and the land cover class it intersected was recorded for the plot. The two methods yielded different results in some cases. For example, if the plot center intersected an opening in a coniferous forest, the land cover call was evergreen tree for the polygon method and herbaceous for the point method. In evaluating the two methods, results showed a 31 percent increase in time efficiency and a 4 percent increase in agreement among interpreters when comparing the point to the polygon method. One disadvantage of using the point method is the lack of contextual information at the plot level. However, by also recording the land use class, which was necessarily polygon-based, the contextual information was made available. Based upon the results of the comparison, the point method was selected for assessing the land cover type and the polygon method was used to evaluate land use. The only attribute that used the plot boundary and not the center point was the agent of change, which was assigned only when there was an LULC change anywhere within the 1.44-acre plot area.

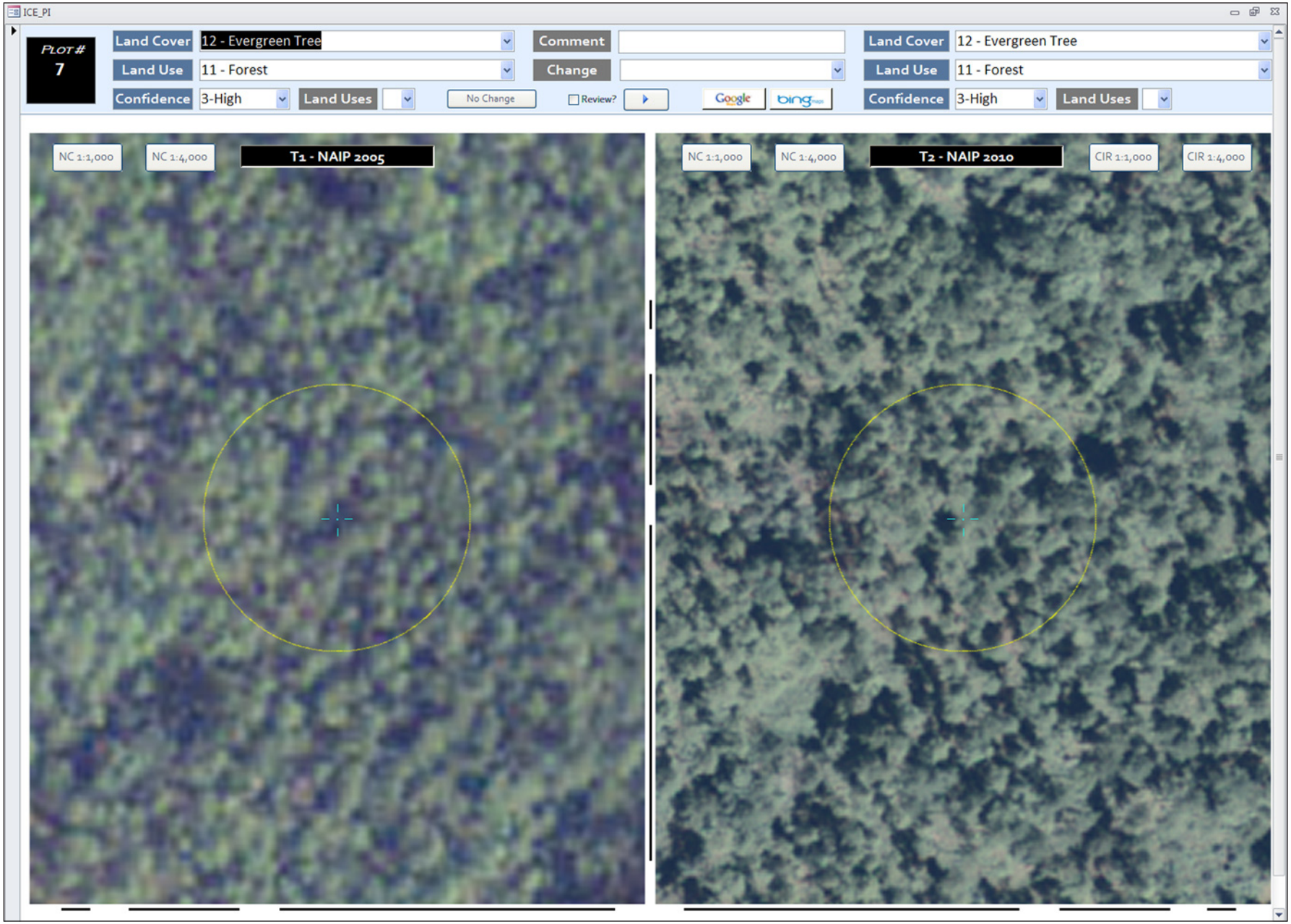


Figure 1.—Microsoft Access form customized for ICE project to view NAIP imagery and record plot data.

After completing the studies, the interpreters began interpreting the actual FIA plots. In order to measure consistencies among interpretations, 5 percent of the FIA plot locations were randomly selected as crosschecks. Half of these plots were repeated by the initial interpreter and the other half were assessed by both interpreters. The FIA panel system, which consists of five panels per state, was used to divide the plots between the two interpreters, with one interpreting two panels and the other interpreting three panels for each state. Photo interpretation was first completed for the state of Colorado followed by Georgia. The two interpreters worked independently of one another throughout the majority of the photo interpretation process. Plots that were difficult to assess were marked for review and later discussed between interpreters to refine class calls and to improve consistencies between them.

RESULTS AND DISCUSSION

The photo interpretation process for the ICE project took an average of 1 minute per plot and eight-person work weeks to complete all plots for Colorado and Georgia. The dominant land cover and land use types for the state of Colorado were Other Vegetation (74 percent of initial total) and Rangeland (32 percent of total), respectively. For Georgia, Tree (62 percent of initial total) was the dominant land cover class with Forest (67 percent of total) being the dominant land use class. Please see Figure 2 and 3 for more information on the land cover and land use results.

Changes occurring within the land use of forests were of particular interest for the ICE project (Fig. 4). Results show that 0.45 percent of the Colorado forest plots changed to a different class in T2. Conversion to rangeland and development had the greatest role in the forest change by making up 47 percent and 40 percent of the forest change, respectively. For Georgia, 1.14 percent of the forest plots changed land uses in T2, with the majority of these changes (73 percent) being a result of development. Additional work, including an intensified sampling of the changed plots, is underway to better quantify the changes. This information, along with other plot specific information (i.e., land cover type and agent of change) will be available in forthcoming reports.

The methodology developed for this project provides a rapid and cost-effective way to assess and estimate LULC changes across large areas and shows potential for nationwide implementation. Through the interpretation of FIA plot locations from high resolution aerial imagery, information regarding land cover and land use changes that are occurring across the United States can be made accessible to scientists and forest managers to assist in the creation of strategies and the making of informed decisions.

ACKNOWLEDGMENTS

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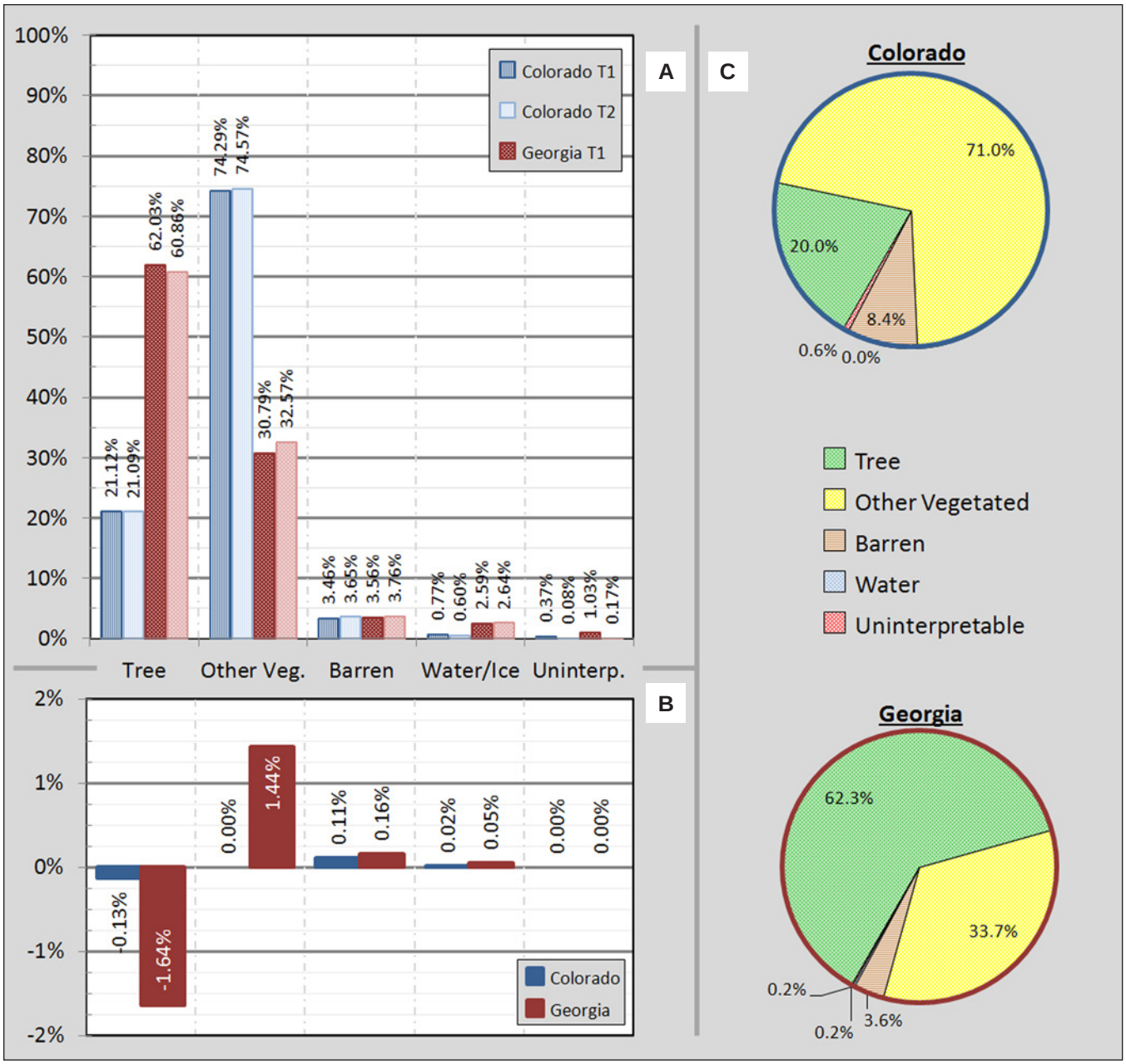


Figure 2.—Land cover data summaries for Colorado and Georgia. (A) Comparison of land cover values for T1 and T2 datasets. (B) Land cover change as a percentage of total plots. (C) Distribution of land cover change by type based on initial plot condition.

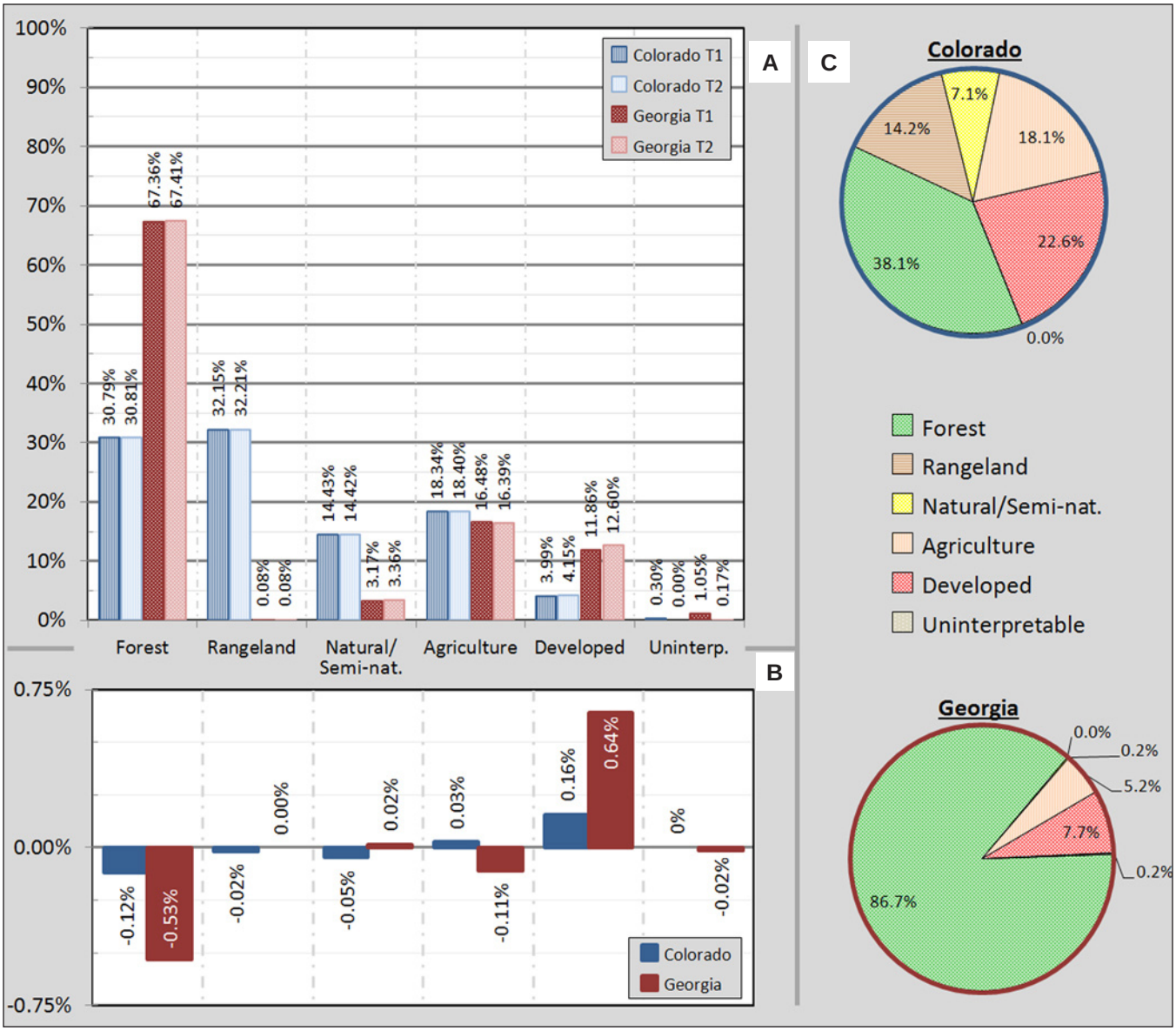


Figure 3.—Land use data summaries for Colorado and Georgia. (A) Comparison of land use values for T1 and T2 datasets. (B) Land use change as a percentage of all plots. (C) Distribution of land use change by type based on initial plot condition.

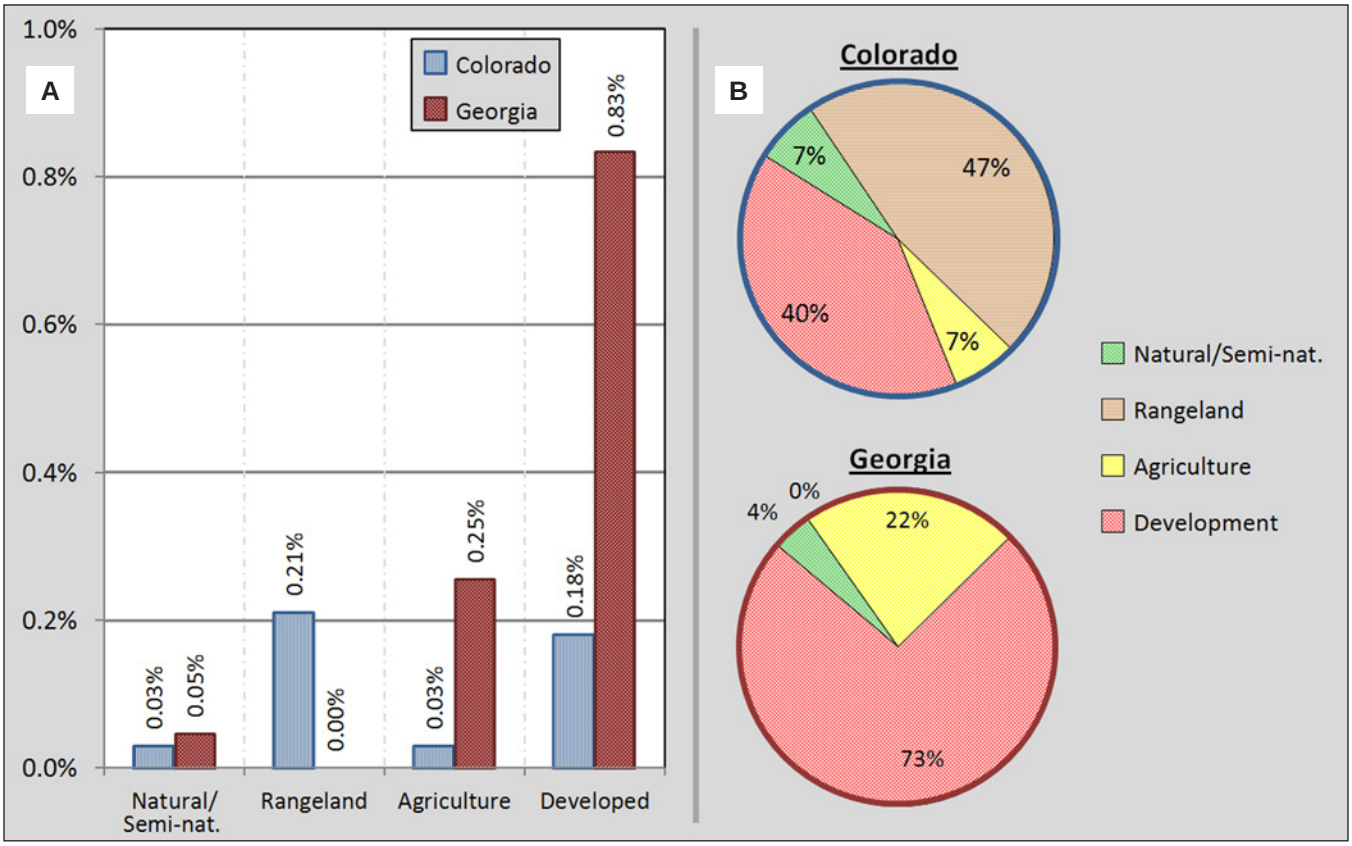


Figure 4.—Summary of changes within forested plots categorized by state. (A) Percent of forested plots that changed to other land use classes. (B) Distribution of land use types to which the changed forest plots transitioned.

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FORECASTING SUSTAINABILITY: GROWTH TO REMOVALS RATIO DYNAMICS

Natasha A. James, Robert C. Abt, Karen L. Abt, Raymond M. Sheffield, and Fredrick W. Cubbage[1]

Abstract.—The growth to removals ratio (G/R) is often used as a measure of forest resource sustainability and as a reference point to forecast future resource sustainability. However, little work has been done to determine if any relationship exists between G/R over time. Forest Inventory and Analysis data for 12 southern states were used to determine if any relationship exists between G/R at a given point in time and G/R in the future. Ordinary least squares results indicated a positive relationship over time, meaning a high G/R ratio in the past is associated with a high G/R ratio in the future. However, after removing the effects of differences across space through the use of fixed effects analysis, the results indicated G/R has a negative relationship with itself over time.

INTRODUCTION

The concern of negative anthropogenic impacts on the natural environment and the concerns of insufficient natural resource availability in the future have led to an international agenda to engage in practices leading to resource sustainability and sustainable development. The Montreal Process Criteria and Indicators (MPCI) were developed to address sustainability concerns of the world's forests. Adopted by 12 countries that represent more than 90 percent of the world's temperate and boreal forest, these criteria and indicators define seven broad value criteria which are measured by various indicators.

Growth to Removals Ratio

Criterion 2 focuses on maintaining the productive capacity of forest ecosystems. Criterion and Indicator 2.13 focuses specifically on the growth to removals ratio (G/R) (Montreal Process Working Group 2009). Within the field of forest management, resource sustainability is often measured by G/R which is calculated by dividing the net growth in inventory volume during a certain time period by the removals (harvest) within the same time period. A G/R ratio greater than 1 indicates growth in inventory outpaces removals and the resource management within that period could be continued without depleting inventory, and thus is considered sustainable. Although G/R presents a useful snapshot of the relationship of forest growth and removals, it is often used as a means of determining forest sustainability. For example, a high G/R ratio today often is seen as an indicator of a high G/R ratio in the future, thus an assurance of sustainability.

Objective

This study examines G/R for growing stock timberland of both hardwood and softwood species in the selected areas. G/R is calculated as the ratio between net annual growth (the difference between gross growth and mortality) and annual removals for timberland. Figures 1-3 depict G/R over time for each state used in this analysis. Although Kentucky is part of the southern FIA, it was not included due to insufficient data.

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Even though it is common practice to use a G/R ratio greater than 1 as an indicator of continued sustainability in the future, Figures 1-3 show a relationship over time where periods of low G/R are followed by periods of high G/R, suggesting a cyclical, negative relationship (Sheffield 2012). The objective of this study was to investigate how well G/R in the past explains G/R today.

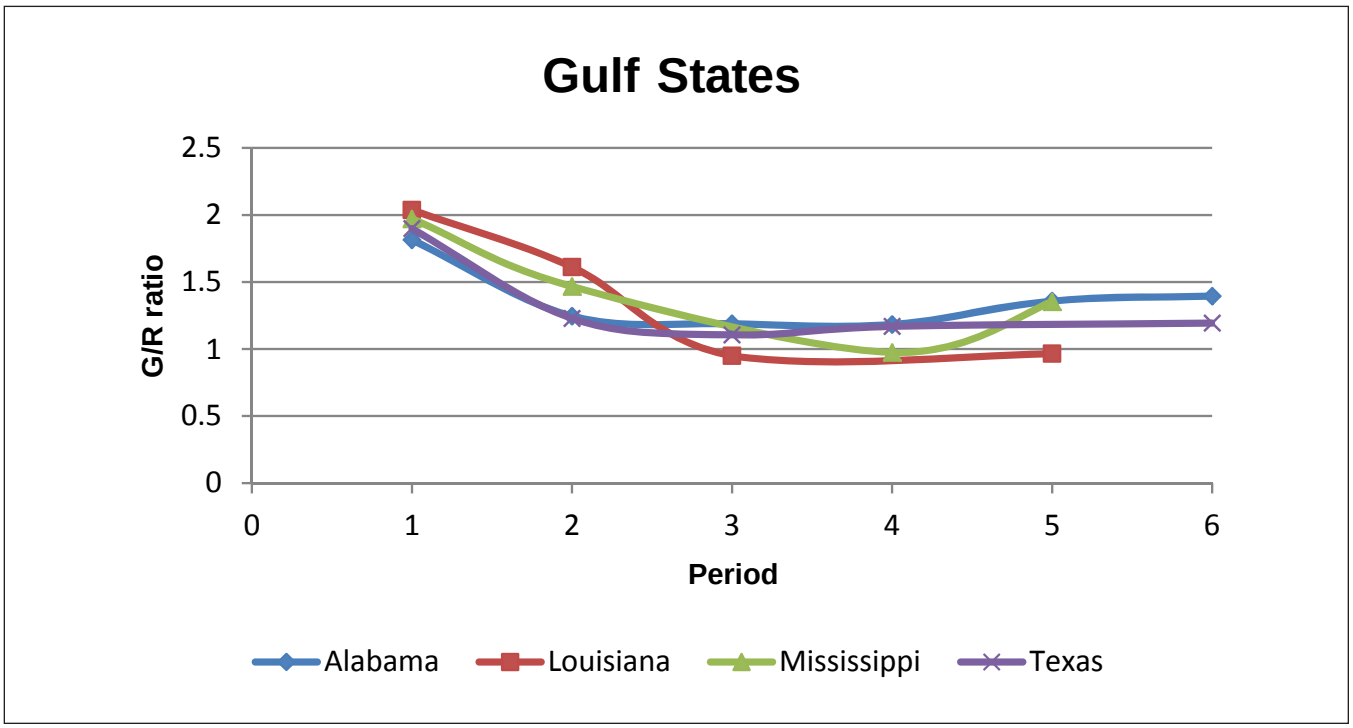


Figure 1.—G/R ratio over time for southern states bordering the Gulf of Mexico.

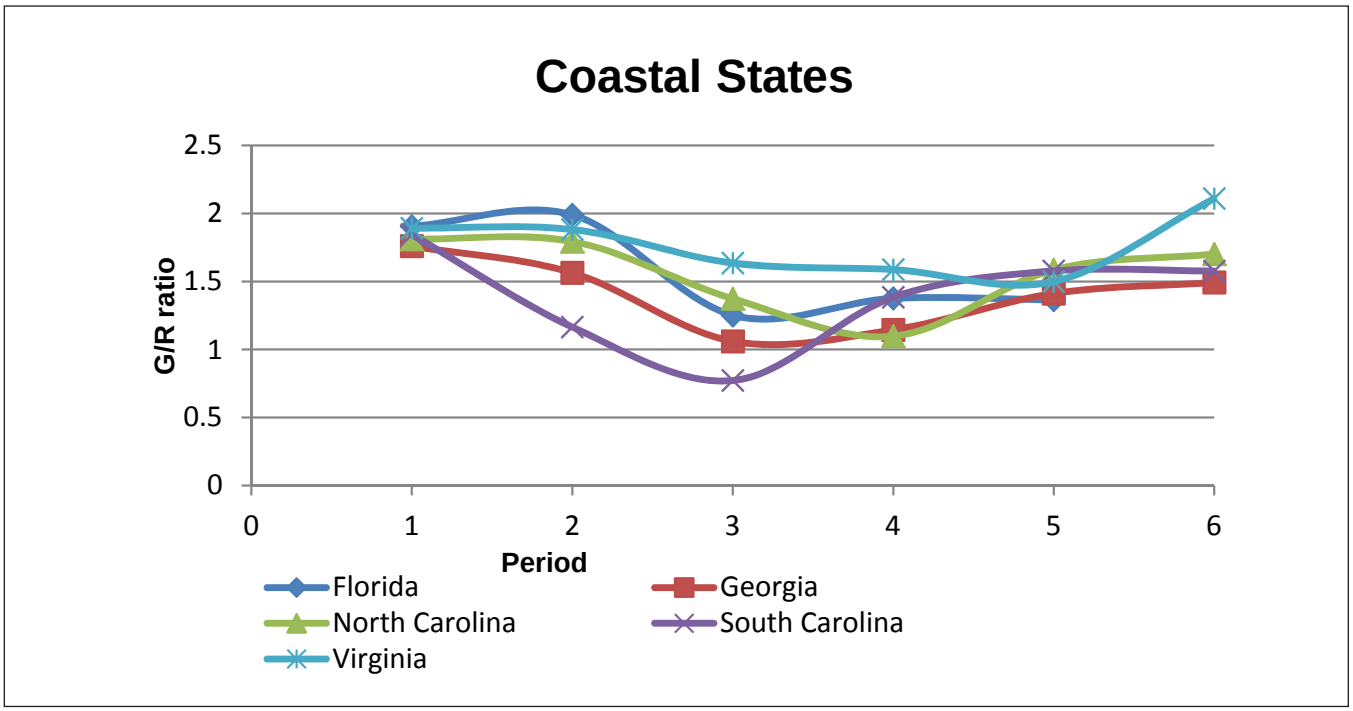


Figure 2.—G/R ratio over time for southern states bordering the Atlantic coast.

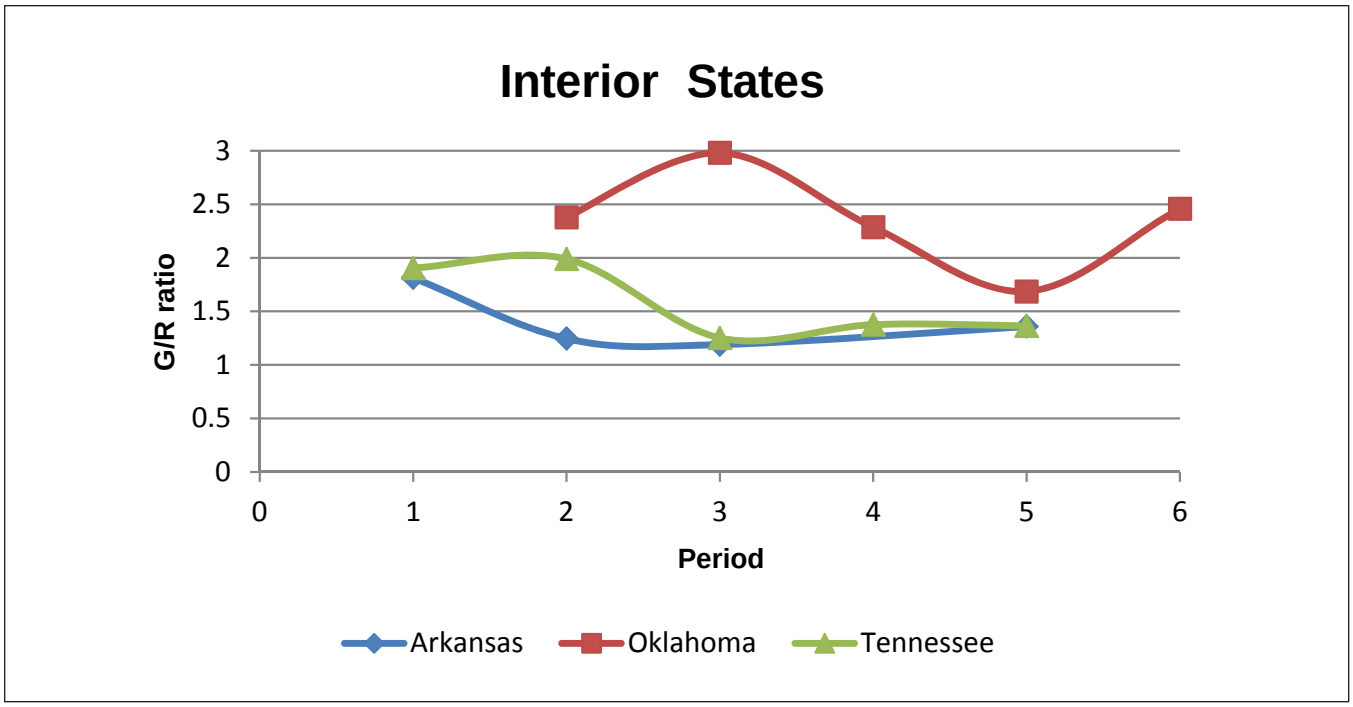


Figure 3.—G/R ratio over time for interior southern states.

DATA

The data used in this analysis were extracted from the Forest Inventory and Analysis (FIA) database. Data relating to annual removals and net growth were collected at the survey unit level for the 12 southern states. Although net growth and annual removals are estimates containing their own standard errors, for the purposes of this paper they are both being treated as population values.

Historically, the FIA Program collected data using a 10-year periodic survey. In 1998, the Agricultural Research, Extension, and Education Reform Act (PL 105-185) required an annual inventory. However, the panel design described by Bechtold and Patterson (2005) was implemented. This panel design allows federal funding for a 10 panel design in the East. Many southern states use a 5 panel design in which 20 percent of plots within a state are sampled each year, creating full inventory reports in 5-year cycles (Smith and Oswalt 2010).

Due to the inconsistency in survey dates, the years in which surveys took place were divided into the following periods:

Period 1: 1970-1978	Period 4: 1994-2003
Period 2: 1979-1987[2]	Period 5: 2004-2008
Period 3: 1988-1993	Period 6: 2009-2010

METHODS

Ordinary least squares (OLS) analysis was used to determine if any relationship exists between G/R today and in the past. In this analysis, each period for each state is a single observation. In addition, fixed effects analysis was applied which controls for the average differences across space (states) in order to observe only the effects of time on G/R. In this analysis, the cross section was defined as the state and the time

[2] Florida had 2 surveys during Period 2 (1980 and 1987). The 1987 survey data are included in Period 3.

series was defined in periods, as shown above. The models analyzed for both procedures were:

Model 1: $(G/R)_T = f((G/R)_{T-1})$
Model 2: $(G/R)_T = f((G/R)_{T-2})$
Model 3: $(G/R)_T = f((G/R)_{T-1}, (G/R)_{T-2})$,

where $(G/R)_T$ is G/R of the current period; $(G/R)_{T-1}$ is G/R lagged one period; and $(G/R)_{T-2}$ is G/R lagged two periods.

RESULTS AND DISCUSSION

Three OLS models and three fixed effects models were used to examine the relationship G/R has with itself over time. The first model focuses on the relationship between G/R of the current period and the G/R lagged one period. The second model focuses on the relationship between G/R of the current period and the G/R lagged two periods. The final model focuses on the relationship between G/R of the current period and the G/R lagged one and two periods. Results from OLS and fixed effects analysis are listed in Table 1 and Table 2, respectively.

In each model the parameter coefficients are positive and significant at the 1 percent level. This result suggests G/R has a positive relationship with itself over time. However, the R2 values are relatively low, ranging from 0.14-0.24.

Through the use of fixed effects analysis, the average differences across states are isolated to determine whether G/R at a point in time has implications for determining G/R in the future. In each model, the F statistic (F_{stat}) is significant at the 5 percent level, indicating there are group effects across space and that OLS would not be expected to produce reasonable results. Although the R^2 values are higher (0.55-0.72), the relationship between G/R today and its values lagged one period and two periods (Model 1 and 2) lack significance even at the 20 percent level. However, when analyzed simultaneously (Model 3), $(G/R)_{T-1}$ and $(G/R)_{T-2}$ show a significant, negative relationship with G/R of the current period. This result implies an inverse relationship where the higher G/R is in the past, the lower it will be in the future.

CONCLUSION AND FUTURE WORK

The results from this study show that when controlling for the average differences across space, empirical evidence suggests that G/R has a negative relationship with itself over time. This analysis is just one of many steps in understanding G/R. In the South, the G/R is rarely below 1. Future work should include regions where G/R is not as stable. Future analysis should include examination of hardwoods and softwoods separately, as these ratios can be different over time.

Table 1.—Results from Ordinary Least Squares (OLS) analysis of G/R on lagged values of G/R for 12 southern states (standard errors in parentheses)

	Model 1	Model 2	Model 3
Constant	0.83	0.96	0.74
$(G/R)_{T-1}$	0.45*** (0.08)		0.30*** (0.10)
$(G/R)_{T-2}$		0.32*** (0.09)	0.16*** (0.10)
Number of observations	102	78	78
Adjusted R^2	0.24	0.14	0.23

Note: ***indicates significance at 1%.

Table 2.—Results from fixed effects analysis G/R on lagged values of G/R for 12 southern states (standard errors in parentheses)

	Model 1	Model 2	Model 3
Constant	1.91	2.02	2.63
$(G/R)_{T-1}$	-0.10[a] (0.14)		-0.33*** (0.14)
$(G/R)_{T-2}$		-0.18 (0.15)	0.21* (0.14)
Number of cross sections	12	12	12
Time series length	5	4	4
Adjusted R^2	0.55	0.66	0.72

[a] ***indicates significance at 1%, *indicates significance at 20%.

In addition, stronger statistical analyses such as spectral analysis or Fourier regression could be applied to determine cyclical relationships.

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DEVELOPMENT OF A REMOTE SENSING-BASED SYSTEM FOR MONITORING LANDSCAPE CHANGE

C. Kenneth Brewer, Sean P. Healey, Brian Schwind, and Kevin A. Megown[1]

Abstract.—The Landscape Change Monitoring System (LCMS) is an interagency remote sensing-based system under development for mapping and monitoring land cover and land use change in the United States. There is a growing need for landscape change information that is coherent across time, space, and different cover types. While a number of relevant datasets exist, work is needed to promote coordination and fill in critical gaps. Assessment of existing agency information requirements, data availability, and institutional activity suggests the greatest return on efforts to establish a national landscape change monitoring system will be in development of a Landsat-based information system. Characteristics that make Landsat data particularly well-suited to comprehensive change monitoring include the longest data record of any synoptic satellite sensor (1972 to present), relatively fine spatial resolution (30 m), spectral and radiometric properties that enable vegetation change detection, no-cost availability and accessibility, future data continuity, and a rich history of scientific investigation. Current activities in the development of LCMS include an independent needs assessment and the formation of a science team, which will evaluate and recommend design criteria and available Landsat-based change detection methodologies. These developments will be described in the presentation.

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THE NORTH AMERICAN FOREST DYNAMICS PROJECT: MOVING FROM STATUS TO TRENDS THROUGH LANDSAT TIME SERIES

ATTRIBUTING CAUSAL AGENTS TO NATIONWIDE MAPS OF FOREST DISTURBANCE

Gretchen G. Moisen, Todd A. Schroeder, Karen Schleeweis, Chris Toney, Warren B. Cohen, and Samuel N. Goward[1]

Abstract.—Currently in its third phase, the North American Forest Dynamics (NAFD) project has launched nationwide processing of historic Landsat data to provide a comprehensive annual, wall-to-wall analysis of U.S. disturbance history over the last 30+ years. Because understanding the cause of disturbance is important to quantifying carbon dynamics, work is underway to attribute causal agents to these nationwide change maps. Developing empirical models of the diverse causal agents in this country involves many decisions. Alternative response designs (such as varying size, shape, quantity, and level of detail in training data) are being evaluated in terms of their costs and benefits for national mapping applications. Many classes of predictor variables such as spectral signatures, textural metrics, extant geospatial disturbance libraries, and bioclimatic information, are being tested for their contribution to classification models. Flexible modeling techniques, such as the Random Forests models used here, are powerful predictive tools but must be coupled with simple rule-based models reflecting expert knowledge. And decisions about appropriate modeling subpopulations are being made in light of available training data, diversity of ecological zones, and computational efficiency. We will be synthesizing results from our initial exploratory work as well as from pilot analyses conducted over 10 Landsat TM scenes representing diverse causal agents, forest types, and forest prevalence levels. We also discuss how these causal disturbance models will enable extensive analyses of temporal and spatial patterns in causal agents across the United States.

INTRODUCTION

The job of inventorying and monitoring the nation's forests requires the U.S. Forest Service Forest Inventory and Monitoring Program (FIA) to do three things. First, we have to provide information about the status of our forests, quantifying how much is out there now and where is it. Second, we have to provide information about how our forests are changing. And finally, we have to try to decipher trends to describe what is happening over the long term. While strongly interrelated, the three questions require different techniques and data. Addressing the status issue has been FIA's primary focus for many years. We regularly produce useful estimates of forest attributes as well as accompanying maps. While there are opportunities to improve precision in estimates, make the maps better, ensure compatibility between maps and estimates, and implement better procedures for small area estimation, the topic of forest status is already receiving considerable attention. However, assessing change and trend both pose larger challenges we are only just beginning to tackle.

The overarching objective of the work we are conducting is to improve FIA's approach to assessing status, change, and trend through Landsat time series. Here we briefly discuss forest disturbance and the

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challenges it poses for monitoring. We also provide an overview of the most recent phase of the North American Forest Dynamics (NAFD) project with emphasis on attribution of causal agents.

FOREST DISTURBANCE AND MONITORING

Forest disturbance is becoming increasingly important to the inventory and monitoring audience. Although it affects only a small percentage of a given forest each year, there are cumulative effects through time. It is a complicated phenomenon in that it can impact canopy, understory, as well as forest floor. The definition of disturbance changes dramatically depending on an individual's perspective and area of expertise. People are having an increasing influence on the frequency and severity of disturbances across the landscape. Consequently, monitoring in ways that improve our understanding of the role of disturbance in our forests is increasingly important.

Disturbances brought on by different causal agents vary in terms of the speed with which they affect a forest and the length of time that the effects persist. For example, urbanization doesn't happen overnight, but once it occurs, it is permanent. Conversely, floods happen quickly, but they can recede equally as fast. Disturbances caused by a variety of agents are also dramatically different in terms of the size of area affected and the severity or magnitude of change they inflict on the forest in that area. For example, the death of one tree is small relative to the area in a 30 m pixel, but it is very severe for that individual tree. Urbanization is also a severe change but occurs over much larger areas. Thinking about disturbance in this way brings out three key points. First, the timing of observation can be critical to detection. Second, the spatial scale of observation on the ground can influence our ability to detect disturbance. And finally, the techniques we use to observe or measure will also factor into the ability to discern different types of disturbance. Can we really see it with our eyes? Can we "see it" with the spectral bands that our remote sensing instrument is equipped with?

Understanding the diversity of disturbance raises issues about how forests are monitored. The advantages of field data collection are well understood and appreciated. FIA produces unbiased estimates at broad scales, the sampling error is well understood, and the measurement error can be assumed to be negligible for many variables that we can physically measure (wrapping a tape, observing a species). However, these estimates are not spatially explicit except at very coarse spatial grains such as counties. In addition, our inventory frequency might cause us to miss some disturbance events, identifying year of disturbance can be problematic, and when observing from the ground, it can be difficult to detect disturbances that affect only crowns.

Conversely, using remotely-sensed information such as dense time series of Landsat imagery offers some advantages for monitoring disturbance, such as a 16-day repeat cycle and 40-year historical archive. The 30 m grain size and spectral bands are adequate for capturing many changes in the landscape, and there is no sampling error because of wall-to-wall coverage. In addition, historic Landsat data can be interpreted visually with the aid of periodic photos to give very detailed information about forest history to augment information collected on the plots themselves. However, measurement error in the observations collected by Landsat can be highly variable and is often poorly understood.

DISTURBANCE ATTRIBUTION IN NAFD PHASE 3

Funded under the North American Carbon Program (NACP), the NAFD is a collaborative project that began nearly a decade ago and in its first two phases grew to include many partners including University of Maryland, National Aeronautics and Space Administration (NASA), FIA, the U.S. Forest Service Pacific Northwest and Northern Research Stations, Canadian and Mexican partners, and others. Because of the NACPs interest in determining the role of forest dynamics in the North American carbon balance

(USCCSP 2007), the NAFD group was funded to study disturbance patterns and recovery rates of forests across the continent. The approach taken in NAFD phase 1 and 2 was to process a complete time series (1985-2008) on a sample of Landsat scenes, resulting in biennial (in phase 1) and annual (in phase 2) maps of forest disturbance (Goward et al. 2008). FIA data were used for calibration and validation.

A third phase of NAFD was launched in the summer of 2011 and consists of three major components. The first component of Phase 3 involves conducting an annual, wall-to-wall analysis of U.S. disturbance history between1985-2010 (Huang et al. 2010). The second component includes conducting a detailed validation of the national disturbance map using TimeSync (Cohen et al. 2010). The third component consists of exploring variations in post-disturbance forest recovery trajectories using repeat measurements from FIA plot data following Masek et al. 2008. Causal agent groups are also being modeled in the final annual disturbance product (with beginning work from Schroeder et al. 2011 and Schleeweis et al., in press). Our pilot phase, which began in January 2012, is designed to address a number of issues through analyses conducted over 10 pilot Landsat scenes which were chosen to represent a diverse set of disturbance regimes and forest types across the country (Fig. 1).

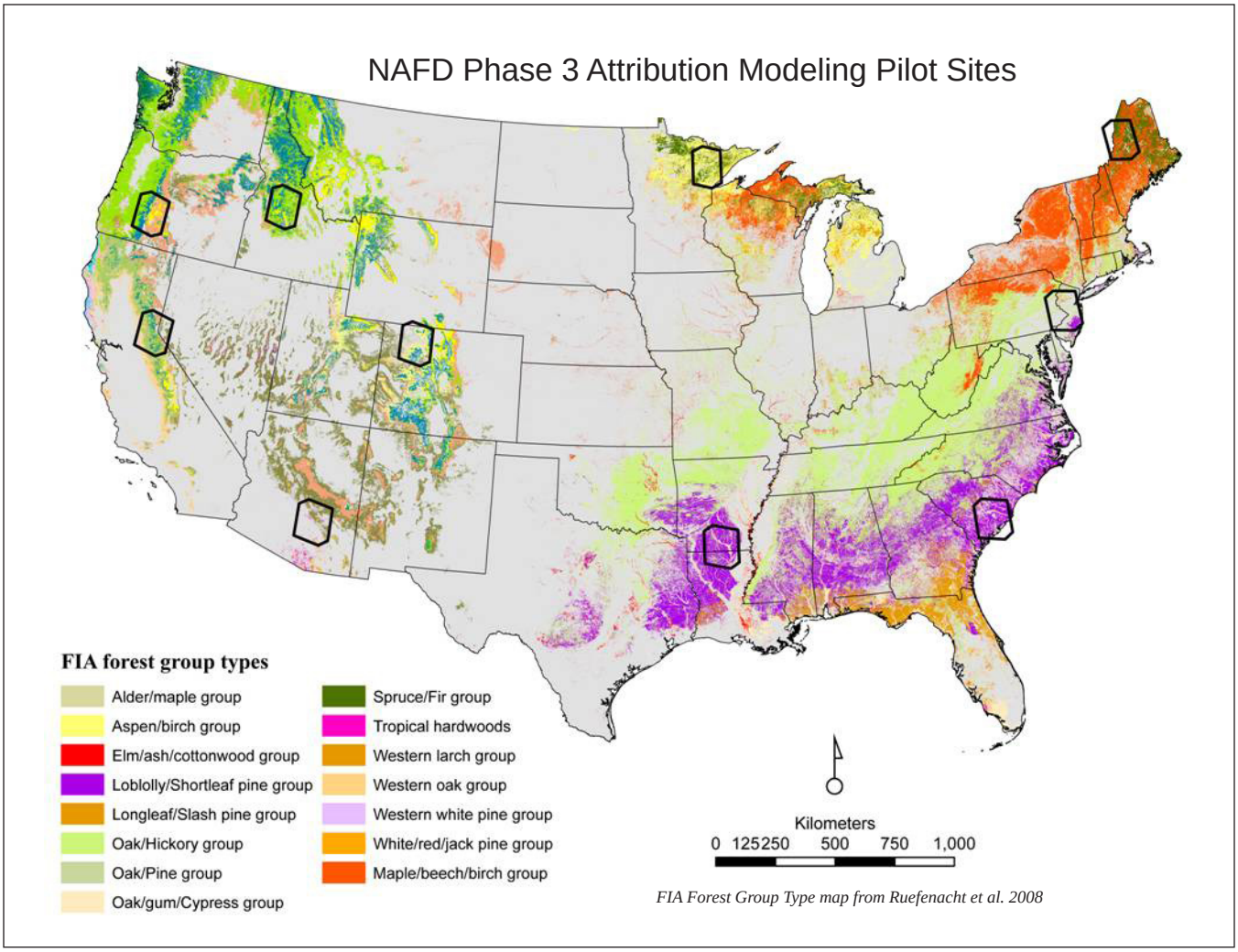


Figure 1.— Ten sample scenes selected for pilot testing causal attribution methods for North American Forest Dynamics (NAFD) Project Phase 3. Scenes were selected to capture a variety of causal agents in diverse forest types.

Issues being addressed in this pilot phase include: choosing the target population, identifying realistic classes to be modeled, testing which predictor variables contribute to our empirical models, choosing between pixel or polygon modeling objects, and combining empirical and rule-based models for the improved predictions. Results from these pilot tests will be presented in December 2012.

CONCLUSION

One take-home message from this overview relates to FIA and collaboration. Increasingly, various groups are approaching FIA requesting access to plot coordinates to conduct a wide variety of research. What is different about the NAFD project is that it involved FIA as full partners in research and helped to secure funding to support our involvement. This has resulted in more than the FIA logo on maps or names of FIA scientists on numerous publications. It has resulted in FIA expanding its capacity through acquisition of new tools, and more importantly, new people and talent within the organization.

ACKNOWLEDGMENTS

This research was supported in part by the North American Carbon Program, NASA grant NNH11AR18I.

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THE NORTH AMERICAN FOREST DYNAMICS STUDY: A DECADE OF LEARNING ABOUT U.S. FOREST DISTURBANCE

Samuel N. Goward, Warren B. Cohen, Chengquan Huang, Jeffery Masek, Gretchen G. Moisen, Rama Nemani, Karen Schleeweis, and Nancy Thomas[1]

Abstract.—The North American Forest Dynamics (NAFD) study is a core project of the interagency North American Carbon Program. The first step in the study, a prototype analysis carried out in the mid-Atlantic region, showed the potential of combining time series Landsat observations with the U.S. Forest Service Forest Inventory and Analysis (FIA) field measurements. With the assistance of FIA staff, the investigators began to explore merging the NASA/USGS Landsat observations with the FIA measurements in order to evaluate forest disturbance dynamics in the United States in the next 6 years the study demonstrated the difficulties encountered in sampling Landsat locations as a means to estimate U.S. national rates in disturbance. What was found is that disturbances occurring in specific Landsat locations dominated estimated national rates in given years. Further by examining Landsat observations every other year, significant low intensity disturbance events were missed. These "lessons learned" have led to NAFD phase III, in which we will conduct an annual, wall-to-wall analysis of the coterminous U.S. disturbance rates and underlying processes and will explore the potential for estimating regrowth rates. Further, we are now developing validation methodology which should permit estimates of the accuracy and precision of these national forest dynamics.

Throughout this decade of research, the NAFD team has maintained a strong partnership with the FIA and related U.S. Forest Service activities. What began as solely North American Carbon Program science goal has now developed a strong relation between NASA research activities and U.S. Forest Service operational responsibilities.

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VALIDATION STRATEGY FOR NAFD LANDSAT TIME SERIES FOREST CHANGE MAPS

Warren B. Cohen, Steve Stehman, Susmita Sen, Peder Nelson, Chengquan Huang, Karen Schleeweis, and Gretchen G. Moisen[1]

Abstract.—Landsat time series (LTS) contain detailed information about land use and cover change. To characterize forest disturbance, automated LTS algorithms are now being developed, tested, and applied over large areas. Because these algorithms are used over broad regions and periods up to 40 years, obtaining a statistically valid sample of independent reference data for map validation is both costly and prohibitively challenging. We present an alternative strategy based on human interpretation of the LTS for a sample of plots, both as image chip series and as spectral plots over time. In addition, we use Google Earth™ historical temporal snapshots of high resolution images to provide critical LTS interpretation support.

Our interpretation system, TimeSync, is being used for validation of Vegetation Change Tracker (VCT) maps for the conterminous United States as part of the North American Forest Dynamics (NAFD) project. Because the collection of validation data must precede the completion of map development, we designed a sequential two-step stratified-random approach with nonforest, undisturbed forest, and disturbed forest map strata. The first step of the sample selection is based on a preliminary VCT map, with approximately one half of the intended number of plots interpreted. When the VCT map stabilizes, after several iterations of the algorithm's implementation, the second step in the selection process will round out the sample to obtain the desired distribution of plots per stratum.

Our validation strategy includes interpretation of each plot by two separate interpreters. A third interpreter arbitrates disagreements to provide a final high quality reference dataset, which has built in confidence scoring, based on the integration over all interpreters. Once the plots are interpreted, an agreement matrix is constructed to assess VCT map accuracy. In our presentation, we present the validation strategy, as described above, and present preliminary results from a set of 10 LTS scenes distributed across the United States.

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POST-DISTURBANCE RECOVERY ANALYZED FROM REMOTE SENSING TIME SERIES AND FIA DATA

Jeffrey Masek, Khaldoun Rishmawi, and Samuel N. Goward[1]

Abstract.—As part of the third phase of the North American Forest Dynamics project (NAFD), the fate of all patches disturbed between 1972 and 2010 in the conterminous United States is being investigated. While forest succession encompasses a wide range of ecological attributes, we are particularly interested in the accumulation rate of aboveground biomass during recovery from disturbance. Previous studies have noted the relative insensitivity of optical remote sensing for measuring biomass in mature stands. However, it has also been demonstrated that early recovery (e.g., the first 10-20 years following disturbance) can be tracked successfully via multispectral metrics. Our goal is to provide as much detail as possible on the early biomass recovery rate on a per-patch basis, while also providing spatially aggregated mean and variance of recovery rate across U.S. ecoregions. Of particular interest is whether recovery rates are changing through time (e.g., comparing the 1980s with the 2000s). Changes in management and growth enhancement in the eastern United States, as well as increased multiple interacting disturbances in the western United States, suggest the hypothesis that recovery rate distributions may not be stationary.

The project involves three approaches for assessing recovery rate: 1) empirical modeling using remeasured FIA plots and Landast spectral trajectories; 2) physical modeling of observed reflectance using canopy radiative transfer models parameterized with FIA attributes; and 3) correlation of time-since-disturbance with contemporary structural information from Lidar and stereo imaging. One innovation of the work is that temporal trends in the Landsat timeseries (rather than single-date reflectances) will be used to model contemporary biomass and biomass change rate. This presentation will review the science context for characterizing post-disturbance recovery, and provide initial results for a set of pilot frames across the United States.

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COOL TOOLS

NEW FEATURES ADDED TO EVALIDATOR: RATIO ESTIMATION AND COUNTY CHOROPLETH MAPS

Patrick D. Miles and Mark H. Hansen[1]

Abstract.—The EVALIDator Web application, developed in 2007, provides estimates and sampling errors for many user selected forest statistics from the Forest Inventory and Analysis Database (FIADB). Among the statistics estimated are forest area, number of trees, biomass, volume, growth, removals, and mortality. A new release of EVALIDator, developed in 2012, has an option to select two statistics and generate a ratio estimate of the pair. The new feature can estimate statistics such as volume or growth per acre or the growth to removals ratio. Also, the program now makes county choropleth maps of all estimates. We provide information on the data and methods used along with sample output from a simple query that demonstrates these new features.

INTRODUCTION

The Forest Inventory and Analysis (FIA) Program of the U.S. Forest Service monitors the status and trends of the Nation's forest resources. FIA delivers data, information, and knowledge to the public via a multitude of products, including online estimation tools. FIA's EVALIDator Web application (http://apps.fs.fed.us/Evalidator/tmattribute.jsp) can produce estimates for 125 attributes falling into the 12 groups depicted in Table 1. Groups are based on subsets of inventory plots, where each subset is a valid sample and the attributes in the group are observed on all of the plots in the subset. FIA uses the term "evaluation" for these subsets of plots and the associated Phase 1 stratification that provides the sample base for the estimation of specific attributes. Area and volume estimates, for example, are based on the plots measured in the current inventory; removals estimates are based on a smaller set of plots measured in the previous inventory and then measured again in the current inventory. The EVAL_TYP column in Table 1 identifies the evaluation used to generate the estimates. Down woody material estimates are based on a small subset of plots on which forest health monitoring (Phase 3) measurements were taken. The right column in this table shows the number of plots in each evaluation (for Minnesota, as an example) where a non-zero value for the first attribute in the group was observed in the specified inventory and provides information on the intensity of the inventory with respect to various attributes.

In addition to the ability to produce population estimates with sampling errors for user specified inventories, the EVALIDator program has the flexibility to place restrictions on the estimates and breakdowns of the estimates into user defined tables. Users can also obtain the Oracle SQL code that produces the estimates for further modification.

METHODS

EVALIDator is flexible with many options selected via radio buttons and dropdown lists. In this new version, once the user selects the attribute to be estimated, there is now a radio button to select between population estimate (default) and ratio estimate. When ratio estimate is selected, the attribute

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Table 1.—The EVALIDator program can produce reports for these types of estimates

EVAL_TYP	ESTIMATE GROUP	Non-zero plots Minnesota 2011
EXPALL	Area of sampled land	17,711
EXPCURR	Area of forest land or timberland	6,208
EXPVOL	# trees, # seedlings, volume, biomass or carbon on forest land	6,089
EXPVOL	# trees, # seedlings, volume, biomass or carbon on timberland	5,751
EXPGROW	Average annual net growth on forest land	5,705
EXPGROW	Average annual net growth on timberland	5,459
EXPMORT	Average annual mortality on forest land	3,296
EXPMORT	Average annual mortality on timberland	3,140
EXPREMV	Average annual removals on forest land	544
EXPREMV	Average annual removals on timberland	605
EXPDWM	Down woody material (#, vol., biomass or carbon) on forest land	xxx
EXPDWM	Down woody material (#, vol., biomass or carbon) on timberland	xxx

initially selected will be the numerator, and a second dropdown list of attributes appears for the user to select the denominator. The user then selects the evaluation(s) (identified by state and inventory years) to be included in the estimate and a classification variable used to break down the estimate in the final table. For ratio estimation, an additional radio button determines how to apply the classification variable to the table of estimates, either to both numerator and denominator (default) or to the numerator but the total of all classes is used for the denominator in every class. For ratio estimates, there are two options (population estimates have just one) for the user to put more restrictions on the estimates through additions to the "where" clause. One option is applied to both the numerator and denominator and the other is applied just to the numerator. Once all of these selections have been made, the program will generate the estimates requested in a table and a county choropleth map will be generated if county was selected as a classification variable. There is an option to generate a second table that contains estimates and their associated sampling errors. All of the estimates of ratios and their associated sampling errors are generated following the stratified ratio-of-means estimators (Bechtold and Patterson 2005).

Users of the ratio estimates produced by EVALIDator need to be aware of three issues. First, ratio estimation requires that the same evaluation be used to estimate both the numerator and denominator. This reduces the evaluation to the smaller of the two. For example, when estimating net growth per acre of forest land, the area of forest land estimate is based on a smaller sample of plots than is normally used to estimate forest area. For this ratio, only those plots measured at two points in time (the EXPGROW evaluation) are used to estimate both the numerator and denominator. Because this estimate of forest land area is based on a somewhat different sample, it probably will not match other estimates of forest land area produced by EVALIDator or those published by FIA.

The second issue is that ratio estimates of all growth, removals, or mortality (GRM) attributes are based only on the components associated with no change in condition classification of the land. These GRM estimates exclude diversions and reversions and the area associated with the change in classification. Thus, the area estimate in the denominator of the net growth per acre of forest land estimate is an estimate of forest land area that was forest at the time of the first measurement and that remained forest at the

time of the second measurement. The numerator and denominator estimates in the ratios usually will not match population estimates obtained from EVALIDator or those published in most FIA reports because those include the diversion and reversion components and associated areas.

The third issue relates to how restrictions on the numerator and denominator are applied and how breakdowns in the table of ratio estimates are made when ratio estimates are computed. Table 2 identifies the type of ratio estimates and classification variables that can be derived using EVALIDator and provides information as to whether the classification variable is derived from data collected during the current inventory or, in the case of GRM, from information collected during the previous inventory (Note: using the previous or current classification variable for GRM ratio estimates may not be appropriate for all analyses). In some cases ratio estimates are not logical and the program will not allow the user to produce an estimate. For example, although it is possible to compute acres of timberland per cubic foot of volume, it is not logical to report these estimates by a classification such as species because area cannot be classified by species. The EVALIDator program will not allow the user to select a tree classification variable when an area estimate has been selected for the numerator. These situations are labeled as "not possible" in Table 2.

RESULTS

Partial output from a simple volume per acre retrieval is presented in Table 3. In this example the user selected "Net volume of live trees in cubic feet on forest land" as the numerator, "Area of forest land, in acres" as the denominator, the 2011 inventories of Minnesota and Wisconsin as the geographic area, and "County code and name" as the classification variable. The EVALIDator first generates the estimates in Table 3 and then, if desired, may also generate more

Table 2.—Limitations on stand and tree level ratio estimates in EVALIDator

Stand or Tree Classification Variable	Numerator Estimate	Denominator Estimate	Classification variable is derived from current or previous inventory	Denominator can be based on class total rather than grand total
Stand	Area	Area	current	YES
Stand	Area	Volume	current	YES
Stand	Area	GRM	previous	YES
Stand	Volume	Area	current	YES
Stand	Volume	Volume	current	YES
Stand	Volume	GRM	previous	YES
Stand	GRM	Area	previous	YES
Stand	GRM	Volume	previous	YES
Stand	GRM	GRM	previous	YES
Tree	Area	Area	not possible[a]	not possible[a]
Tree	Area	Volume	not possible[a]	not possible[a]
Tree	Area	GRM	not possible[a]	not possible[a]
Tree	Volume	Area	current	NO
Tree	Volume	Volume	current	YES
Tree	Volume	GRM	current	YES
Tree	GRM	Area	previous	NO
Tree	GRM	Volume	previous	YES
Tree	GRM	GRM	previous	YES

[a]Not possible - Tree classification variable cannot be applied to area estimate.

Table 3.—All live volume per acre of forest land by county, Minnesota and Wisconsin 2011

County Code and Name	Ratio Estimate (cf/acre)	Estimate of Numerator (cubic feet)	Estimate of Denominator (acres)
Total	1,244.22	42,739,454,212	34,350,476
27001 Aitkin	1,114.52	922,606,356	827,809
27003 Anoka	1,402.15	91,676,643	65,383
27005 Becker	1,289.74	430,711,212	333,953
…	…	…	…

statistics that include sampling errors, variances, and number of plots used in the estimate. "County code and name" was selected as the classification variable so the user also has the option of producing a county choropleth map as depicted in Figure 1.

DISCUSSION

The EVALIDator program continues to evolve to meet user needs. This latest version introduces two new features, ratio estimates and county choropleth maps. Recent changes to the FIADB have also made it possible to generate population estimates for down woody material. The ability to produce ratio estimates for down woody material was not included in the EVALIDator program due to a paucity of data for down woody estimates. As the FIADB evolves, additional reporting of forest health monitoring estimates will be added to the EVALIDator program.

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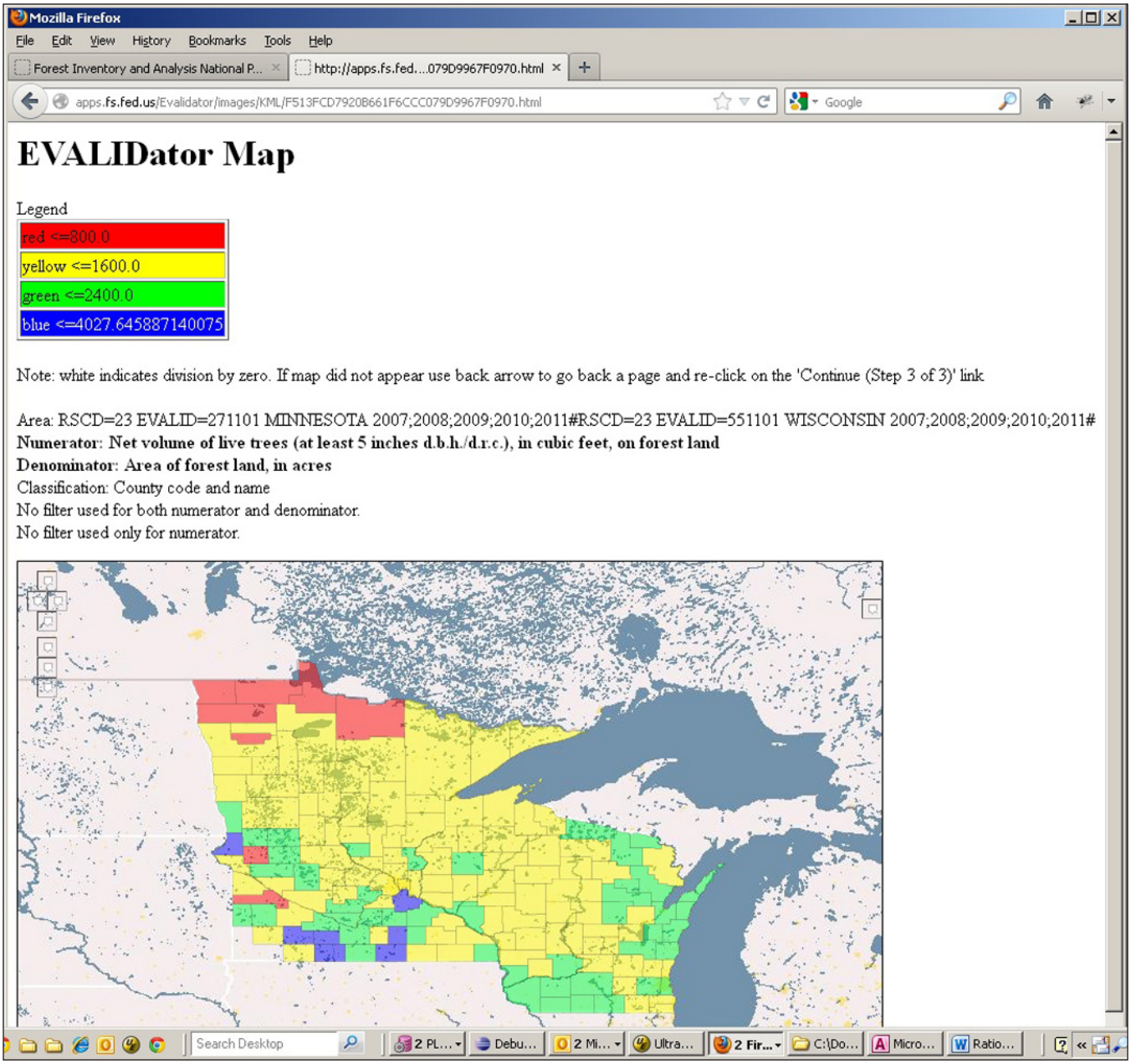


Figure 1.—All live volume per acre of forest land by county, Minnesota and Wisconsin 2011.

USING FIESTA, AN R-BASED TOOL FOR ANALYSTS, TO LOOK AT TEMPORAL TRENDS IN FOREST ESTIMATES

Tracey S. Frescino, Paul L. Patterson, Elizabeth A. Freeman, and Gretchen G. Moisen[1]

Abstract.—FIESTA (Forest Inventory Estimation for Analysis) is a user-friendly R package that supports the production of estimates for forest resources based on procedures from Bechtold and Patterson (2005). The package produces output consistent with current tools available for the Forest Inventory and Analysis National Program, such as FIDO (Forest Inventory Data Online) and EVALIDator. FIESTA was developed as an alternative data retrieval and reporting tool that is functional within the R environment, allowing customized applications and compatibility with other R-based analyses. FIESTA generates estimates and percent sample errors of the estimates for area, population totals, and ratios, while allowing user-defined boundaries, stratification schemes, and data filters. The features of the tool are demonstrated using temporally sensitive data over diverse areas.

INTRODUCTION

Traditional analytical tools of the Forest Inventory and Analysis (FIA) Program have been developed for reporting state-level estimates of forest resources. The growing popularity of the FIA Program, the diverse range of questions and data requests from our customers, and the ongoing advancements of remote sensing technology have expanded our analytical needs. We now require capabilities to monitor annual data trends, report on different areas of interest, and incorporate diverse ancillary data layers for reducing estimation variances. In essence, we need a flexible estimation engine that we can use to answer many forest estimation questions using many different sources of ancillary data.

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FIESTA

FIESTA (Forest Inventory Estimation for Analysis) is a package developed in the R environment (R Development Core Team 2011). R is a powerful statistical computing and graphical program language that is becoming more popular within the natural resource analysis community. It is free software that provides a flexible, cross-platform environment for statistical tool development and application through R package-building. The comprehensive library of contributed package applications along with R's base functions and extensive user-community provides powerful resources for analysts including statistical, spatial, and graphical tools. The main objective of FIESTA is to provide a data-retrieval and reporting tool for FIA analysts and scientists that is more flexible than existing FIA tools and is adaptable to analysts' changing needs.

The major components of the FIESTA package are:

1. Extracting data from the FIA database for a user-defined area of interest.
2. Acquiring user-defined stratification layers.

3. Generating area estimates and standard errors within user-defined populations.
4. Generating tree attribute and ratio estimates: for example, the number of aspen trees per acre in the Lodgepole Pine forest type.

Specific features of FIESTA include: extracting data from the national or regional FIA National Information Management System database (NIMS) (Woudenberg et al. 2011); allowing for user-defined populations, strata, and data filters; ability to generate tabled estimates with sample error of area, population totals, and estimation of ratios; and providing additional tools for data exploration and spatial data manipulation, such as frequency tables and bar plots as well as raster clipping and pixel or polygon data extraction. FIESTA can be run through a graphical user interface environment or by supplying specific input parameters defined by the user. Because it is developed in R programming language, it also can easily interact with other R functions and packages, opening up many opportunities for further customization and development of tools within FIESTA.

EVALIDator AND FIESTA COMPARISON

EVALIDator is FIA's Web-based or personal computer tool for producing tables of population estimates including sampling errors (this tool is available at www.fia.fs.fed.us/tools-data/other/default.asp). EVALIDator was used to validate the accuracy of output from FIESTA. For example, Table 1 shows a comparison of the output from EVALIDator and the output from FIESTA for estimating cubic feet per acre by forest type in Montana. The percent difference is less than 1 percent for the estimates, most likely from rounding errors. The percent difference in the sampling error is also less than 1 percent in most cases. The larger differences are in types where the sampling error is already high.

FIESTA EXAMPLES

FIESTA originated from a request from the San Carlos Apache Indian Reservation in southeastern Arizona to support a cost-effective woodland inventory to

Table 1.—Comparison of EVALIDator and FIESTA. The difference in per-acre estimates and sampling error of net volume of live trees (at least 5 inches diameter) by forest type on forest land, Montana, 2003-2009. Subset of actual table.

Forest type	EVALIDator Estimates (ft^3/acre)	FIESTA Estimates (ft^3/acre)	Difference Estimates (%)	EVALIDator Error (%)	FIESTA Error (%)	Difference Error (%)
Rocky Mtn. juniper	328.797	327.603	0.363	8.425	8.427	-0.0237
Juniper woodland	358.052	357.705	0.097	23.955	23.281	2.8136
Douglas-fir	1835.605	1820.685	0.813	2.694	2.687	0.2598
Ponderosa pine	963.91	957.834	0.630	5.27	5.264	0.1139
Engelmann spruce	3038.053	3011.842	0.863	6.32	6.301	0.3006
Grand fir	2486.062	2464.538	0.866	18.416	18.325	0.4941
Subalpine fir	1669.218	1654.858	0.860	4.949	4.922	0.5456
Mountain hemlock	3428.542	3402.067	0.772	21.038	21.074	-0.1711
Lodgepole pine	2210.947	2192.483	0.835	3.312	3.304	0.2415
Western hemlock	8401.806	8323.888	0.927	15.173	15.101	0.4745
Western redcedar	4225.783	4196.477	0.694	9.299	9.251	0.5162
Western larch	2722.67	2698.901	0.873	7.252	7.198	0.7446
Limber pine	517.243	513.428	0.738	23.943	24.184	-1.0066
Whitebark pine	1906.364	1888.815	0.921	7.466	7.477	-0.1473

quantify woodland resources on its 1.8 million acres. It is currently difficult to generate estimates using FIA data for populations other than a state using FIA's estimation tools. With FIESTA, it is possible to extract FIA plots within a specific area, such as the San Carlos Reservation boundary, and produce estimates based on a given stratification layer and the total area of the population.

We generated estimates of area by forest type groupings (Table 2) and area, basal area, and trees per acre of woodland types using FIA plot data and a spatial layer of biological plant communities that was provided for stratification. The resulting information was helpful for an initial look at quantifying the forest resources within the boundary and identifying areas or forest types having high sampling errors that would need further sampling to minimize variance.

Table 2.—Area estimates for San Carlos Apache Indian Reservation forest type groups

Class	Number of Plots	Area (acres)	Sampling error (%)
Nonforest	173	1,073,858	4
Ponderosa	14	78,786	24
PJandJ	61	378,460	10
Oak	30	161,079	16
Non-stocked	21	123,989	21
Mesquite	5	30,870	45
Cotton/Misc.	2	12,445	71

Another topic of interest in the Western region is looking at temporal changes of species distributions. This information is useful for monitoring trends and potential changes in individual species distributions through time. It is currently difficult to generate estimates by year from FIA's estimation tools, but with the programming and customization features of FIESTA, it is a simple routine that can be applied to any species.

We used FIESTA to look at estimates of live net cubic-foot volume annually for lodgepole pine (Pinus contorta) and aspen (Populus tremuloides) species in Colorado, Montana, and Utah (Figs. 1 and 2). The scale of the figures reflects the amount of each species in the respective state. A simple function was developed to generate bar plots of estimates by inventory year using the total plots sampled each year and a simple statewide stratification scheme. The figures are useful as initial data exploratory tools but are not conclusive evidence for real changes on the ground.

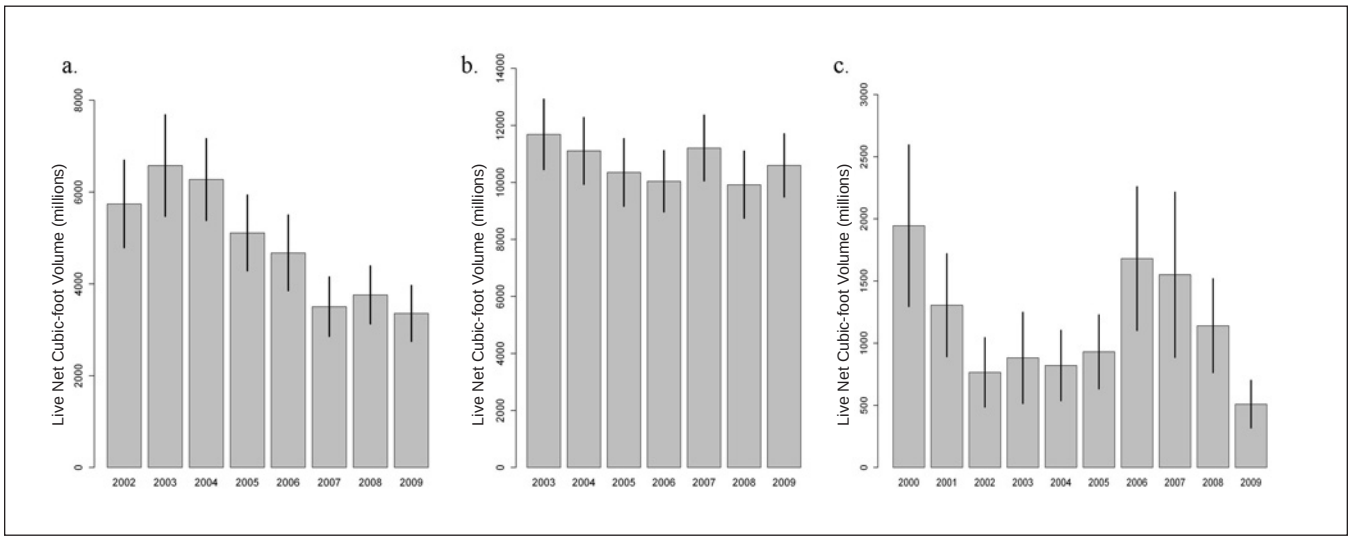


Figure 1.—Net cubic-foot live volume for lodgepole pine by inventory year for three states in the Interior West: a. Colorado; b. Montana; c. Utah.

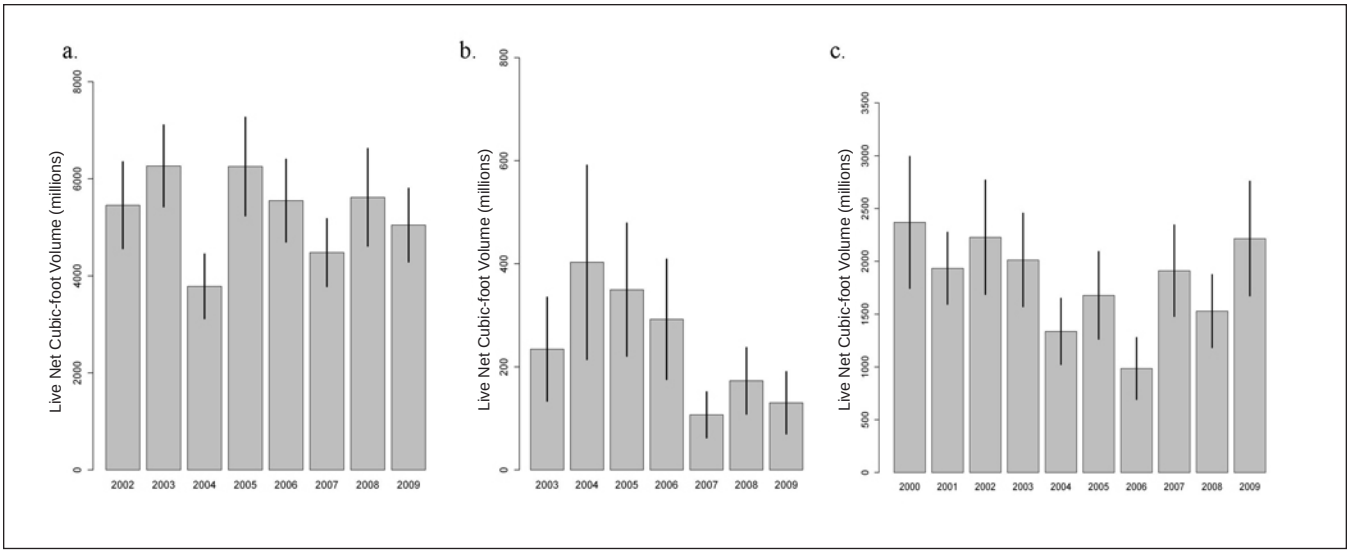


Figure 2.—Net cubic-foot live volume for aspen by inventory year for three states in the Interior West: a. Colorado; b. Montana; c. Utah.

STATUS AND FUTURE OF FIESTA

The FIESTA package was designed as a base program for accessing the FIA NIMS database and generating estimates of forest attributes using user-defined boundaries, strata, and filters.

The functionality and efficiency of the base program will be periodically analyzed and updated for speed and consistency. Updates will also occur to reflect changes in the NIMS database schema, including the addition of new reference tables or regional tables, changes in variable names, or general structural changes. The base program will be continuously augmented with additional data exploration tools and spatial tools to assist with estimation.

Plans for current and future work with FIESTA, incorporating additional customized capabilities and tools for different needs, are as follows:

- Adding small area estimation capabilities to generate estimates for areas within user-defined boundaries that contain only a few FIA field-sampled plots.
- Adding compatibility with R packages, such as ModelMap (Freeman 2009) and PresenceAbsence (Freeman and Moisen 2008), to coordinate estimates of FIA attributes with pixel-based mapping of the same attributes.
- Adding a mechanism to compensate for nonresponse within the FIA sample.
- Adding functionality to integrate remotely sensed observations, such as photo interpretation from large-scale aerial photographs or measurements from Landsat or Light Detection and Ranging.
- Exploring alternatives to the moving average.
- Communication with Forest Vegetation Simulator to generate estimates of future growth simulations.

ACKNOWLEDGMENTS

The authors would like to acknowledge Mark Rubey for his assistance with understanding the structure of the FIA NIMS database, Jim Menlove for his extensive knowledge of EVALIDator, and the reviewers of the paper.

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AREA CHANGE REPORTING USING THE DESKTOP FIADB

Patrick D. Miles and Mark H. Hansen[1]

Abstract.—The estimation of area change between two FIA inventories is complicated by the "mapping" of subplots. Subplots can be subdivided or mapped into forest and nonforest conditions, and forest conditions can be further mapped based on distinct changes in reserved status, owner group, forest type, stand-size class, regeneration status, and stand density. The boundaries of these mapped conditions may change from one inventory to the next, resulting in complex geometries when the two sets of boundaries are combined. The SUBP_COND_CHNG_MTRX (CMX) table was added in version 4.0 of the FIADB to "facilitate the tracking of area change" between annual inventories. The AreaChangeReports form (located within downloadable FIADB Microsoft Access databases) uses the CMX table to link remeasurement plots from two successive annual inventories to produce estimates of area change. An example is provided to illustrate shifts in land use over a 5-year remeasurement period. FIADB databases for each of the 48 contiguous states and southeast Alaska, along with built-in reporting tools including the AreaChangeReports form, are available for downloading from the FIADB DataMart (http://apps.fs.fed.us/fiadb-downloads/datamart.html) as Microsoft Access 2007™ databases.

INTRODUCTION

FIADB data have been available on the Web since FIADB version 1.0 was developed in 2001. Initially FIADB data were available for downloading as comma-delimited files. In 2007 a small subset of FIADB tables, and a few SQL scripts for generating population estimates, were available in Microsoft Access database format for downloading from the Web (Miles 2008). By 2009, however, all of the FIADB tables, along with a fully developed reporting tool for generating population estimates and their associated sampling errors, were available for downloading as MS-Access databases (Miles 2009).

Under the annual inventory system, subplots can be subdivided or "mapped" into forest and nonforest conditions, and forest conditions can be further mapped based on distinct changes in reserved status, owner group, forest type, stand-size class, regeneration status, and stand density. These subplots, when remeasured several years later, are mapped again based on the same six criteria if there is an obvious change. The mapping information from these two inventories is combined in the CMX table to form a subplot condition change matrix. The SUBP_COND_CHNG_MTRX (CMX) table was added to the FIADB (version 4.0) in 2010. The CMX table facilitates the generation of area change reports. A detailed explanation of this process is provided in The Forest Inventory and Analysis Database: database description and users manual version 4.0 for Phase 2 (pp. 230-240 in Woudenberg et al. 2010).

METHODS

Area change estimates can be computed only for those states with remeasured data collected under the annual inventory design. Therefore, area change estimates are

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currently not available for Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming. Microsoft Access databases containing FIADB data and reporting tools can be downloaded from the FIA DataMart (http://apps.fs.fed.us/fiadb-downloads/datamart.html).

The AreaChangeBetweenInventories reporting tool is an MS-Access form. Double-clicking on the form name will initiate the program and the form in Figure 1 will appear. The user is required to (1) pick an evaluation or reporting year, (2) pick a classification variable, (3) pick a set of plots to be used in generating the estimate, and (4) specify an additional filter if desired. In the following example, a database containing FIADB data for Minnesota is used.

Pick an Evaluation

In Minnesota, annual inventory plots were first remeasured in 2004 and every year thereafter through 2011 so there are eight different "evaluations" or reporting years to choose from. For the evaluation "Minnesota 2011: 2002-2006 to 2007-2011"

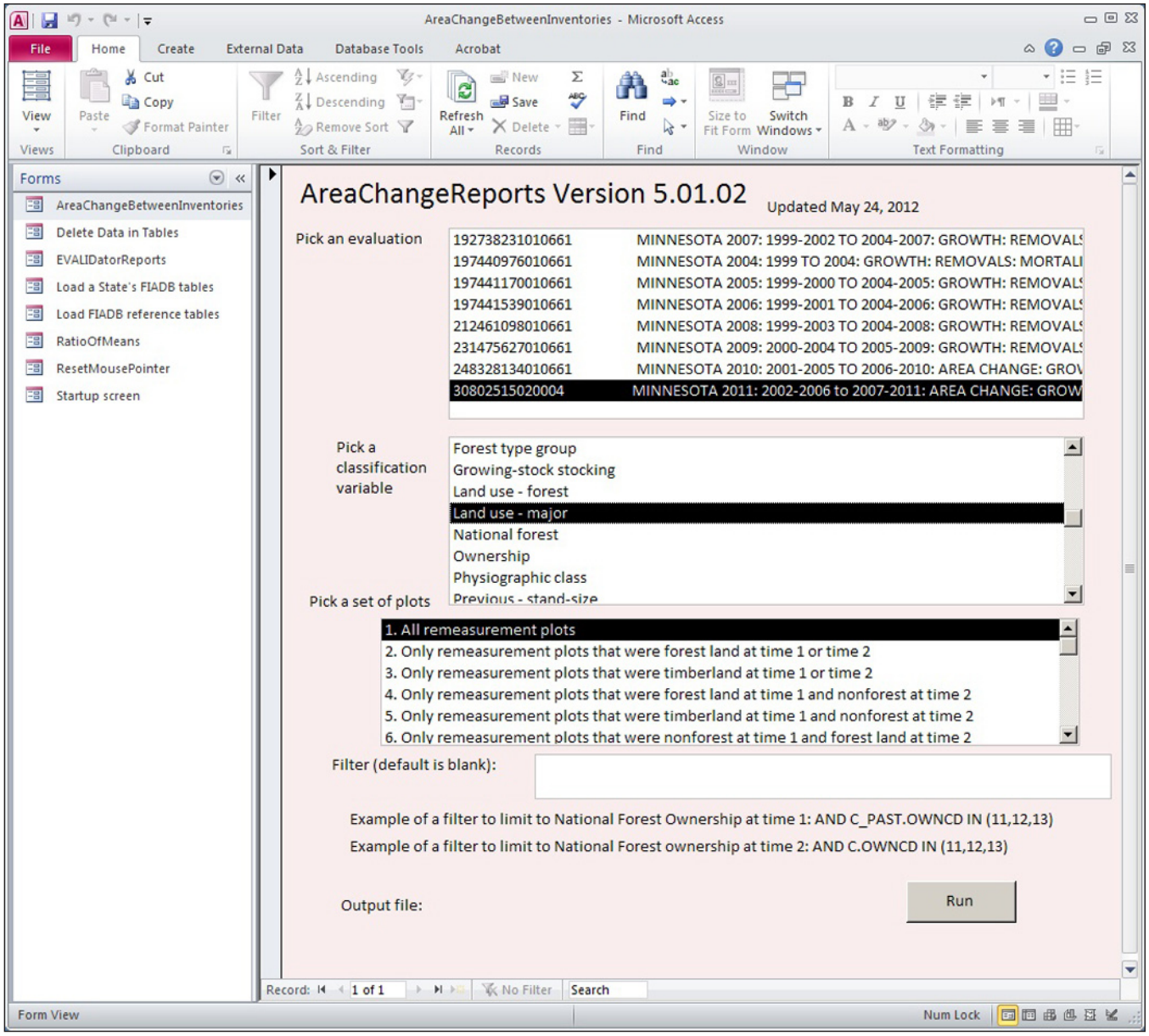


Figure 1.—AreaChangeBetweenInventories reporting form.

(highlighted in Figure 1), plots measured in 2002-2006 were remeasured in 2007-2011.

Pick a Classification Variable

Classification variable names are stored in the MS-Access table REF_PRC. Only classification variables based on a condition characteristic can be used in the AreaChangeBetweenInventories reporting tool. A list of these classification variable names is provided in Table 1. In Figure 1 the classification variable "Land use-major" is highlighted.

The FIA inventory is designed to track changes in forest land. Most of these classification variables above are not observed on conditions that are nonforest at both measurements. It is not possible to use the FIA data to estimate things such as ownership class changes on nonforest lands.

Pick the Area of Interest

The set of plots used in generating the estimate is either the entire set of remeasured plots or a subset of those plots (Table 2). "All remeasured plots" is highlighted in Figure 1 because, in this example, we are interested in how land use changed on the entire land area of Minnesota. If we were interested in how forest land made the transition between forest-type groups over the remeasurement period, we would have selected "Only remeasurement plots that were forest land at time 1 or time 2."

Specify an Additional Filter

More specific estimates may be required in some instances. For example, if a user wanted to determine what happened on timberland that was in the jack pine forest type at the time of the previous inventory, the user would enter "AND C_PAST.FORTYPCD IN (101)" in the filter textbox. In this example no additional filter was specified.

RESULTS

A simple retrieval was run (Fig. 1) using the AreaChangeReports form. The evaluation chosen used plots measured in 2002-2006 and remeasured in 2007-2011. The classification variable selected was "Land use–major" and the report was based on all land and water. The output from this retrieval is presented in Tables 3 and 4. Table 3 contains a cross-tabulation of the number of acres by past and present major land use. Table 4 provides information on the number of plots used in providing this estimate. The retrieval also outputs the SQL script used by the AreaChangeReports form to generate the report.

Table 1.–Classification variables available in AreaChangeBetweenInventories reporting tool

All live stocking	Forest type	Ownership	Stand origin
Artificial regen species	Forest-type group	Physiographic class	Stand treatment code 1
Basal area live tree	Growing-stock stocking	Previous-stand-size	Stand treatment code 2
Disturbance code 1	Land use-forest	Site index	Stand treatment code 3
Disturbance code 2	Land use-major	Site productivity	Stand-age
Disturbance code 3	National forest	Slope	Stand-size
Forest Service Region			

Table 2.–Area of interest options in the AreaChangeBetweenInventories reporting tool

1. All land and water
2. Only land that was forest land at time 1 or time 2
3. Only land that was timberland at time 1 or time 2
4. Only land that was forest land at time 1 and nonforest at time 2
5. Only land that was timberland at time 1 and nonforest at time 2
6. Only land that was nonforest at time 1 and forest land at time 2
7. Only land that was nonforest at time 1 and timberland at time 2

Table 3.—Acres by past and present major land use, MN, 2002-2006 to 2007-2011

	Present Land Use - Major				
Past Land Use - Major	**Total**	**Forest**	**Nonforest**	**Noncensus Water**	**Census Water**
Total	54,008,529	17,292,981	33,415,843	214,121	3,085,584
Forest	16,335,759	16,096,331	224,383	9,685	5,360
Nonforest	34,289,917	1,125,577	32,945,644	86,916	131,780
Noncensus water	373,750	40,478	135,668	86,484	111,119
Census water	3,009,103	30,595	110,148	31,035	2,837,325

Table 4.—Number of plots by past and present major land use, MN, 2002-2006 to 2007-2011

	Present Land Use - Major				
Past Land Use - Major	**Total**	**Forest**	**Nonforest**	**Noncensus Water**	**Census Water**
Total	17,454	5,274	11,106	64	1,010
Forest	4,976	4,902	69	3	2
Nonforest	11,380	353	10,959	26	42
Noncensus water	113	10	43	26	35
Census water	984	9	35	9	931

The estimated area of forest land in 2011, based solely on remeasurement plots, is 17,292,981 acres, which is close to the estimate using all plots (17,370,394 acres) and within the 0.54 percent sampling error for this estimate. Of this total, 16.1 million acres, or 93.1 percent, was also forest land in 2006. Approximately 1.1 million acres, or 6.5 percent, was nonforest 5 years earlier, and 0.4 percent was in census or noncensus water. Only 0.2 million acres went from being classified as forest land in 2006 to being classified as nonforest or water in 2011. More than 98 percent of the land that was forested in 2006 remained forested in 2011. The result is a net increase in forest land over the 5-year period, from 16.3 million acres in 2006 to 17.3 million acres in 2011.

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THE DEVELOPMENT OF A LEGACY FIA REPORT SIMULATOR

Stephen P. Prisley, W. Brad Smith, and John W. Coulston[1]

Abstract.—The U.S. Forest Service Forest Inventory and Analysis Program (FIA) has a long history of providing crucial data on the nation's forest resources. Since 1928, the Forest Service has periodically conducted forest inventories and compiled and published data on the status and trends of the nation's forests. While more recent data is available digitally to the public, much of the historic data are available only in hardcopy publications, limiting its utility for computerized access and analysis. This presentation will describe a project begun in 2010 to compile information extracted from hundreds of published reports into a digital database we refer to as the FIA Legacy DB. This database contains tables of published estimates for common inventory parameters, such as timberland area by state and ownership, growing stock inventory, growth, removals, mortality, and species distributions. In addition to data tables containing estimates from published reports, interpolation routines were developed to provide estimates at common years by interpolation between report years. A set of reporting tools allows users to specify states or combinations of states, a time period, and then select from a variety of common reports. Example queries and reports will demonstrate the utility of this tool for quickly and easily delivering data previously available only in increasingly rare hardcopy reports.

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NONTIMBER FOREST PRODUCTS OUTPUT INFORMATION SYSTEM

James Chamberlain, John Munsell, Stephen P. Prisley, and Tom Hammett[1]

Abstract.—Nontimber forest products (NTFPs) are important commodities and critical components of healthy forests. They have not been sufficiently monitored to assess population status or trends in the dynamics of supply and demand. Over the last decade, U.S. Forest Service Forest Inventory and Analysis (FIA) of the Southern Research Station has reported on the status of NTFPs in particular states through state reports and at the national level through RPA assessment and the Sustainable Forests reports. In 2011, FIA and Virginia Tech initiated an effort to develop a nontimber product output (NTPO) information system similar to the timber product output (TPO) system. The protocol will systematically monitor harvested NTFPs. The initial focus of this project is on medicinal NTFPs in central Appalachia. This work provides a starting point for developing a replicable output system that can periodically report on medicinal NTFP production for the entire Appalachian forest region. Findings from the analysis of medicinal forest products will be integrated into a geographic information system that will spatially depict biological, socioeconomic, infrastructure and political aspects of the medicinal forest products segment. The long-term goal of this effort is to create a mechanism whereby nontimber forest products outputs across the nation can be tracked regularly and more completely valued. Authors will present the status of NTFPs in the south and report progress on development of the NTPO system. We also will encourage dialogue and suggestions with the audience regarding future efforts.

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CONNECTING FOREST INVENTORY WITH CLIMATE DATA

NEW APPROACHES TO FIA DATA FOR UNDERSTANDING DISTRIBUTION, ABUNDANCE, AND RESPONSE TO CLIMATE CHANGE

Kai Zhu, Souparno Ghosh, Alan E. Gelfand, and James S. Clark

Abstract.—We are using Forest Inventory and Analysis data to examine evidence for tree responses to climate change. By comparing seedling and tree occurrence data, we found that there is not yet evidence that tree populations in the eastern half of the United States are shifting geographic ranges to higher latitude in response to warming temperature. We are developing novel statistical methods to quantify seedling abundance in relation to climate and biotic variables, and to compare seedling and tree responses. We summarize how combining abundance data for seedlings and trees is allowing us to identify differences in how trees respond to climate change in the eastern half of the United States.

INTRODUCTION

Forest Inventory and Analysis (FIA) data provide evidence for the effects of climate variation at broad geographic scales. We are using FIA data to quantify relationships between tree distributions and environmental variation as part of a larger study on the consequences of climate change.

First, to determine whether trees shift ranges to track warming climates, we compared geographic distributions of juvenile and adult trees based on the assumption that a migrating population is characterized by offspring extending beyond adults at leading edges and the opposite at trailing edges. Through comparisons of approximately 100 species having range limits within the eastern United States (all states from Minnesota south to Louisiana and eastward), we found that there is not yet evidence for climate-mediated migration.

Second, to better interpret climate variables important for recruitment, we developed a novel zero-inflated statistical model for seedling counts with extreme incidence of zero observations. FIA seedling counts at plot level contain too many zeros to allow accurate inference using current models. Our zero-inflated general model, with *k* layers of zero-inflation (*k*-ZIG model) allows more flexible handling of both the zero-inflation and the nonzero counts. Whereas current zero-inflated models perform poorly, the *k*-ZIG model shows that seedling abundances can be explained by climate despite high proportions of zeros.

The third area we summarize here concerns the possibility that trees undergo ontogenetic niche shifts. We quantified the differences between juvenile and adult trees' climate relationships based on the FIA seedling and tree data. We are in the process of determining whether there are different patterns of ontogenetic niche expansion and contraction from juveniles to adults.

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RANGE SHIFTS AND GEOGRAPHIC DISTRIBUTIONS

Anticipating whether species' geographic ranges can track climate change is a goal of global change research. Mean annual temperatures increased substantially during the 20th century in the Midwest and Northeast, but have only recently begun to show substantial change in the Southeast, where warming summers were balanced by cooling winters in the past (Fig.1a). When viewed in terms of a climate change velocity, i.e., the ratio of temporal change over spatial gradient, regions in the Northeast and Upper Midwest have undergone climate shifts of more than 100 km during the 20th century (Fig. 1b).

Can tree distributions keep pace with the rapid climate warming? We used FIA data to directly compare seedling and tree 5th- and 95th-percentile latitudes for approximately 100 species for more than 40,000 plots across the eastern United States, and their relationship with climate change during the 20th century (Zhu et al. 2012). Our analysis is based on the rationale that a population that is migrating north in response to warming is expected to have offspring extending to higher latitudes than adults in regions that have warmed over the last century, but not in regions where climate has remained essentially constant. Likewise, a population retreating from a warming southern boundary is expected to have adults south of the southern extent of new recruitment by offspring.

We found that there is essentially no evidence that latitudinal migration has yet occurred for more than half of the approximately 100 tree species in eastern U.S. forests and there is a substantial migration lag behind climate change velocity (Fig. 2). In fact, results suggest that approximately 60 percent of the tree species examined show the pattern expected for a population undergoing range contraction, rather than expansion, at both northern and southern boundaries. Fewer species show a pattern consistent with a northward shift and fewer still with a southward shift. Only about 4 percent are consistent with expansion at both range limits. Comparing results with the 20th-century climate changes that have occurred at the

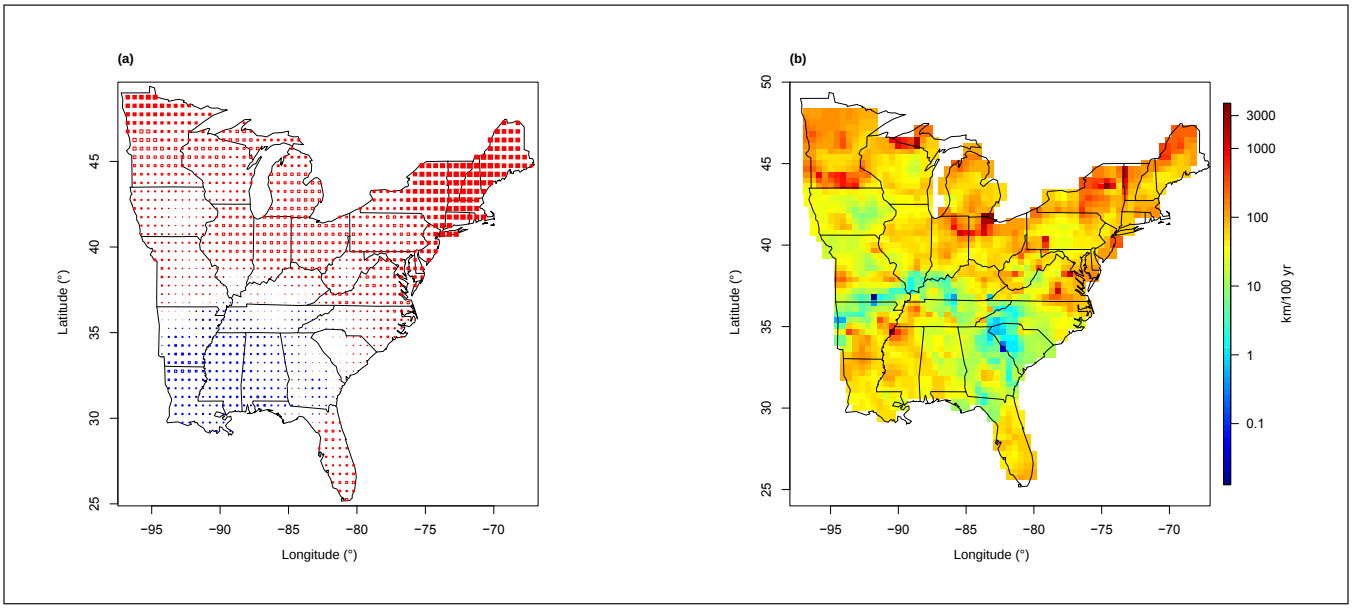


Figure 1.—Temperature change in time and space during the 20th century in the eastern United States. Data are extracted from 10 decadal mean annual temperatures from the Climate Research Unit dataset, 1901-2000 (Mitchell and Jones 2005). Squares in (a) denote the slope of the linear regression of decadal data (red – increasing trend, blue – decreasing trend); square size is proportional to the absolute value of the slope. Spatial velocity of temperature change (b) is defined as the quotient of the temporal gradient (a) and the north-south directional spatial gradient of temperature distribution (Loarie et al. 2009). Adapted from Zhu et al. (2012).

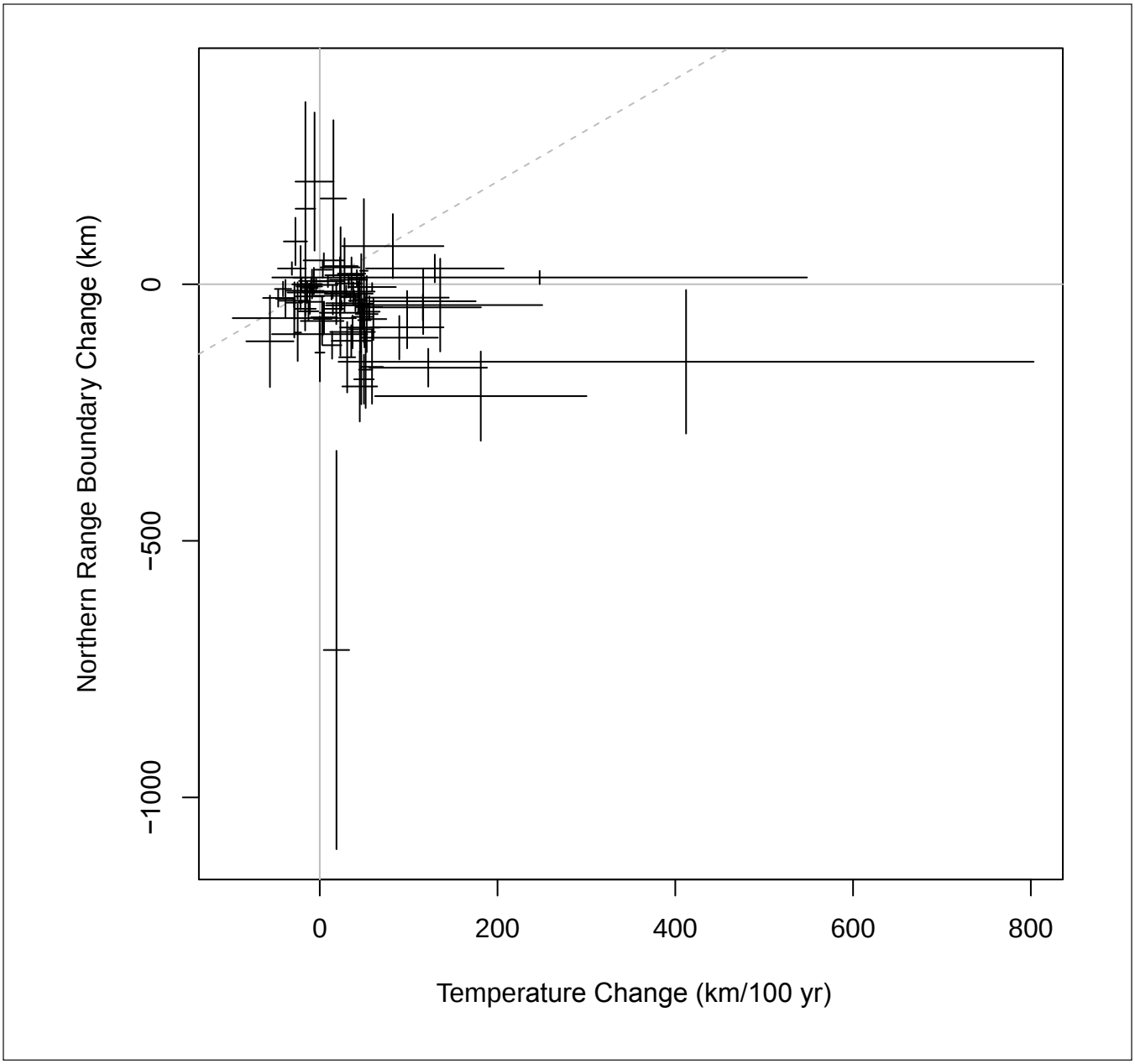


Figure 2.—Temperature change during the 20th century in comparison with latitudinal difference between seedlings and trees at northern range boundary. Each crosshair is a species with mean ± standard error. Positive temperature change means temperature distribution is moving to the north; negative, moving to the south. Positive northern range boundary change means species is consistent with expansion at the northern range limit; negative means contraction. Species above the 1:1 line (gray dashed) may be tracking temperature change. Adapted from Zhu et al. (2012).

range boundaries themselves, we find no consistent evidence that population spread is greatest in areas where climate has changed most, nor are patterns related to seed size or dispersal characteristics. The fact that the majority of seedling extreme latitudes are south of those for adult trees should increase concerns for the risks posed by climate change.

SPECIES ABUNDANCE AND CLIMATE RELATIONS

To explore the relationship between seedling abundance and variables that might be especially important for recruitment, we developed a novel zero-inflated statistical model for seedling counts with extreme incidence of zero observations. All species in the FIA data are absent in at least 60 percent of seedling plots, and some are absent from more than 90 percent of seedling plots.

In the statistical literature, zero-inflated count models, in particular, the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models, along with Poisson and negative binomial hurdle models, are commonly used to address this problem. However, these models struggle to explain extreme incidence of zeros (e.g., > 80 percent), especially to find important covariates. In fact, the ZIP may struggle even when the proportion is not extreme. To redress this problem we developed the class of *k*-ZIG models (Ghosh et al. 2012). These models allow more flexible modeling of both the zero-inflation and the nonzero counts. The models are fitted within a Bayesian framework.

For the FIA data, we fit the model for seedling abundance of two representative species: red maple (*Acer rubrum*) and yellow-poplar (*Liriodendron tulipifera*), with 62.7 and 93.8 percent of zeros, respectively. We used climate (winter temperature and annual precipitation) and biotic variables (basal areas of conspecific and all species) as covariates. Whereas current ZIP and ZINB models perform poorly, the *k*-ZIG model shows that, despite high proportions of zeros, the seedling counts could be explained by both types of variables.

SPECIES' RESPONSES TO CLIMATE CHANGE

Biogeographic responses of plant species to climate change are determined by the requirements of juveniles, which can limit spread to new environments. However, most models of climate response are calibrated to adults, which may not reflect the climate that determined their original establishment. Despite a large literature on ontogenetic niche shifts in animals, there is little direct evidence for plants that could provide insight on the consequences of climate change for migration potential. Using the FIA data, we built a species distribution model to jointly quantify juvenile and adult trees' abundance distributions in relationship with the two most commonly used climatological variables, temperature and precipitation. To accommodate the mismatch between fine-scale biological processes and coarse-scale climate variables we introduced an aggregation approach to climate calibration. The fitted model allowed us to compare differences between juveniles and adults in climate relationships.

Adults and juveniles of a given species respond differently: some species showed broader climate calibrations for adults, whereas others showed broader climate calibration for juveniles. The differences could be partly because of ontogenetic niche shifts and partly because of other factors that impact climate response. For example, American hornbeam (*Carpinus caroliniana*) juveniles tend to be abundant in cold and dry climates relative to adults (Figs. 3a,b). The relative recruitment intensity, i.e., the ratio of seedling counts over tree basal areas, also shows cold and dry climate benefits juveniles while warm and wet climate benefits adults (Fig. 3c). Finally, the 90-percent volume under the fitted surface within the geographic range suggests a broader climatic niche for juveniles than adults (Fig. 3d). This pattern could be consistent with ontogenetic niche contraction, but there are alternative explanations as well.

Both types of ontogenetic niche differences could have important ecological implications. Niche expansion would be suggested when adult niches are broader

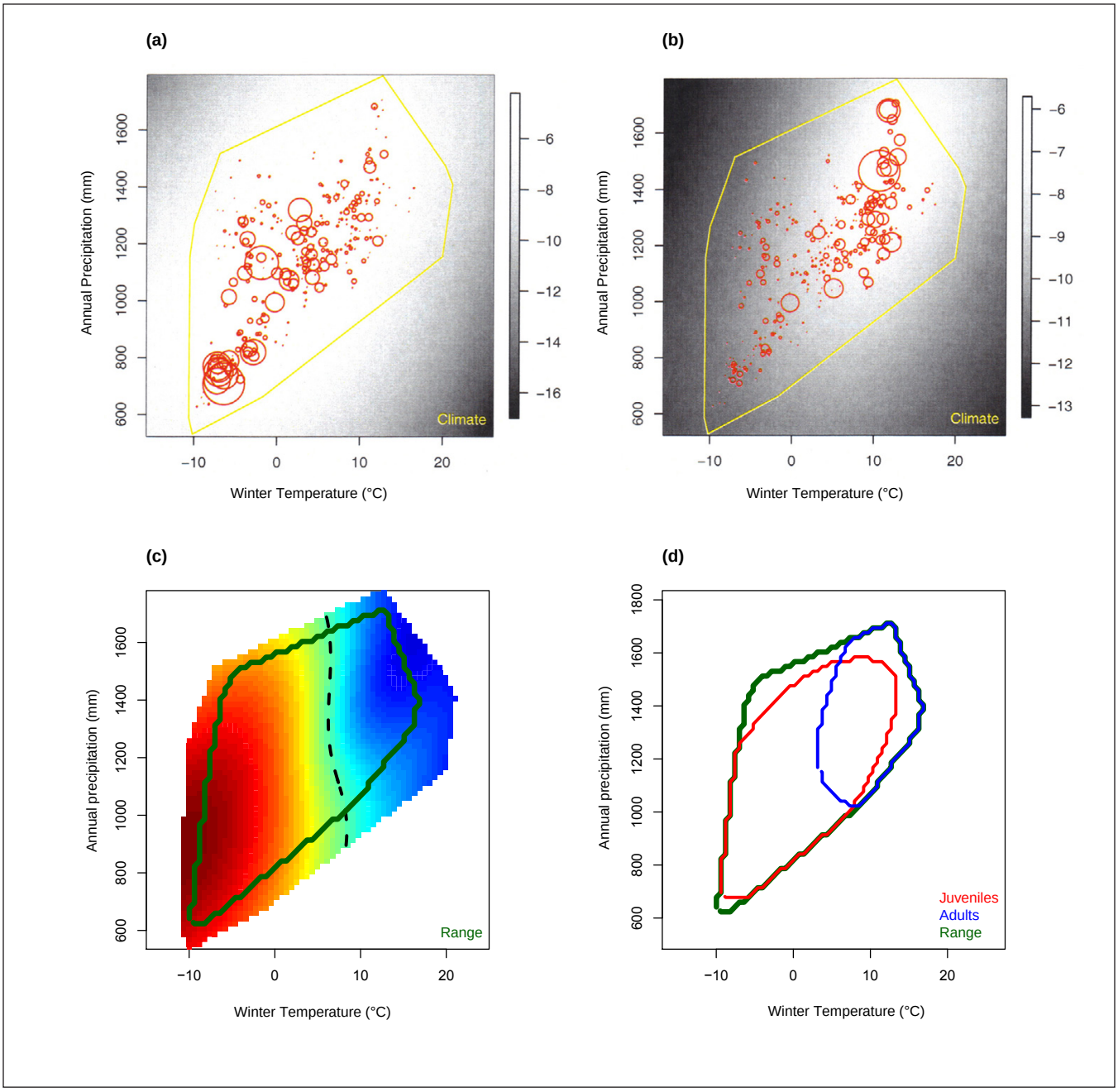


Figure 3.—Comparison of juvenile vs. adult of American hornbeam (*Carpinus caroliniana*) abundance surfaces as an example of ontogenetic niche shift. (a) is the observed (red bubble) and fitted (gray surface) seedling counts on log scale, with all available climate (yellow box) in the eastern United States. (b) is the observed (red bubble) and fitted (gray surface) tree basal areas on log scale, with the same climate boundary (yellow box). (c) is the relative recruitment intensity, defined as the ratio of seedling counts over tree basal areas on log scale. Warm colors show high values, cold colors show low values, and black dashed line shows zero references. It was calculated only within the available climate, superimposed with the actual geographic range mapped into the climatic space (green box). (d) is the 90 percent volume under the fitted surface within the geographic range (green box), where a large contour suggests a flat surface, and a small contour suggests a peaked surface. It approximates different climatic niche requirements for juveniles (red) and adults (blue).

than juvenile niches. This expansion could be expected if adults integrated over fluctuating windows for juvenile establishment in the past, while juveniles more narrowly reflect the current climate conditions. Seedlings can have narrower niche requirements owing to limited root systems, low carbon reserves, and reduced photosynthetic capacity. In contrast, niche contraction could be suggested by adult niches that appear narrower than those of juveniles. Contraction could occur if seeds can establish in sink populations, where they ultimately do not replace themselves due to competition or herbivory. We are examining a large number of species across the eastern United States to determine how climate calibrations of both adults and juveniles are impacted by climate change and the emerging role of new competitive environments and natural enemies.

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INVESTIGATING FOREST INVENTORY AND ANALYSIS-COLLECTED TREE-RING DATA FROM UTAH AS A PROXY FOR HISTORICAL CLIMATE

R. Justin DeRose, W. Shih-Yu (Simon) Wang, and John D. Shaw[1]

Abstract.—Increment cores collected as part of the periodic inventory in the Intermountain West were examined for their potential to represent growth and be a proxy for climate (precipitation) over a large region (Utah). Standardized and crossdated time-series created from pinyon pine (n=249) and Douglas-fir (n=274) increment cores displayed spatiotemporal patterns in growth differences both between species and by region within Utah. However, the between-species interrelationship of growth was strong over much of the state and indicated both species respond similarly to climate variations. Indeed, pinyon pine and Douglas-fir exhibited a significant and spatially coherent response to instrumental precipitation data. Previous water year (5-month lag) exhibited the strongest relationship to tree-ring increment for both species. Results suggest increment cores collected by Forest Inventory and Analysis are excellent proxies for historical precipitation.

INTRODUCTION

Tree-ring data have long been recognized as trustworthy proxies for historical climate conditions because of their potential sensitivity to particular climate factors and their precise annual resolution (Fritts 1976). The spatial representation of tree-ring chronologies for the western United States, however, is sparse and can be exceedingly limited for particular areas such as the Great Basin. Due to the gridded nature of the Forest Inventory and Analysis (FIA) sampling design, forest data are collected at a spatial density unparalleled by any station data or dendrochronological data. As a result, increment cores collected by the Intermountain West FIA during the Periodic Inventory (~1990s) represent a potentially valuable source of dendro-climatic data.

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The conventional preparation of tree-ring chronologies sensitive to climate requires careful selection of species and sites (e.g., elevation), sample replication of individual trees within sites, crossdating, and finally chronology development (Fritts 1976). As a result, creating an extensive spatial coverage of tree-ring data for paleoclimate reconstruction or growth analysis can be expensive and time-consuming, justifying an examination of possible alternatives. Previous research has indicated that pinyon pine (*Pinus edulis* Engelm.) and Douglas-fir (*Pseudotsuga menziessii* var. *glauca*) exhibit substantial tree-ring sensitivity, making these species candidates for proxy climate data. There are, however, two important differences between conventionally collected chronologies and the FIA-collected increment cores. These differences can be thought of as trade-offs in the quality or quantity of proxy climate information. First, a conventional tree-ring site is subjectively sampled to maximize both the climate signal and chronology length, and has associated statistical representation issues (Carrer 2011). In contrast, the FIA grid represents a systematic random sample for making population-level inferences. The trade-offs are (1) the differences

in temporal length of the resultant proxy time-series (conventional are longer, FIA shorter) and (2) the degree to which a climate signal is expressed at a particular point (conventional should be very sensitive; FIA data should reflect normal growing conditions within the specifications of the sampling). Second, conventional chronologies consist of multiple, averaged series, which require intense investment in time and resources for each sampling point. In contrast, increment cores from FIA plots were collected as part of a standardized protocol on plots ~5 km apart. Given the relatively high spatial density of FIA data in a state or region, tree-ring series combined within a certain distance might reasonably correspond to the variability of tree-ring increment recorded in conventional chronologies.

In this study we explore the potential of using FIA-collected increment cores for studies of spatiotemporal patterns of growth and as possible proxies for historical climate. Specifically, we asked whether pinyon pine and Douglas-fir tree-ring series from Utah (1) display individual variation in ring width, both within and between species and (2) have a predictable relationship with instrumental precipitation data.

METHODS

To address the study questions two data sets were constructed from the available increment cores in Utah (Fig. 1), one for two-needle pinyon pine (n=249) and one for Douglas-fir (n=274). Increment cores were mounted, sanded, and digitized following conventional

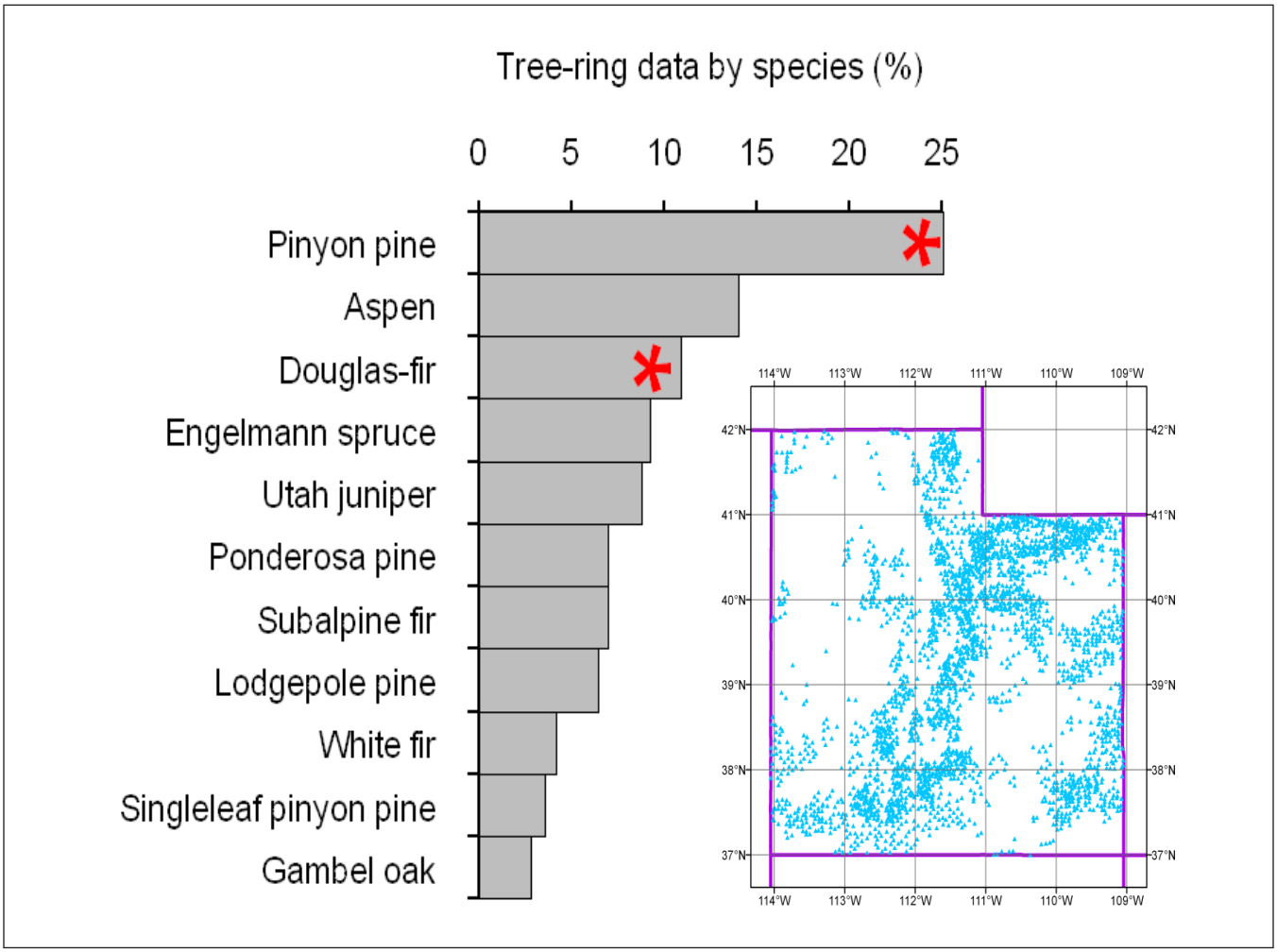


Figure 1.—Representation (%) of species in the Utah FIA tree-ring data set and all plot locations (blue triangles). Red asterisk indicates pinyon pine and Douglas-fir used in this study.

dendrochronological methods before crossdating with the nearest available chronologies. Dated series were then detrended using the "super smoother" (Friedman 1984) in program ARSTAN (Cook et al. 2007) and exported as individual standardized series. The series were used in combination with their jittered coordinates (Note: the term "fuzzswapped" is used within FIA to denote the process that decouples actual spatial locations from landowner information) to create gridded maps, after which we applied the Cressman (1959) objective interpolation scheme at 1/8° (longitude by latitude) grid spacing over the Utah FIA network. The Cressman scheme does not include a first-guess field, which has the disadvantage of potentially creating spurious values, as a result of interpolation. The advantage, however, is that the gridded result completely reflects the time-series and is not biased by the first guess, which is impossible to construct for tree-ring data. We gridded the data with a 1/8° setting (Fig. 2a) using four radii of influence: 1/8°, 1/4°, 1/2°, and 1° from inner radius to outer radius. An inverse-square distance ($1/r^2$) weighting centered at the site was then applied to the data.

To examine the spatiotemporal relationship between the FIA data and gridded instrumental precipitation data, a point-by-point correlation map was computed between each grid point of the FIA data and the gridded instrumental precipitation data (1950-1995). Contours were smoothed by averaging over the nearest neighbors. To examine the coherence between the FIA tree-ring data, which reflect the growing season, and the seasonal climate cycle, we calculated the cross-correlation between the FIA data and precipitation, both averaged over Utah. A 12-month precipitation average with a 1-month time-lag, from year-12 (previous calendar year) to year+12 (next calendar year) was calculated to examine lags in the relationship between precipitation and the FIA data (Fig. 3c). Observed precipitation was obtained from the station-based, 1/8°-resolution gridded data constructed by Maurer et al. (2002) beginning in 1949.

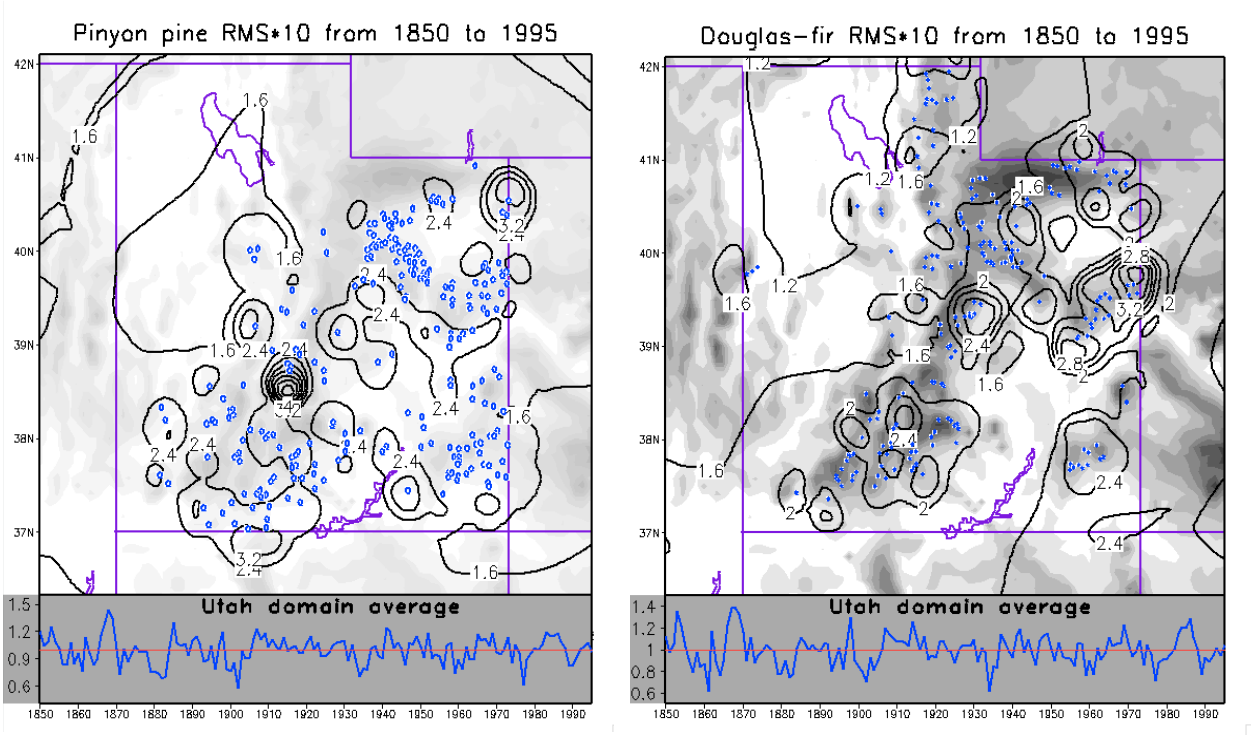


Figure 2.—Contour plots of root mean square (RMS)*10 (to visually accentuate variability) between all pinyon pine (n=249) and Douglas-fir (n=274) tree-ring data. Blue dots indicate FIA plot locations. Lower panel depicts the Utah domain average (37°-42°N latitude and 108°-114°W longitude) tree-ring index (mm), 1850-1995.

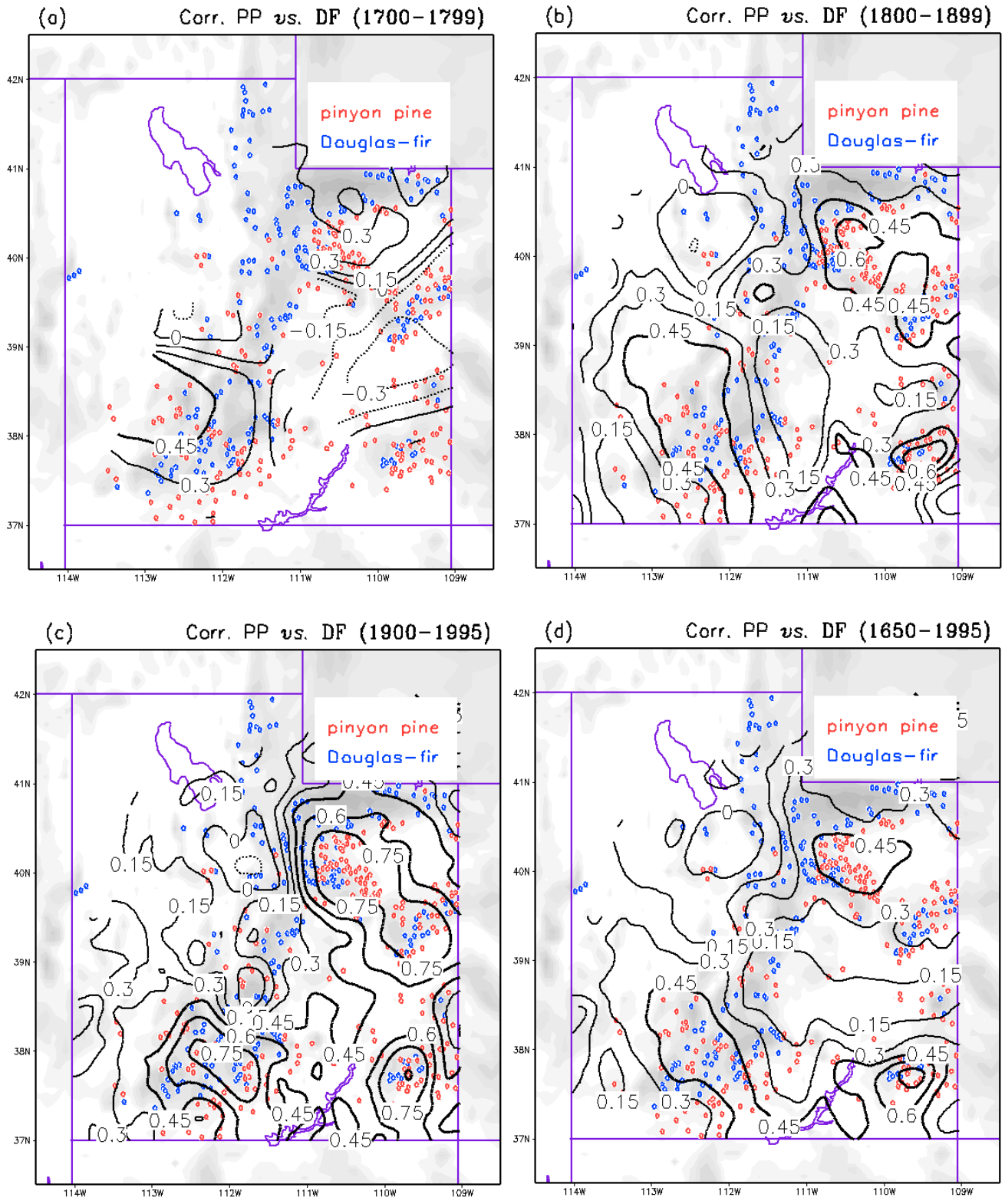


Figure 3.—Contour plots of point-to-point correlations between pinyon pine (PP) and Douglas-fir (DF) gridded tree-ring data for (a) 1700-1799, (b) 1800-1899, (c) 1900-1995, and (d) the1700-1995. Bold contours indicate significance at the 99-percent level.

RESULTS AND DISCUSSION

Pinyon pine and Douglas-fir were two of the most represented species in the Utah tree-ring data set (Fig. 1), and grow virtually throughout the state (Fig. 2; note the evident pinyon pine northern range limit). Although the totality of tree-ring data could not be crossdated, the preliminary data shown herein included 30 percent of the pinyon pine and 83 percent of the Douglas-fir samples available for Utah. Ongoing work seeks to increase the representation of both species and other species in Utah and the other Intermountain West states (Arizona, New Mexico, Colorado, Wyoming, Idaho, Montana, and Nevada).

Spatiotemporal Patterns of Growth

Contours of the root mean square (RMS) of tree-ring width indicated substantial variability in growth for both species (Fig. 2). Pinyon pine had a larger range of variability in growth than Douglas-fir, which was expected, considering that pinyon pine inhabit low-elevation, dry sites. However, there was notable correspondence between increasing RMS and increasing elevation for both species (Fig. 2). This pattern was especially prevalent for both species in the central and east-central part of the state (i.e., Book Cliffs) and the Wasatch Mountains, which run roughly north-south through the state (Fig. 2). Domain average ring width exhibited striking similarity between species; the pluvials of the late1860s and early1980s were evident, as were the droughts of the 1880s, late 1890s, late1930s, and late1970s. These drought-pluvial cycles are consistent with those that have prevailed in Utah (Wang et al. 2012). Although occupying somewhat different ecological niches, pinyon pine and Douglas-fir exhibited similarities in interannual growth that suggested both species were suitable for spatiotemporal analyses of growth. However, in the northern tier of Utah (greater than 41°N latitude), where only Douglas-fir were analyzed, the RMS was reduced substantially. This result hinted at potential larger regional patterns of growth that could be driven only by climate.

Inter-species Correspondence

Although both pinyon pine and Douglas-fir chronologies have been previously recognized as having tree-ring growth sensitivity to precipitation (Watson et al. 2009, Woodhouse et al. 2006), further testing was necessary to determine whether the FIA data were also sensitive. Indeed, point-by-point correlation between the two gridded datasets revealed strong spatiotemporal relationships between the two species. There was an increase in significant correlations (bold lines) from 1700-1799 (Fig. 3a), where strongest coherence was in the southwest, to 1800-1899 (Fig. 3b) where the Uinta Basin and the southeast mountains become strongly correlated. During the period 1900-1995 (Fig. 3c) the relationships become significantly correlated for nearly all the mountainous portion of the state. By looking at the entire tree-ring record (1700-1995, Fig. 3d) the southwest, Grand Staircase, southeast, and western Uinta Basin areas were highly significant. It is noteworthy that there were no areas of negative correlation between these two species (Fig. 3). Finally, although pinyon pine and Douglas-fir occupy different ecological niches, their strong interrelationships, particularly for certain regions, suggested tree-ring increment responded similarly to climatic drivers.

FIA Tree-rings as Precipitation Proxy

If the strong growth interrelationship between pinyon pine and Douglas-fir was caused by climate, one would expect a similarity between the species in the response to that driver. Therefore, we examined the point-to-point relationship between gridded instrumental precipitation and tree-ring width from 1949 to 1995 for both species. Results showed highly significant relationships for both species and coherent spatial relationships between species (Fig. 4). For example, both species exhibited their strongest relationships to precipitation in the southwest and western Uinta basin areas of Utah. Additionally, both species showed lower correspondence to precipitation

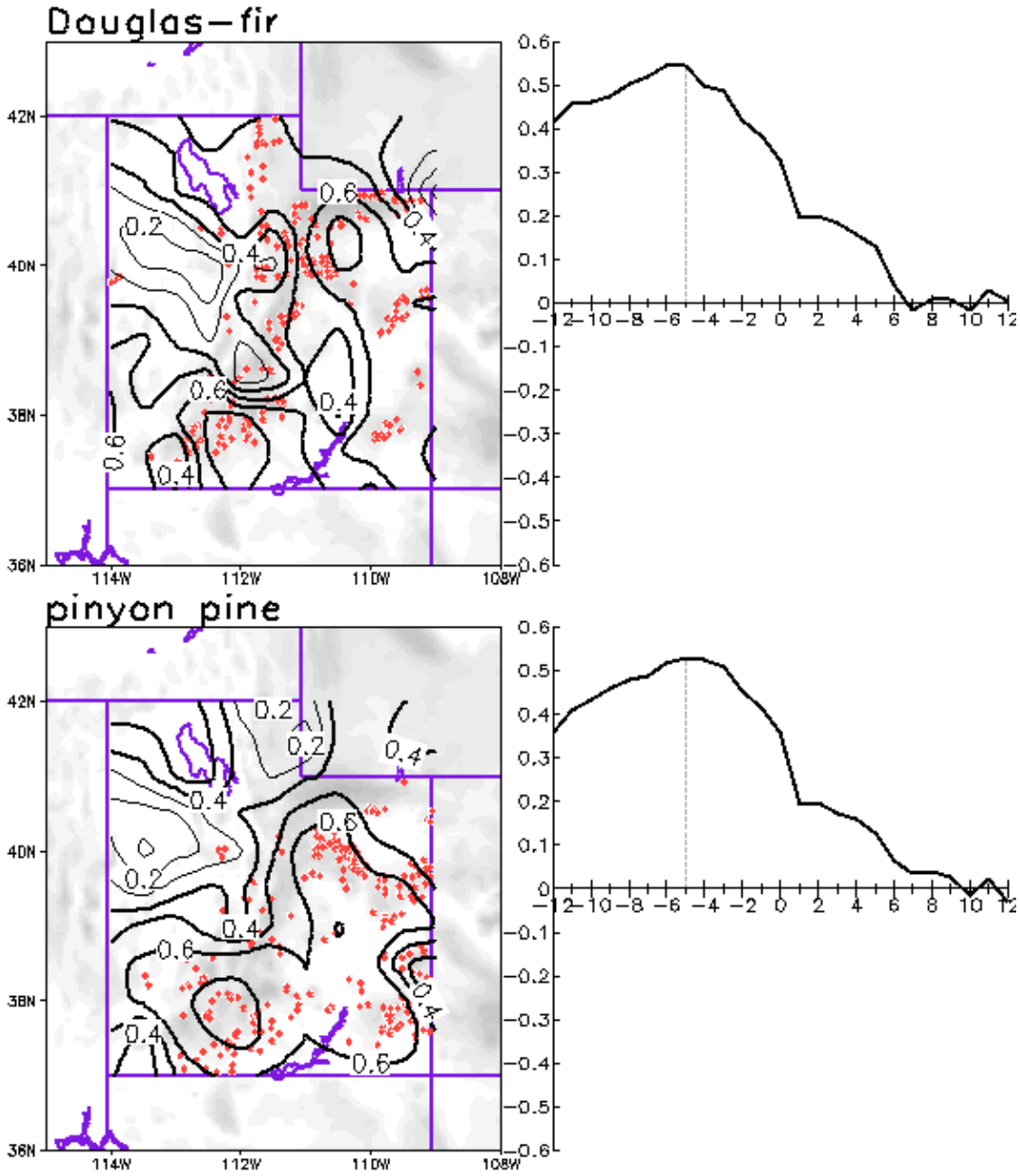


Figure 4.—Contour plots of point-to-point correlations of the gridded pinyon pine and Douglas-fir data sets to precipitation reanalysis data (left panels) and the correlation between Utah domain (37°-42°N latitude and 108°-114°W longitude) average tree-ring index and monthly precipitation data from 1949-1995, lagged from 12 months previous (-12) to 12 months following (12). Bold contours indicate significance at the 99-percent level.

in the basins and western desert, where data were limiting. The peak correlation coefficients between ring width and precipitation for both species occurred around lag-5 month, with a broad peak in significance centered over the water year (previous August through current July), which strongly indicated that water year precipitation drives tree-ring increment in this region. This finding strongly supports using the gridded tree-ring data sets as a precipitation proxy, augmenting the currently limited station data-based gridded precipitation data sets.

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UNLOCKING THE CLIMATE RIDDLE IN FORESTED ECOSYSTEMS

Greg C. Liknes, Christopher W. Woodall, Brian F. Walters, and Sara A. Goeking[1]

Abstract.—Climate information is often used as a predictor in ecological studies, where temporal averages are typically based on climate normals (30-year means) or seasonal averages. While ensemble projections of future climate forecast a higher global average annual temperature, they also predict increased climate variability. It remains to be seen whether forest ecosystems will respond more to changes in mean climate conditions or changes in climate variability. Our objective was to compare the relative importance of climate mean versus variability metrics as predictors of tree mortality and regeneration. Using the 4-km PRISM and 32-km NARR climate datasets, both mean and variability metrics were derived for Forest Inventory and Analysis (FIA) plot locations across the eastern United States. Tree mortality and seedling abundance data were obtained from FIA plots that were visited twice in the years from 2000 to 2010. A number of statistical approaches (including correlation analysis, and an algorithmic method, Random Forests) were used to examine the relative importance of mean versus variability of climate data in the context of evaluating changes in tree and seedling attributes.

INTRODUCTION

The climate system plays an essential role in forested ecosystems, controlling inputs of energy and moisture and setting constraints that intersect with species' ecological niches to determine forest community composition and structure. As such, climate information is often used in models of species' ecological niches or climate envelopes. In addition, spatial and temporal variability of climate can inform investigations of tree mortality and regeneration dynamics in forested ecosystems. Such studies typically use temporal averages representing climate normals (30-year averages) or seasonal means. Climate change projections predict not only a shift in mean climate regimes in many locations, but also increased variability. If trees are locally adapted to a particular climate, increased variability could lead to increased mortality or decreased regeneration. Using forest inventory data from the eastern United States, we investigated whether climate variability provides more explanatory power of tree mortality and seedling abundance than climate means by applying classical correlation analysis and the Random Forests algorithm (Breiman 2001a).

METHODS

Forest data from the U.S. Forest Service's Forest Inventory and Analysis (FIA) database (Woudenberg et al. 2010) were analyzed. The analysis was restricted to plots in the eastern United States that had been visited twice during annual inventories between 2000 and 2010, and more than 23,000 plots were available for the analysis. The two continuous response variables, volume mortality (m^3 ha^{-1}) and change in seedling abundance (stems ha^{-1}), were calculated from differences in adjacent time periods. Other FIA data were used as additional predictor variables, such as stand age, relative density, live/dead biomass, Lorey's height, and disturbance history (Table 1). It should be noted that plots were revisited several years

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Table 1.—Summary of analysis methods, response variables, climate predictor variables, and forest stand metrics used to assess the relationships between climate means, climate variability, and tree mortality and regeneration

			Analysis Method	
	Source	Variable	Random Forests	Correlation
Response variables	FIADB	volume mortality	x	x
	FIADB	seedling abundance change	x	x
Climate predictor variables	NARR	mean annual temperature	x	x
		interannual temperature standard deviation	x	x
		mean annual precipitation	x	x
		interannual precipitation standard deviation	x	x
	PRISM	mean annual temperature	x	x
		interannual temperature standard deviation	x	x
		mean annual precipitation	x	x
		interannual precipitation standard deviation	x	x
Stand predictor variables	FIADB	stand age	x	
		relative density	x	
		live biomass	x	
		dead biomass	x	
		Lorey's height	x	
		disturbance code 1	x	
		disturbance code 2	x	
		disturbance code 3	x	

apart (mode = 5 years, range = 1 to 10 years), and it is therefore not possible to know when mortality occurred (akin to censoring in survival analysis) or how changes to seedlings abundance were distributed across the time interval.

Monthly climate data were used from the PRISM dataset (Daly 2002), including minimum and maximum daily temperature (Tmin and Tmax, respectively) and total precipitation. Tmin and Tmax were averaged to obtain a monthly average temperature. In addition, temperature and precipitation data from the North American Regional Reanalysis Project (NARR) (Mesinger et al. 2006) were assembled in order to create a second, comparable monthly climate dataset.

To investigate the relative explanatory power of mean climate and climate variability, mean and interannual standard deviation were calculated from the monthly data for both total precipitation and average temperature. As previously stated, the exact timing of tree mortality and changes in seedling density is unknown relative to plot observations, and furthermore, forest responses are known to lag climatic conditions, sometimes by a number of years. As a result, six different lag periods were investigated, ranging from 1 to 6 years preceding the initial plot observation (Fig. 1). The endpoint of each climate averaging interval was the midpoint of the FIA observation interval. Given the unknown timing of mortality or seedling change, this endpoint is a compromise and can result in a climate time interval that is either offset (precedes) or overlaps with the forest response. Climate means and standard deviation were calculated for each of the six averaging periods for both temperature and precipitation, resulting in 24 climate variables from both the PRISM and NARR datasets. In turn, correlation coefficients were calculated for each climate variable in relation to volume mortality and seedling abundance change (for 96 variable pairs).

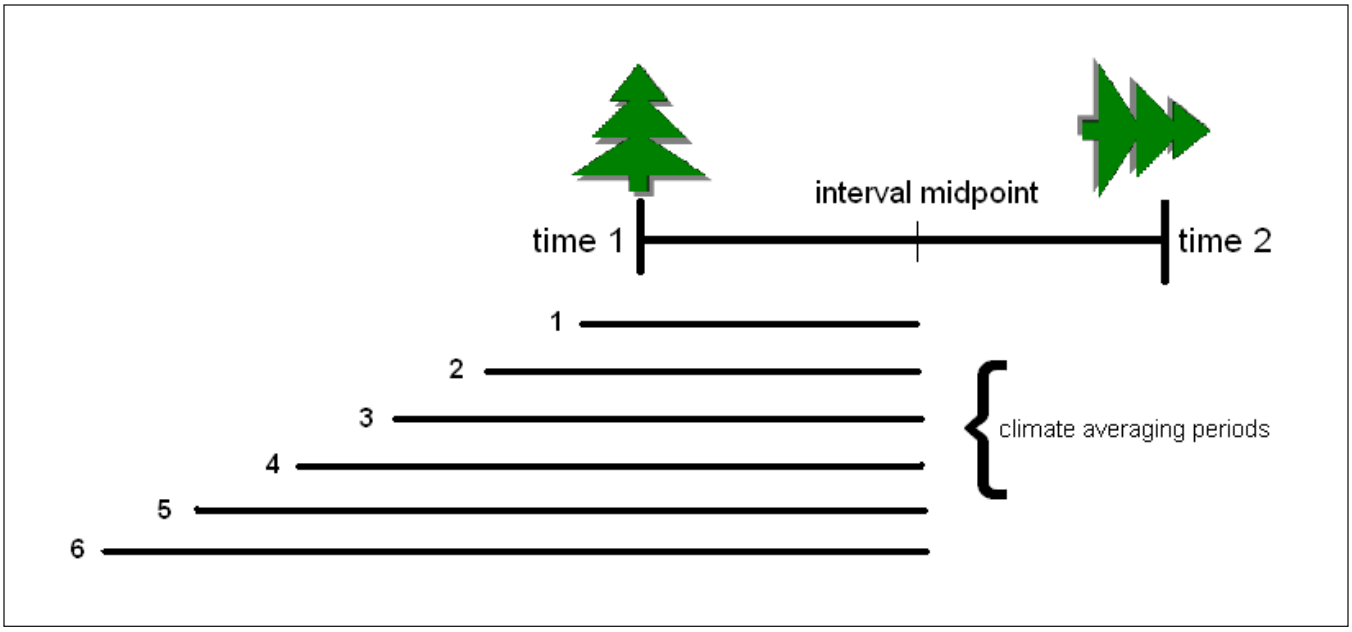


Figure 1.—Depiction of time periods used to average climate variables relative to repeated forest inventory observations. Six different lag periods ranging from 1 to 6 years preceding the first inventory observation were used to calculate annual means and interannual standard deviation.

All variables, except seedling abundance change, were found to be non-normal and were transformed using the Box-Cox method (R v. 2.13, "car" package, bcPower function; Weisberg 2005). Pearson product correlations were calculated for the transformed data. Plots with non-zero mortality were included in the mortality correlation analysis (59 percent of all available plots). Plots with less than 10 cm of floodwater or snow cover were included in the seedling analysis in order to avoid observation bias; outliers and plots with zero change were removed, and 61 percent of all available plots remained for the seedling analysis.

While considerable debate exists between proponents of classical statistical methods and newer algorithmic methods (e.g., Breiman 2001b), we considered such methods to be a useful exploratory tool to investigate the relative importance of climate predictor variables. The Random Forests algorithm has appealing features, such as automatic consideration of interactions between variables, accommodation of nonlinear relationships, and built-in analysis of variable importance. We built predictive models of mortality and seedling density change using Random Forests (R v. 2.13, "randomForest" package) (Liaw and Wiener 2002). A total of eight models were constructed (all possible combinations of mortality vs. seedling change, NARR vs. PRISM, and temperature vs. precipitation, Table 1).

RESULTS

Correlation analysis resulted in very few statistically significant coefficients relating climate variables to tree mortality, with interannual standard deviation of precipitation the only exception (PRISM dataset; 3, 4, 5, and 6-year lag periods; coefficients range from 0.017 to 0.018). While nearly all seedling/climate correlation coefficients were significant (exceptions were interannual standard deviation of temperature for both PRISM and NARR; 1, 2, 3, and 4-year lag periods), none exceeded 0.11. A few other patterns are apparent, such as a general insensitivity of correlation coefficients to the lag period, a higher correlation of seedling change to precipitation than to temperature, and inconsistency in the relative magnitude of

correlations for mean and variability climate metrics. It should be noted, the climate mean variables followed a bi-modal distribution and a more robust transformation may be required for an adequate comparison.

Importance measures from the Random Forests analysis indicate standard deviation of both temperature and precipitation are frequently better predictors than the corresponding mean (Table 2). Additionally, the top climate predictors often provide better or at least comparable information to the three highest ranked FIA stand metrics. The most important stand metrics for the four mortality models and the two temperature/seedling models were consistently Lorey's height, stand age, and live biomass (in various orders), while the most important stand metrics for the seedling change models involving precipitation included disturbance history rather than stand age. The difference in importance between mean and standard deviation of climate variables derived from PRISM was consistently larger than the difference derived using NARR data.

DISCUSSION

Our intent was to investigate whether climate variability data provides more information about tree mortality and regeneration in forested ecosystems when compared climate mean data. We present initial results toward that aim, using more than 23,000 remeasured inventory plots spanning a variety of climatic regimes in the eastern United States. While correlation analysis did not indicate that variability provides more information than mean values, the Random Forests algorithm does indicate interannual standard deviation of both temperature and precipitation may be better predictors of mortality and seedling regeneration than annual mean values.

Future work will include a classic regression approach to modeling tree mortality and seedling regeneration in an attempt to reconcile the seemingly contradicting results from the correlation and Random Forests analyses. In addition, more robust time series methods will be applied in order to quantify variability at numerous time scales. For example, interannual

Table 2.—Variable importance measures for eight Random Forests models of tree mortality and seedling abundance change using climate mean, climate standard deviation (SD), and forest inventory data (stand metrics) as predictors. Temperature (Temp) and total precipitation (PPT) data were derived from two different datasets (PRISM and NARR). Importance is measured by the increase in mean square error when a variable is removed from the model. Values are based on the climate variables with the highest importance score and the three most important stand metrics.

% Increase in MSE						
Tree Mortality						
Climate Variable	Mean	SD	Lorey's Height	Stand Age	Live Biomass	
PRISM Temp	15.17	24.58	24.35	19.03	18.66	
NARR Temp	16.16	17.25	26.77	18.39	18.66	
PRISM PPT	17.21	22.10	20.59	24.74	16.05	
NARR PPT	18.91	22.18	20.85	26.87	17.04	
Seedling Change						
Climate Variable	Mean	SD	Lorey's Height	Stand Age	Live Biomass	Disturbance Code 1
PRISM Temp	7.88	17.03	14.24	10.64	11.19	-----
NARR Temp	12.37	13.74	22.86	12.75	10.78	-----
PRISM PPT	9.26	23.60	9.88	-----	9.48	10.59
NARR PPT	18.83	16.34	10.09	-----	9.27	7.95

seasonal variability could be an informative predictor, as well as decadal or even intra-annual variability. A nationwide, consistent protocol for gathering forest inventory information across a large climate gradient in the United States presents great opportunity for unlocking the complexity of climate/forest interactions. The FIA program is beginning to assemble remeasurement data on a regular return interval (e.g., 5-10 years). This work represents an early attempt to connect temporally rich climate data with observations of change in the Nation's forested ecosystems.

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ADAPT, MOVE, OR DIE: FIA DATA IN ASSESSMENTS OF FOREST TREE GENETIC DEGRADATION RISK FROM CLIMATE CHANGE AND OTHER THREATS

Kevin M. Potter, Barbara S. Crane, and William W. Hargrove[1]

Abstract.—Changing climatic conditions may pose a severe threat to forest tree species, forcing three potential population-level responses: 1) toleration/adaptation, 2) movement to suitable environmental conditions, or 3) extirpation. All could have negative genetic consequences. It will be important, therefore, to safeguard existing adaptedness and to create conditions conducive for future productivity and evolution. To efficiently conserve the genetic variation of species, it is necessary to understand where climate change pressure will be greatest, and what species and populations are more highly predisposed to genetic degradation from climate change and other threats. Forest Inventory and Analysis (FIA) data represent an unmatched resource for conducting broad-scale, spatially explicit assessments of the risk posed by climate change and other threats to the genetic integrity of forest tree populations and species. We used FIA data to 1) generate 4 km^2 resolution maps predicting the genetic pressure that could be imposed by climate change on forest tree species; and 2) compile information about the biological attributes and genetic diversity of individual species. The first assessment tool, Forecasts of Climate-Associated Shifts in Tree Species (ForeCASTS), has generated climate change pressure maps for more than 300 North American tree species and quantifies potential climate change genetic pressure, as defined by the straight-line Minimum Required Movement (MRM) distance from the existing locations of each species to the nearest favorable future habitat. The second assessment tool, the Forest Tree Genetic Risk Assessment System (FORGRAS) framework, ranks the predisposition of forest tree species to genetic degradation, based on demographic and occurrence information, ecological and life-history traits, species-specific projections of climate change pressure, and predictions of pest and pathogen susceptibility. Both assessment tools should be valuable for scientists and managers attempting to determine which species and populations to target for monitoring efforts and for proactive gene conservation and management activities.

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TREE SPECIES MIGRATION IN THE PACIFIC COASTAL UNITED STATES

Heather Lintz, Andrew N. Gray, Andrew Yost, and Vincente Monleon[1]

Abstract.—We analyzed mean changes in longitude, latitude, and elevation for tree species in the Pacific coastal United States (California, Oregon, and Washington). Our analyses show that species migration distance and direction is highly variable, and Pinus monticola and Cornus nuttallii are leading the pack in polar opposite directions. All drought tolerant species are moving northward. Tree species producing the greatest seed abundance are moving the farthest. The distance and direction of migratory gradients correspond to changes in both means and anomalies of summer relative humidity, summer vapor pressure deficit, summer growing season length, and summer precipitation.

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ESTABLISHING BASELINES AND PROJECTING TRENDS

EMERALD ASH BORER MODELING METHODS FOR FUTURE FOREST PROJECTIONS

Ryan D. DeSantis, W. Keith Moser, Robert J. Huggett, Jr., Ruhong Li, David N. Wear, and Patrick D. Miles[1]

Abstract.—The emerald ash borer (*Agrilus planipennis* Fairmaire; EAB) is a nonnative invasive insect that has caused considerable damage to ash (*Fraxinus* spp.) in North America. Unlike invasive organisms that can be mitigated, contained, controlled, or even eradicated, EAB continues to spread across North America. The loss of the North American ash resource is possible considering literature suggests close to 100 percent probability of host tree mortality. We modeled future spatial and temporal changes in forest composition from 2010 to 2060 with and without ash mortality anticipated from EAB spread for the purpose of examining anticipated effects of EAB on tree species composition. To forecast midwest and northeast United States future forest conditions, we utilized Forest Inventory and Analysis (FIA) data, the extent of EAB in the United States and Canada, estimated EAB spread rate, estimated EAB host mortality probability, and models of human population, energy, consumption, land use, and economics. We found that in most cases, EAB will not substantially affect the ecosystem function of future forests measured by FIA because ash comprises a small proportion of midwest and northeast U.S. forests, and it will be replaced by associated species. Although the transition from ash to other species could take decades, forests may eventually recover when associated species replace ash.

INTRODUCTION

Knowledge of host tree susceptibility risk and temporal and spatial knowledge of insect spread rates are important for efforts to help mitigate adverse economic and ecological effects of invasive insects on forests (e.g., Tobin et al. 2004). Consequently, modeling EAB spread can drive the decisionmaking process and could help with detecting, monitoring, and slowing EAB spread (Prasad et al. 2010). EAB ash infestation has negatively affected the economic, ecological, aesthetic, and cultural interests of a variety of stakeholders including forest land owners, landowners in urban areas, tree nurseries, and Native American tribes (e.g., using black ash (*Fraxinus nigra* Marsh.) as a cultural resource for basket weaving) (Poland and McCullough 2006). Private landowners can protect individual ash trees with various chemical treatments but there does not appear to be any effective broad-scale treatment to mitigate the effects of EAB. Projections of future forest composition would be beneficial for forest resource management in North American forests with ash, especially considering the economic and ecological consequences. Research indicates the effects of EAB on North American forests with ash may already be visible in FIA data (Pugh et al. 2011). We used FIA data and EAB current range, estimated spread rate, and host mortality data to project future EAB spread and subsequent

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ash mortality. In this paper, we briefly describe our modeling structure, provide some insight into the intensity and trajectory of the impact of EAB, and discuss consequences for future stand development.

MODELING METHODS

This document is part of an effort to forecast the effect of current and future societal and natural resource trends on the structure and composition of future forests and to project how those effects alter forest ecosystem services (Shifley et al. 2012). These efforts forecasted future forest conditions for 20 states in the Northern Research Station region by assessing current forest conditions and recent forest changes (USDA Forest Service 2012). Forecasts were created in 5-year increments for the period 2010-2060 and projections of future forests were based on FIA forest-type groups (Wear et al. in press) which were used to group forest types developed from multiple sources including lists from FIA and the Society of American Foresters. Forecasting used a scenario approach with a range of plausible futures responsive to human population distributions, global economic conditions, energy and technology use, climate (combinations of three Intergovernmental Panel on Climate Change [IPCC] scenarios and four General Circulation Models [GCMs]; hereafter referred to as "storylines"), timber harvesting, land use change, other disturbance factors, and natural succession.

By incorporating EAB effects into one of the storylines (the A2 CGCM 3.1 storyline as described in USDA Forest Service 2012), we projected forest changes from 2010 to 2060 with and without the anticipated effects of EAB. We assigned an EAB spread rate of 20 km/year (Prasad et al. 2010) and a host mortality probability estimate of 100 percent (Herms et al. 2010) without any ash regeneration, in order to model the future effects of EAB infestation on black, green (*Fraxinus pennsylvanica* Marsh.), and white ash (*Fraxinus americana* L.) in midwest and northeast U.S. forests. Data from the U.S. Department of Agriculture, Animal and Plant Health Inspection Service (APHIS), Plant Protection and Quarantine program and the Canadian Food Inspection Agency were used to identify the core infested area of U.S. counties and Canadian regional municipalities where EAB was detected by 31 December 2010. We forecasted a 20 km/year spread rate from this core infested area from 2010 to 2060 (Fig. 1). Ash is found throughout the midwest and northeast United States but the highest concentrations are located in Maine, Michigan, Minnesota, New York, Pennsylvania, and Wisconsin, so this is where we focused our analyses. Ash mortality was applied for each inventory unit when it was subsumed by EAB spread, and projections commenced in 2015 because the range of EAB as of 31 December 2010 was applied to the 2015 projections. Our projections of future forests were carried out through 2060, but the anticipated EAB spread encompassed the entire midwest and northeast United States by 2050 (Fig. 2). Here, we compare results of a non-EAB ("standard") scenario to results of the same scenario with the projected EAB effects included ("EAB").

RESULTS

Future forest projections suggested a decrease in the number of all trees ≥2.54 cm diameter at breast height (d.b.h.) by 2060 with the standard model. The EAB model projected a larger decrease over the same period, and it projected the loss of ash in all 20 states to occur by 2050 (Table 1, Fig. 2). Volume projections suggested substantial variation across states (Table 2). The standard model projected smaller volume decreases in most forest-type groups than did the EAB model (Table 3). This trend was apparent with forest-type groups where ash was a major component such as elm-ash-cottonwood (E-A-C), but this was not the case with forest-type groups where ash was a minor component, such as spruce-fir. However, in Maine the standard model projected larger volume decreases in E-A-C than did the EAB model, in Minnesota the standard model projected larger decreases in the oak-hickory forest-type group (O-H) than did the EAB model, and in Pennsylvania the standard model projected larger decreases in O-H than did the EAB model.

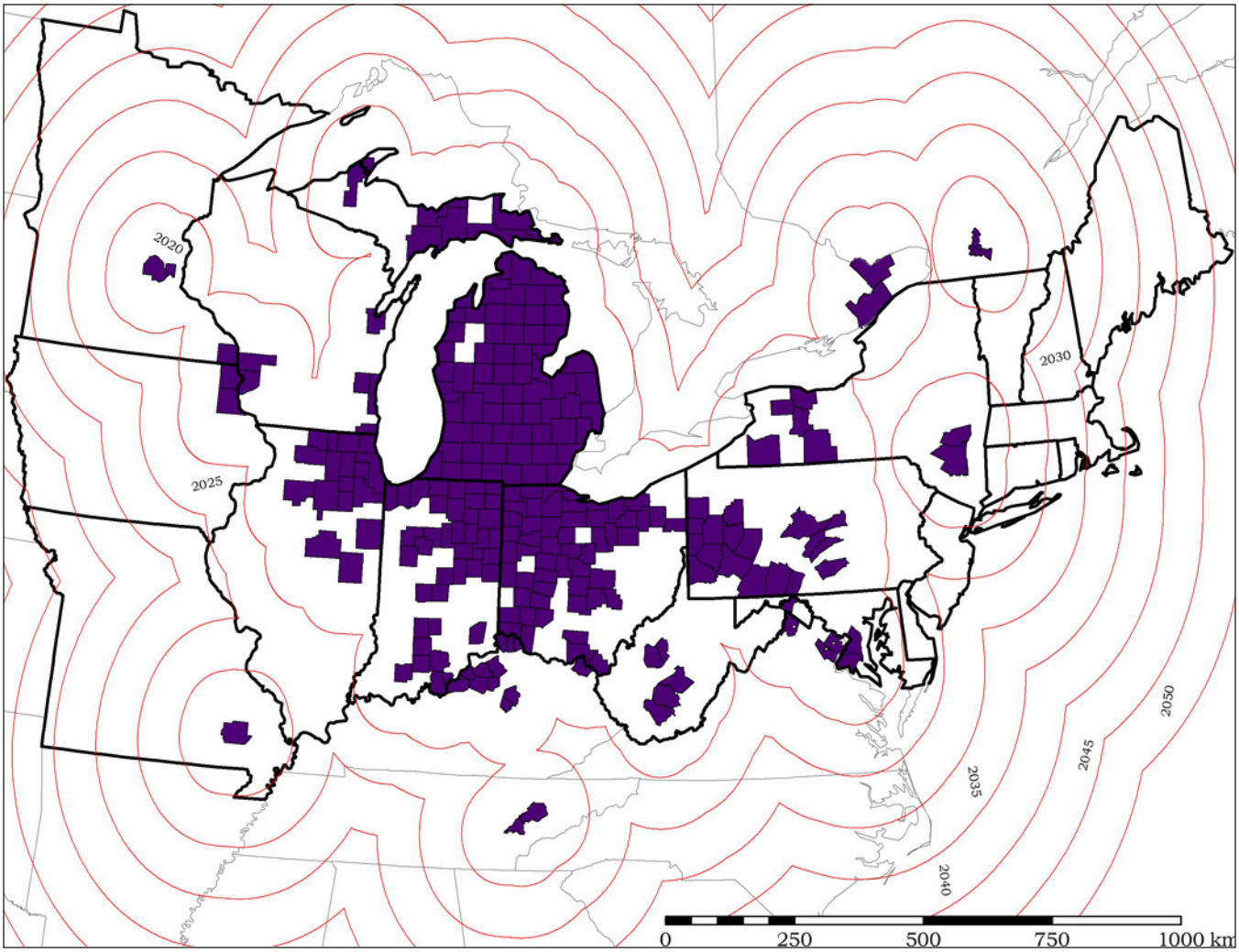


Figure 1.—United States counties and Canadian regional municipalities where EAB was detected by 31 December 2010 are shown in purple and were based on data from USDA Animal and Plant Health Inspection Service, Plant Protection and Quarantine program and Canadian Food Inspection Agency. The projected EAB spread rate of 20 km/year is shown in 5-year intervals in dark red lines, whereby the innermost (from center) dark red spread line corresponds with 2020 and outermost 2050.

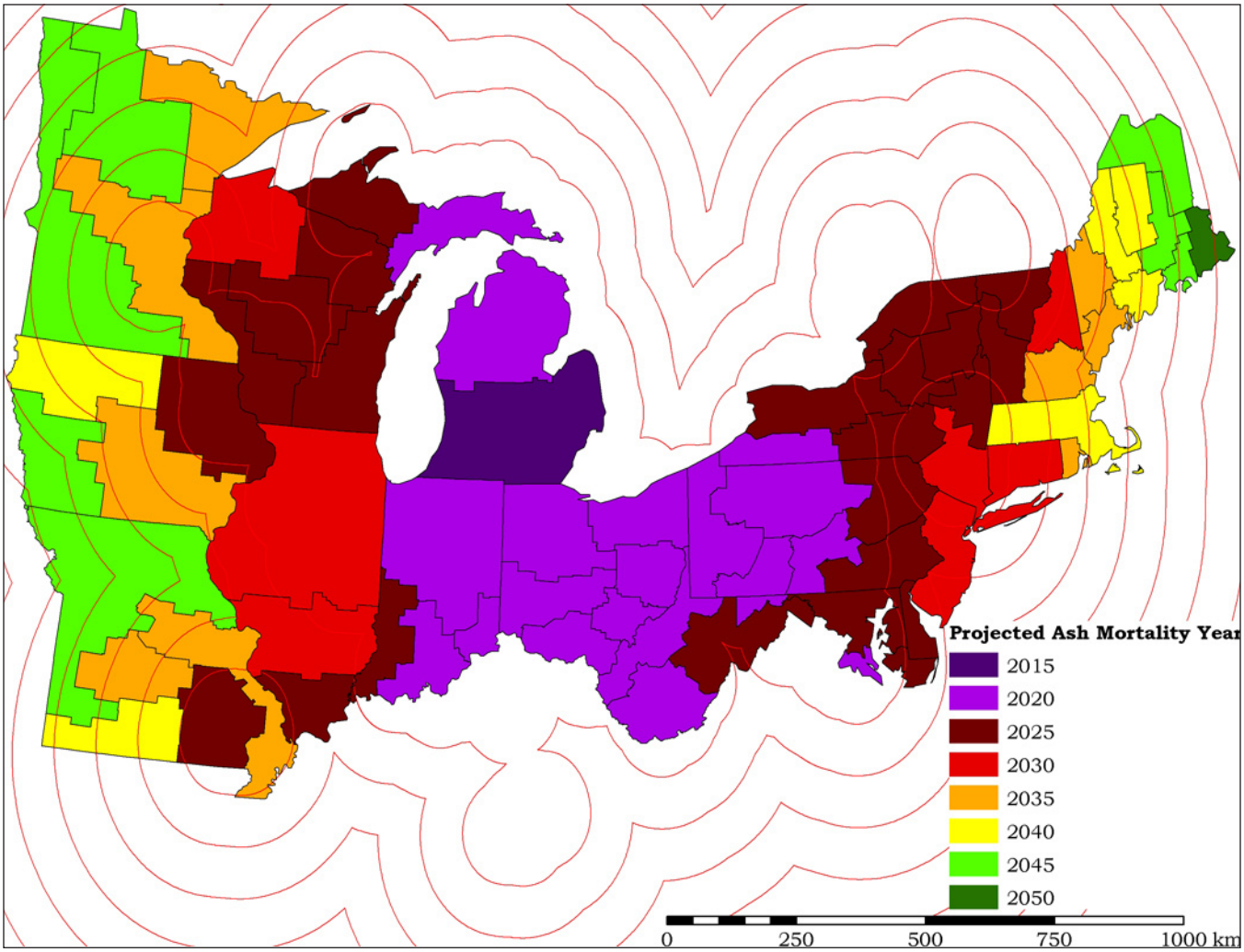


Figure 2.—Using dates when EAB spread subsumes each inventory unit (black lines within each state), the projected mortality of ash due to EAB is shown for each midwest and northeast FIA inventory unit. EAB spread in New York, Vermont, New Hampshire, and Maine was influenced by EAB infestations in Ontario and Québec, Canada regional municipalities. EAB spread was not influenced by EAB infestations in Tennessee, Kentucky, or Virginia or in other Canadian locations. This projection assumed EAB spread caused ash mortality once the spread subsumed each inventory unit.

Table 1.—Total number of all trees ≥2.54 cm d.b.h. on forest land in billions by state, year, and model. See text for model descriptions.

		Standard model		EAB model	
State	2010 number of all trees ≥2.54 cm d.b.h. (billions)	2060 number of all trees ≥2.54 cm d.b.h. (billions)	Percent change (2010 to 2060)	2060 number of all trees ≥2.54 cm d.b.h. (billions)	Percent change (2010 to 2060)
Maine	23.32	20.87	-11	20.54	-12
Michigan	14.03	12.25	-13	11.25	-20
Minnesota	13.06	11.37	-13	9.97	-24
New York	12.19	11.54	-5	10.93	-10
Pennsylvania	8.35	7.27	-13	6.94	-17
Wisconsin	10.92	9.56	-12	8.67	-21
Total	81.87	72.86	-11	68.30	-17

Table 2.—Total volume of all trees ≥12.70 cm d.b.h. on forest land in million cubic meters, by state, year, and model. See text for model descriptions.

State	2010 percent of total land area in forest land	2010 volume	Standard model		EAB model	
			2060 volume	Percent volume change	2060 volume	Percent volume change
Maine	89	721.53	765.77	6	735.67	2
Michigan	55	893.47	970.97	9	927.14	4
Minnesota	33	512.51	634.39	24	591.84	15
New York	63	1,121.59	1,197.25	7	1,152.14	3
Pennsylvania	58	1,002.02	986.75	-2	984.24	-2
Wisconsin	48	658.13	817.09	24	766.66	16
Total	53	4909.25	5372.22	9	5157.69	5

Table 3.—Total volume of trees ≥12.70 cm d.b.h. on forest land in million cubic meters, and percent change in total volume of trees on forest land, by state, forest-type group, and model. See text for model descriptions.

Maine

Forest-type group	2010 total volume	Percent change 2010-2060	
		Standard model	EAB model
White-red-jack-pine	77.38	0	1
Spruce-fir	212.64	11	4
Oak-hickory	18.30	13	5
Elm-ash-cottonwood	11.54	-45	-23
Maple-beech-birch	308.64	10	5
Aspen-birch	67.19	-13	-9

Michigan

Forest-type group	2010 total volume	Percent change 2010-2060	
		Standard model	EAB model
White-red-jack-pine	100.58	52	49
Spruce-fir	109.21	-6	-9
Oak-hickory	150.92	1	0
Elm-ash-cottonwood	84.98	-7	-28
Maple-beech-birch	313.00	8	6
Aspen-birch	105.35	2	-9

Minnesota

Forest-type group	2010 total volume	Percent change 2010-2060	
		Standard model	EAB model
White-red-jack-pine	49.70	21	23
Spruce-fir	79.76	5	-3
Oak-hickory	91.12	-23	-8
Elm-ash-cottonwood	52.00	115	39
Maple-beech-birch	53.77	-18	-26
Aspen-birch	170.84	48	44

New York

Forest-type group	2010 total volume	Percent change 2010-2060	
		Standard model	EAB model
White-red-jack-pine	90.04	22	3
Spruce-fir	35.84	17	33
Oak-hickory	167.49	71	46
Elm-ash-cottonwood	57.72	-79	-83
Maple-beech-birch	663.28	1	3
Aspen-birch	29.89	-57	-61

Pennsylvania

Forest-type group	2010 total volume	Percent change 2010-2060	
		Standard model	EAB model
White-red-jack-pine	26.46	16	15
Spruce-fir	1.32	-25	-25
Oak-hickory	538.25	1	-3
Elm-ash-cottonwood	14.62	55	-15
Maple-beech-birch	364.00	-8	-1
Aspen-birch	10.37	61	53

Wisconsin

Forest-type group	2010 total volume	Percent change 2010-2060	
		Standard model	EAB model
White-red-jack-pine	80.51	126	114
Spruce-fir	40.27	10	4
Oak-hickory	182.85	4	7
Elm-ash-cottonwood	58.27	23	2
Maple-beech-birch	180.86	-4	-7
Aspen-birch	88.20	11	-1

DISCUSSION

There was little or no difference in the number of all trees ≥2.54 cm d.b.h. and volume between the standard and EAB models in states where ash was not an important genus (e.g., Maine, 2 percent of total growing stock volume) (Table 4). Differences between the standard and EAB models were greater in states where ash was a more prominent genus (e.g., Minnesota, 8 percent of total growing stock volume). For example, the effect of ash mortality on differences between the EAB and standard models was most apparent in Minnesota and least apparent in Maine because ash contributed a much larger portion of the total growing-stock volume in Minnesota than it did in Maine. This led to a greater difference between the standard and EAB models in Minnesota than in Maine. Ash represented a larger component of forest and was predominately found in E-A-C forests in Minnesota, so the majority of changes involved forest types in the E-A-C forest-type group. Similarly, Minnesota volume differed between the standard and EAB models (Tables 2 and 3). Ash represented a very small component of forest and was more prevalent in O-H than E-A-C forests in Maine, so most changes in forest types did not involve forest types in E-A-C forests. Therefore, in Maine the projected number of all trees ≥2.54 cm d.b.h. and volume were similar for both the standard and EAB models, indicating that the EAB model did not appear to substantially alter Maine's E-A-C projections trajectory. Maine O-H volume trends between the standard and EAB model results were similar as well. Maine standard and EAB model results for E-A-C and O-H forests were probably similar because ash represented a very small proportion of total growing stock. The forest changes predicted by the standard model were based on trends observed between FIA inventories prior to 2010. For the standard model, those trends greatly influenced the probability of forest compositional changes, including transitioning into or out of forest type-groups with ash such as E-A-C or O-H. For example, the Minnesota standard model projected an increase in E-A-C volume because E-A-C volume increased between recent prior inventories. Likewise, the Maine standard model projected a decrease in E-A-C volume because E-A-C volume decreased between recent prior inventories. For the same reason, the Michigan standard model projected a decrease in E-A-C forests. Considering EAB has been established in Michigan since the early 1990s (Siegert et al. 2007), the decrease between recent inventories may have been partly due to EAB effects on ash.

We summarized the effects of EAB on the number and volume of ash trees for the broad category of forest-type groups and the large scale of states. It is important to consider geographic differences in the composition of each forest-type group since we analyzed changes by forest-type group. For example, ash does not comprise a substantial amount of any forest-type group

Table 4.—Total volume of growing-stock trees and total volume of ash growing stock ≥12.70 cm d.b.h. on forest land, in million cubic meters, by state.

State	2010 total trees growing-stock volume	2010 ash trees growing-stock volume	2010 ash percentage of growing-stock volume
Maine	673.66	14.87	2
Michigan	827.05	40.08	5
Minnesota	443.82	35.11	8
New York	1032.29	76.11	7
Pennsylvania	939.29	46.54	5
Wisconsin	601.61	37.15	6
Total	4517.71	249.86	6

in Maine, Minnesota E-A-C is comprised mainly of green and black ash, and ash might comprise a larger portion of O-H than E-A-C in other states. Our modeling suggested the transition from ash to other species could progress slowly as ash is replaced by a variety of associated species, despite our assumption that EAB will cause 100 percent ash mortality. Our modeling suggested that EAB effects in non-urban forests measured by FIA may not cause forest-type group changes because associated species not prone to EAB infestation have the potential to offset the loss of ash trees and their associated volume. On the other hand, EAB infestation could lead to canopy gaps and facilitate an increase in native and nonnative invasive plant species (Gandhi and Herms 2010). Ultimately, our modeling may not apply to urban areas not measured by FIA, where there could be a larger impact due to the extensive distribution of urban ash.

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EXPANSION AND CONTRACTION TENSION ZONES IN WESTERN U.S. PINON-JUNIPER WOODLANDS UNDER PROJECTED CLIMATE CHANGE

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EXTENDED ABSTRACT

Populations of piñons and junipers across the interior west have been highly dynamic over the last two centuries, undergoing an overall expansion but punctuated with regional mortality. Accumulating demographic studies across the interior west indicate the drivers of expansion and contraction of populations are compounded by regional land use legacies, but have an underlying climatic component. The key implication is that piñon and juniper distributions respond to climatic variation across spatial and temporal scales by expansion from, and contraction to, areas of long-term persistence relative to their centurial (piñons) and millennial (junipers) life spans. Individualistic climatic tolerances among piñon and juniper species lead to temporally dynamic assemblages in the landscape that vary regionally. Failure to recognize species-specific zones of contraction, expansion, and persistence across the landscape and across regions has led to controversial management practices developed for certain species under certain conditions but extrapolated to different species under disparate conditions (Romme et al. 2009). Contrasting demographics between expanding, contracting, and persisting populations of piñons and junipers enables localized field classifications of these species-specific zones and their emergent woodland types. However, differential mortality rates among piñons and junipers during the last decade indicate distribution-wide shifts in co-occurrence have already begun in response to contemporary climate change (Breshears et al. 2009). Needed, therefore, is a similar classification of woodlands at a scale relevant to global climate change (e.g., Wiens et al. 2009) to aid in identifying regional conservation priorities and provide context for extrapolating management practices, such as regeneration prescriptions.

The response of woody plant distributions to climate can be elucidated in a variety of ways, and both piñons and junipers have provided model systems for empirical and experimental investigations. Yet the physiological mechanisms underlying mortality are far from integrated at the whole-tree level (e.g., Plaut et al. 2012). Although mechanistically linking individual trees to global climate change forecasts is infeasible in this regard (Sala et al.), strong empirical relationships between growth rates and climate over the last century have been found across the greater geographic breadth of several western conifer species, including *P. edulis*, and have been extrapolated to forecast climates (Williams et al. 2010). A similar technique is to empirically relate the probability of the current presence/absence of a species to current climatic conditions often referred to as species distribution models (SDMs, Guisan and Zimmermann 2000). Such models may then be extrapolated to forecast climate change scenarios (Iverson et al. 2008, Refheldt et al. 2008).

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There are many interwoven technical and conceptual challenges to the process of creating SDMs that have received legitimate criticism. Technically, the development of SDMs relies on statistical techniques challenged by the availability of presence/absence observations and by the availability of relevant predictor variables at an appropriate scale (e.g., Weins et al. 2009). This situation is complicated further by the degree to which the potential distribution is realized. Although a species current distribution may be modeled with prefect statistical accuracies, such a static SDM may not be amenable to the application of climate change scenarios that may introduce no-analog climate conditions for which no empirical relationships currently exist for modeling purposes. A statistically accurate SDM that is built with appropriate variables will be indicative of geographic shifts in the climatic conditions in which a species is currently most competitive, but introduces the added complexity of the processes by which species track this shift with respect to biotic, topographic, and edaphic interactions. Because sessile species must track climate through completion of the life cycle, it is necessary to consider the nested nature of life stage-specific niche dimensions (i.e., the regeneration niche, Jackson et al. 2009). To address these interwoven challenges, we develop a nested scale, life history-based framework for organizing the vast and varied research addressing the life history of piñons and junipers to guide an empirical approach to build, parameterize, and interpret species-specific distribution models. Biotic interactions modify the overarching influence of climate on piñon and juniper distributions, leading to lagged or accelerated responses of individuals, landscape populations, and continental distributions. Discordance between climatic suitability and spatial distribution generates zones under pressure of expansion or contraction but held in tension by spatial constraints and biotic interactions. We delineate these tension zones under forecast climate change scenarios of the 21st century.

Technical challenges surrounding this process are minimized by using presence/absence observations from the Forest Inventory and Analysis Program (FIA) (McRoberts et al. 2005) that maintains a systematic inventory of forests across the U.S with an underlying probabilistic design. We investigated numerous environmental predictor variables hypothesized as related to the species distributions and chose the simplest expressions of seasonal temperature and moisture to avoid problems associated with forecast climatic conditions having no contemporary analog. We used Random Forests (RF) (Brieman 2001; Cutler et al. 2007), a commonly employed statistical tool for distribution forecasting.

Conceptual challenges are minimized by working with presence observations from across the entirety of each species distribution, thereby sampling the breadth of the realized distribution (Pearman et al. 2008). Absences are drawn from a biologically meaningful, spatially defined sample frame (e.g., Zarnetske et al. 2007). This sample frame addresses the implication of geographic disequilibrium between species distributions and the current climate by limiting model development to areas where the species has actually had a likely opportunity to grow and excludes areas where the species has likely never had an opportunity to grow. This constraint in absence selection avoids overfitting models, which typically leads to higher decay rates in forecast probabilities. Initial modeled distributions are limited to this model-building domain and are evaluated in their ability to describe the current, observed distribution. The initial distribution models are applied to forecast climate change scenarios through life stage-specific thresholds within spatial constraints. The modeling domain and spatial constraint are based on a review of quaternary distribution dynamics in conjunction with current demographic and dispersal studies. The life stage thresholds are empirically estimated by relating FIA plot measures of seedlings and mortality with modeled climatic suitability within the context of reviewed life history studies.

These species-specific models were applied to two climate change scenarios, following the Intergovernmental Panel on Climate Change (IPCC) storylines A2a and B2a, representing extreme and moderate global change at the time of publication (Hijmans et al. 2005). We use the Hadley Center Coupled Atmosphere-Ocean Global Circulation Model (HadCM3 GCM) as the basis of the climate projections. Climate change scenarios were applied at three 30-year time steps over the 21st century. After the initial distribution is set for each species, the life stage thresholds and spatial constraints determine the ability for distributions to track forecasted climate change. The emergent distribution is composed of a sequence of possible local extinction, recruitment, and sustained populations expected from a nested-niche model (Jackson et al. 2009). The variety of possible states across the forecast climate probabilities of each species are collapsed into classes of contraction, persistence, and expansion. With a spatial resolution of 1 km, these classes designate spatial zones reflective of distribution behavior at both a landscape/ multi-decadal scale and at a continent/ centurial scale. Shifts in the landscape are measured as changes in modeled elevation bands and correspond to shifts in the altitudinal zonation of life zones. Continental shifts in distribution are measured as changes in modeled latitudinal and longitudinal distribution and correspond to regional zones of expansion, contraction, or persistence. We present the modeled expansion and contraction as indicative of pressures corresponding to the leading and trailing edge dynamics of these distributions. The assemblage of these species distribution models, in turn, is classified into zones of species increase, decrease, or turnover.

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PROJECTED TRENDS IN FOREST HABITAT CLASSES UNDER CLIMATE AND LAND USE CHANGE SCENARIOS

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Abstract.—Wildlife species have diverse and sometimes conflicting habitat requirements. To support diverse wildlife communities, natural resource managers need to manage for a variety of habitats across a large area and to create long-term management plans to ensure this variety is maintained. In these efforts, managers would benefit from assessments of potential climate and land use change effects on habitats. As part of the U.S. Forest Service's Northern Forest Futures Project (NFFP), we assessed climate and land use driven changes in the areas of forest (≥66% canopy cover) and woodland (66% > canopy cover ≥ 10%) habitat across the Northeast and Midwest by 2060. Our assessments were made using NFFP projections based on three future storylines developed by the Intergovernmental Panel on Climate Change (IPCC). The total area of forest and woodland habitat is currently 173.4 million acres and is evenly split between forest and woodland (49% and 51%, respectively). Our assessments suggest that total forest and woodland habitat area will decrease in the future, but the magnitude of habitat loss differed among IPCC storylines, ranging from 5.9 to 11 million acres. Regardless of storyline, forest habitat was projected to gain area and woodland habitat was projected to lose area. As a result, forest was projected to represent a slight majority of the total habitat area (55% vs. 45% for woodland). Projected declines in woodland habitat represent a continuation of historical trends and have the potential to negatively affect woodland-dependent wildlife via reduced patch sizes, patch isolation, and edge effects.

INTRODUCTION

A significant challenge in natural resources management is providing sufficient habitat for wildlife species that have diverse and sometimes conflicting habitat needs (Noon et al. 2009). Suites of species are associated with particular forest habitat classes characterized by different compositions, ages, and structures (Patton 2011). For example, some species (e.g., Cerulean warbler, *Setophaga cerulea*) are associated with mature, deciduous forests while others (e.g., Kirtland's warbler, *Setophaga kirtlandii*) are found in disturbance-dependent, early successional, coniferous habitat. Successful conservation and management of species with different habitat associations requires management plans that are large scale and long term in scope; such plans are necessary to ensure that diverse habitat needs are simultaneously met and maintained through time (Hamel et al. 2005).

Efforts to conserve diverse groups of wildlife would benefit from assessments of projected climate and land use change effects on a suite of forest habitat classes. The Northern Forests Futures Project (NFFP), a joint effort by the U.S. Forest Service and several partners, is projecting and assessing the potential impacts of climate and land use changes on forest extent, composition, and structure across 20 states in the Northeast and Midwest. As part of the NFFP effort,

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we used projections of 2060 forest conditions and ancillary datasets to assess potential changes in areas of forest and woodland habitat classes.

DATA AND METHODS

Using a wildlife-habitat matrix developed by NatureServe (2011), we identified six current forest and woodland habitat classes: forest-hardwood, forest-conifer, forest-mixed, woodland-hardwood, woodland-conifer, and woodland-mixed. NatureServe defines forest habitats as having ≥66 percent total canopy cover and woodland habitats as having 40 to 66 percent canopy cover. Savanna, another NatureServe habitat associated with tree cover, is defined as having between 10 and 40 percent cover by trees and shrubs. Savanna is a rare ecosystem in northern forests and should not be confused with early successional stages of woodland or forest habitats, which also exhibit canopy cover of 10 to 40 percent. Therefore, we coded canopy of 10 to 40 percent as woodland. Canopy cover thresholds also are used to separate habitat composition within both forest and woodland classes. Areas are labeled as hardwood or conifer when >66 percent of the forest or woodland canopy consists of hardwood or conifer tree species, respectively. Habitats are labeled as mixed when neither hardwood nor conifer tree cover exceeds 66 percent of the total canopy cover.

We used NFFP projections to assess potential climate and land use driven changes in the areas of the six habitat classes from 2010 to 2060. NFFP's projections of future forest conditions were based on current data and historical trends from the U.S. Forest Service's Forest Inventory and Analysis (FIA) Program. FIA does not provide estimates of canopy cover, so we used a computer algorithm to derive estimates of canopy cover from FIA data, enabling us to crosswalk NFFP area projections to forest and woodland habitat classes. Details of the methods used to derive canopy cover estimates are provided by Toney et al. 2009 and Nelson et al. (in this proceedings).

NFFP projected future forest conditions under climate and land use change scenarios consistent with the Intergovernmental Panel on Climate Change's (IPCC) A1B, A2, and B2 storylines. A1B assumes rapid economic growth, a global population that peaks in the middle of the 21st century and then declines, and mixed energy use from fossil and non-fossil fuel resources; A2 assumes that the global population continues to grow throughout the century and that economic development will be regionally oriented; and B2 assumes regional and local economic growth with per capita income similar to A2 but assumes projected population growth that is lower than the other scenarios (USDA Forest Service 2012). For each storyline, climate conditions were projected using multiple General Circulation Models (GCMs) to examine model-based uncertainty.

RESULTS

Across the Northeastern and Midwestern U.S., the current total area of all forest and woodland habitat classes (as defined above) is 173.4 million acres (Table 1). The region is dominated by the forest-hardwood (41% of forest habitat) and woodland-hardwood (34%) habitat classes with no other class exceeding 10 percent of forest habitat. Forest land is about evenly split between the groups of forest and woodland habitat classes (49% and 51%, respectively).

Projected changes in habitat for IPCC storylines did not differ across GCMs, possibly because NFFP projected habitat conditions over a relatively short 50-year time period. For this reason, we did not stratify assessments results by GCMs.

Loss of total forest and woodland habitat area was projected under all three IPCC storylines although the magnitude ranged from 5.9 million acres under B2 to a loss of 11 million acres under A1B (Table 1). Patterns of change for habitat classes were consistent across all three IPCC storylines (Table 1). All three forest habitat classes gained area; percent gains were greatest

Table 1.—Area (millions of acres) and percent change of six forest and woodland habitat classes across the Northeast and Midwest.[a]

IPCC Storyline	Total Habitat	Forest-Hardwood	Forest-Conifer	Forest-Mixed	Woodland-Hardwood	Woodland-Conifer	Woodland-Mixed
Baseline	173.4	70.4	4.3	10.8	59.5	16.7	11.7
A1B	162.4 (-6.4%)	73.1 (3.8%)	5.2 (20.9%)	11.4 (5.6%)	48.5 (-18.5%)	14.3 (-14.4%)	9.9 (-15.4%)
A2	164.1 (-5.4%)	74.3 (5.5%)	5.0 (16.3%)	11.6 (7.4%)	48.7 (-18.2%)	14.5 (-13.2%)	10.1 (-13.7%)
B2	167.5 (-3.4%)	74.9 (6.4%)	5.0 (16.3%)	12.1 (12.0%)	50.6 (-15.0%)	14.6 (-12.6%)	10.2 (-12.8%)

[a] Estimates are provided for 2010 baseline conditions and for 2060 based on the A1B, A2, and B2 storylines from the Intergovernmental Panel on Climate Change (IPCC). Changes in habitat classes between 2010 and 2060 were driven by projected land use changes, forest succession, and forest harvest. See text for explicit definitions of forest habitat classes.

for forest-conifer and least for forest-hardwood. Conversely, all three woodland habitat classes lost area; percent losses were greatest for woodland-hardwood and least for woodland-conifer. Forest habitat classes were projected to increase relative to woodland habitat classes as a percent of total habitat (55% versus 45%, respectively).

DISCUSSION AND CONCLUSION

Our assessments suggest that the total area of forest and woodland habitat classes will decrease across the Northeast and Midwest by 2060. This loss in total forest and woodland habitat acreage has the potential to negatively affect wildlife populations. Although we did not directly assess spatial patterns of habitat loss, reduced habitat area can lead to smaller and more isolated forest patches. These patches support fewer individuals and are less likely to receive immigrants from other areas, increasing the likelihood of local extinctions and decreasing the likelihood of recolonization or population rescue. Smaller forest patches in this region of North America are also more exposed to negative ecological influences (e.g., nest predators) from surrounding nonforest land uses, contributing to local population declines. If habitat loss is widespread, regional declines and extinctions may result. These effects may be of more immediate concern for woodland habitat classes than forest habitat classes, which are projected to increase in area. Nevertheless, land conversion to nonforest land use types ultimately constrains the area and spatial distribution of all forest and woodland habitat classes. Our assessments suggest that uncertainty about future demographic, economic, and technological conditions (as represented by different IPCC storylines) contributes to uncertainty about the extent of habitat loss. Policy (e.g., promoting growth near existing urban centers) and financial mechanisms (e.g., tax deductions resulting from conservation easements) might be used to limit the negative effects of land use change on forest wildlife.

Researchers have reported decades-long declines in the area of early successional forest habitat across the Northeast and Midwest (Trani et al. 2001). These declines have been attributed to a number of different causes including forest maturation of abandoned farmland, altered forest management practices, forest ownership patterns that discourage harvest, disrupted natural disturbance regimes (e.g., fire suppression), and land use conversion (Trani et al. 2001). Assuming that early successional forests can be characterized as having more open canopies, projections of woodland habitat classes in our assessment suggested that declines of this habitat type may continue into the near future. We found that all woodland habitat classes declined and that regional habitat became dominated

by forest habitat classes. These projected declines may negatively affect not only woodland-associated species but also species typically associated with forest habitats that are dependent on woodland areas during certain times of the year (e.g., Streby et al. 2011, Vitz and Rodewald 2006). Ultimately, the future status of wildlife species dependent on young forests or woodland habitat will depend on the scale, type, and frequency of anthropogenic and natural disturbances occurring in landscapes across the Northeast and Midwest. These disturbance patterns will be affected by future management decisions (e.g., type of forest harvest) as well as changing socioeconomic (e.g., changing ownership patterns) and ecological conditions (e.g., climate change).

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SITE PRODUCTIVITY – CURRENT ESTIMATES, CHANGE, AND POSSIBLE ENHANCEMENTS FOR THE NORTHERN RESEARCH STATION

Scott A. Pugh[1]

Abstract.—Site productivity (SP) is the inherent capacity to grow crops of industrial wood. SP identifies the potential growth in cubic feet/acre/year and is based on the culmination of mean annual increment of fully stocked natural stands. Changes in SP were summarized for timberland and the associated effects on net growth and removal estimates were investigated using data from the Forest Inventory and Analysis program from the early to late 2000s. Change in area by SP class ranged from 4.8 to 19.6 percent, depending on the state. Actual changes on the ground are not this common. Net growth credited to unproductive-to-productive change varied from 0.0 to 11.2 percent of total net growth depending on the state; removals due to productive-to-unproductive change varied from 0.0 to 38.7 percent of total removals, depending on the state. A comparison of SP derived from current methods versus complementing with net growth information shows 12.5 percent of currently classified unproductive area could be classified productive and 10.3 percent of forest land area could receive a more productive SP class. Artificial change in SP class should be minimized, especially for sites that are marginally productive or unproductive. Restricting new calculations of SP when valid measurements already exist will lessen erroneous change.

INTRODUCTION

Forest site productivity (SP) is the inherent capacity to grow crops of industrial wood. SP identifies the potential growth in cubic feet (ft^3)/acre/year and is based on the culmination of mean annual increment of fully stocked natural stands (U.S. Forest Service 2010). By definition, forest land assigned a SP less than 20 ft^3/acre/year is unproductive. Timberland is productive, i.e., capable of producing at least 20 ft^3/acre/year, so changes in SP status affect net growth and removal estimates on timberland. This study's objectives include summarizing changes in SP and the associated effects on annual net growth and removals. Following these results, the study focuses on ways to improve SP assignments using observed net growth estimates and limit artificial change in SP assignments.

Data from the Forest Inventory and Analysis program of the Northern Research Station (NRS-FIA), U.S. Department of Agriculture, Forest Service, were compared from the early to late 2000s (Table 1). NRS-FIA uses site index (SI), the most commonly accepted measurement, to estimate SP. SI represents the average total height in feet that dominant and codominant trees are expected to attain in fully stocked, even-age stands at a specific base age (usually 50 years for NRS-FIA states). Changes in SI can represent magnitudes of change in SP. For eastern white pine (*Pinus strobus* L.), an SI of 48-59 feet represents an SP of 50-84 ft^3/acre/year, and an SI of 60-74 feet represents an SP of 85-119 ft^3/acre/year. NRS-FIA uses seven SP classes expressed in ft^3/acre/year as follows: class 1 at 225+, class 2 at 165-224, class 3 at 120-164, class 4 at 85-119, class 5 at 50-84, class 6 at 20-49, class 7 at 0-19.

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Table 1.—Change in SP class and effects on net growth and removal estimates for growing stock on timberland, by state, NRS-FIA 2005-2010

Region	State	Total forest-to-forest area	Forest-to-forest area changed SP class	Total net growth	Net growth on unproductive-to-productive area	Total removals	Removals on productive-to-unproductive area
		million acres	*percent*	*million ft³/year*	*percent*	*million ft³/year*	*percent*
Western NRS-FIA	Illinois	4.4	19.6	214.9	0.0	66.1	13.2
	Indiana	4.5	10.7	274.0	0.0	89.0	0.0
	Iowa	2.7	10.3	79.1	0.0	40.6	0.0
	Kansas	1.9	9.5	36.6	0.0	12.9	28.6
	Michigan	19.1	10.6	695.1	0.6	337.5	2.2
	Minnesota	15.9	17.1	384.9	3.4	255.7	3.1
	Missouri	14.4	12.3	464.2	2.3	174.4	2.8
	Nebraska	1.1	9.5	21.7	2.5	14.2	1.9
	North Dakota	0.7	8.1	6.8	11.2	2.6	38.7
	South Dakota	1.7	9.5	38.2	6.1	25.5	0.1
	Wisconsin	16.1	11.8	563.8	0.5	308.9	1.6
	Western NRS-FIA	82.6	12.8	2,779.3	1.2	1,327.4	3.4
Eastern NRS-FIA	Connecticut	1.7	7.4	93.4	4.6	17.2	0.0
	Delaware	0.3	13.9	15.2	0.0	13.8	7.4
	Maine	17.5	11.4	663.2	0.6	587.7	0.0
	Maryland	2.4	15.7	145.5	0.0	56.8	0.0
	Massachusetts	2.9	10.2	176.0	0.9	40.2	2.0
	New Hampshire	4.7	7.4	185.9	0.1	100.0	0.2
	New Jersey	1.9	9.0	81.9	4.0	24.2	14.8
	New York	18.3	9.5	617.8	1.0	288.9	0.0
	Ohio	7.7	11.0	393.6	0.0	182.7	0.0
	Pennsylvania	16.1	4.8	762.9	0.1	374.7	1.3
	Rhode Island	0.3	7.1	18.0	9.7	2.7	0.0
	Vermont	4.5	8.1	195.0	0.0	102.1	0.0
	West Virginia	11.7	8.9	608.5	0.9	248.1	3.4
	Eastern NRS-FIA	90.3	9.1	3,956.8	0.7	2,039.0	0.9
NRS-FIA	NRS-FIA	172.9	10.8	6,736.2	0.9	3,366.4	1.9

METHODS

Site Productivity via NRS-FIA

NRS-FIA crews measure diameter at breast height (d.b.h.) and height of a suitable SI tree to represent each forested condition on a plot. This information is used to estimate SI and subsequently SP; data is maintained in the National Information Management System (NIMS). An acceptable SI tree should meet minimum requirements of size (≥5 inches d.b.h.), age (15 to 120 years), quality, and species. Crews may reuse a previous SI tree. Crews have the option to reject previous trees if they do not meet the minimum requirements. This option is usually employed when there is an assessment difference between the previous and current crew. If no previous valid tree exists, the crew should collect data from a new tree pending availability. With no suitable trees, a default or estimated SP class is assigned later in NIMS. For the western NRS-FIA states[2], an average SI and associated SP are assigned for the species most frequently observed for the field forest type and physiographic class of the condition in question. For the eastern NRS-FIA states[2], a default SP class of 6 is assigned and the default class is also assigned when the calculation of SI and SP indicate an unproductive status (class 7) but the crew in the field classified the condition as productive. Unproductive assignments by crews for eastern NRS-FIA states also supersede productive assignments indicated by SI and SP calculations.

Sometimes more than one valid SI tree is available from previous inventories and this circumstance often results in different SPs. The suitable tree with the highest SP should be prioritized (the rule used in NIMS) but the crews do not have the SP information. At times, crews have chosen the tree associated with the relatively lower SP and deleted the other formerly valid ones.

[2] Western NRS-FIA states include IL, IN, IA, KS, MI, MN, MO, NE, ND, SD, and WI. Eastern NRS-FIA states include CT, DE, ME, MD, MA, NH, NJ, NY, OH, PA, RI, VT, and WV.

Analysis

This study examined changes in SP and effects of this change from the 2005 (2001-2005) to 2010 inventory (2006-2010). Structured Query Language (SQL) determined estimates. Area by SP for each state was compared. Average annual net growth of growing stock on timberland was estimated for unproductive-to-productive change. With a change to productive status, the volumes of associated trees are credited, not only the average annual net growth between inventories. Average annual removals of growing stock on timberland were estimated for productive-to-unproductive change. Volumes of trees cut since the previous inventory and volumes of trees still living in the recent inventory are credited with changes to unproductive status. Only living trees are included in the effects on removals presented in this study. To potentially improve SP class assignments, a new class was assigned using the net growth of growing stock for each condition of the 2010 inventory when the net growth indicated a higher SP than the normally employed methods. To minimize artificial change in SP class, the study determined where measurements of SI could be prohibited when valid measurements were previously acquired. This is currently feasible when a one-forest-condition plot occurred in a previous inventory (time 1) and remains a one-forest-condition plot in the next inventory (time 2). Lack of acceptable SI trees can contribute to changes in SP so the study identified how often SP was estimated versus calculated from SI.

RESULTS

Change

Working with the forest-to-forest areas (forest at time 1 to forest at time 2) from the 2005 to 2010 inventory, change in area by SP class and state ranged from 4.8 to 19.6 percent (Table 1). Across NRS-FIA states, 10.8 percent of area changed SP class with 2.3 percent changing by two or more SP classes. Thirty-four percent of unproductive area changed to productive (460,000 acres) and less than 0.5 percent of productive

area changed to unproductive (393,000 acres). Net growth credited to unproductive-to-productive change varied from 0.0 to 11.2 percent of average annual total net growth, and removals due to productive-to-unproductive change varied from 0.0 to 38.7 percent of average annual total removals, depending upon the state.

Complementing with Net Growth

Working with the forest-to-forest areas from the 2005 to 2010 inventory, a comparison of SP derived from current methods versus complementing current methods with net growth information shows that 12.5 percent (260,000 acres) classified as unproductive could be classified productive and 10.3 percent of forest land area (18.4 million acres) could receive a more productive SP class assignment across NRS-FIA states (Table 2). Results varied by region; 14.3 and 6.2 percent of currently classed unproductive area could be classed productive in the western and eastern NRS-FIA states, respectively. A more productive class could be assigned to 5.6 and 14.7 percent of forest land area in the western and eastern NRS-FIA states, respectively.

Consistency

Across the NRS-FIA states for the 2010 inventory, 76 percent of forest-to-forest plots were one-forest-condition plots at time 1 and time 2 and had previously valid SI trees. In the 2010 inventory, about 95 and 79 percent of SP assignments were derived from SI trees for the western and eastern NRS-FIA states, respectively. Remaining SPs were estimated or assigned a default SP class value.

DISCUSSION

Change

Estimates of change in acreage by SP are substantial for some states. Actual changes in acreage by SP are not as common on the land as predicted in the estimates, but estimates change, usually from using different SI trees or obtaining an acceptable SI tree for the first time. In many cases there are only marginally acceptable trees or no acceptable tree (McRoberts 1996). Subsequently, this increases the chance of choosing different SI trees for a given plot and condition over time. In some states, artificial change in SP status accounts for substantial portions of average annual net growth and/or removals on timberland. For net growth, the volume per tree credited with a change to productive status is usually many times more than the average annual change in volume credited with no change. Removal estimates are impacted by counting the volumes of living trees associated with a change to unproductive status. The most noticeable impacts are usually associated with states that have relatively low total removals.

Complementing with Net Growth

Complementing current methods with net growth estimates can identify productive areas that are currently classified unproductive. Barring no major site quality changes, holding SP class as productive on these sites would decrease effects on net growth and removal estimates for timberland. Net growth estimates also identify areas that should probably be designated at higher SP classes. This is most evident in the eastern NRS-FIA states where more investigation is warranted. More study is also required for some species in the western NRS-FIA states where SP is used when calculating volume, which subsequently influences net growth. Inaccurate values of SP can confound net growth estimates. Benefits of these possible enhancements should be weighed against the cost of implementation. Maintaining a steady SP class over time on marginally productive or unproductive areas provides the greatest benefit.

Consistency

SI tree collection on one-forest-condition plots at time 1 and time 2 with previously valid SI trees should be prohibited to minimize erroneous changes in SP. Based on observations between the 2005 and 2010 inventory, consistency could be ensured on about 76 percent of forest-to-forest plots.

Table 2.—Change from unproductive to productive and increase in productivity using average annual net growth of growing stock versus SI, by state, NRS-FIA 2005-2010

Region	State	Unproductive forest-to-forest area using SI	Unproductive area using SI but productive using net growth	Forest-to-forest area more productive using net growth vs. using SI
		thousand acres	*percent*	*percent*
Western NRS-FIA	Illinois	14.9	0.0	5.4
	Indiana	0.0	0.0	3.7
	Iowa	40.8	46.2	4.4
	Kansas	102.9	3.8	2.0
	Michigan	247.5	29.4	7.9
	Minnesota	488.5	11.9	5.3
	Missouri	175.9	16.2	3.7
	Nebraska	94.3	0.0	6.4
	North Dakota	214.7	1.0	2.3
	South Dakota	87.3	13.5	14.6
	Wisconsin	155.3	23.1	5.2
	Western NRS-FIA	1,622.3	14.3	5.6
Eastern NRS-FIA	Connecticut	8.5	0.0	22.4
	Delaware	3.6	0.0	17.8
	Maine	178.8	3.1	11.7
	Maryland	5.3	0.0	11.3
	Massachusetts	41.2	0.0	19.7
	New Hampshire	25.5	12.7	11.6
	New Jersey	13.6	0.0	14.4
	New York	41.4	0.0	13.8
	Ohio	5.3	0.0	15.0
	Pennsylvania	57.7	18.3	18.9
	Rhode Island	0.0	0.0	16.8
	Vermont	20.2	0.0	14.0
	West Virginia	55.2	16.0	14.4
	Eastern NRS-FIA	456.4	6.2	14.7
NRS-FIA	NRS-FIA	2,078.6	12.5	10.3

When multiple SI trees are available for a condition, NIMS and subsequent public reports use the tree with the highest associated SP. Following this precedent, only trees with the highest SP should be sent to the field. Otherwise, field crews can unknowingly chose a different tree which can change the assigned SP class. Some SP values are estimated or assigned a default value when there are no suitable SI trees. The number of sites without suitable trees should decrease by measuring the same plots over time. After suitable trees are acquired, new SP values and associated classes can be used in most subsequent inventories.

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THE MYTH OF A BUSINESS-AS-USUAL BASELINE: A REVIEW OF FOREST INVENTORY PROJECTIONS

Stephen P. Prisley, W. Brad Smith, and John W. Coulston[1]

Abstract.—With the advent of forest carbon accounting schemes that compare projected forest carbon sequestration against a baseline, there is an increasing demand to project forest inventories into the future. Often, the desired comparison baseline is termed "business as usual", implying there is a known or anticipated trajectory of forest growth and harvests that will occur and against which we can compare alternate management scenarios. This raises the question "how well can we project forest inventories into the future?" The U.S. Forest Service has decades of experience with developing national projections of forest inventories for the Resources Planning Act (RPA) periodic assessments.

We have compiled some of the projections made in the 1965, 1974, 1982, and 1993 RPA assessments, including timberland area by region and ownership, and timberland growing stock, net growth, removals, and mortality by region and softwood/hardwood. These projections are compared with interpolated Forest Inventory and Analysis data for the same regions and years. Differences between projected and measured values are expressed as RMSEs to quantify the performance of projections by length of projection, spatial resolution (national versus regional), and quantity being projected (area, growth, removals, mortality, inventory).

Results demonstrate the challenge of making projections based on extrapolation of recent trends. We also discuss some of the primary reasons for discrepancies between projections and reality.

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MAPPING FOREST DISTURBANCE

UNDERSTANDING TRENDS IN OBSERVATIONS OF FOREST DISTURBANCE AND THEIR UNDERLYING CAUSAL PROCESSES

Karen Schleeweis, Samuel N. Goward, Chengquan Huang, Jeffrey Masek, and Gretchen G. Moisen[1]

Abstract.—Estimates of forest canopy areal extent, configuration, and change have been developed from satellite-based imagery and ground-based inventories to improve understanding of forest dynamics and how they interact with other Earth systems across many scales. The number of these types of studies has grown in recent years, yet few have assessed the multiple change processes underlying observed forest canopy dynamics across large spatio-temporal extents. To support these types of assessments, a more detailed and integrated understanding of the geographic patterns of forest change processes across the contiguous United States (CONUS) is needed.

This work uses forest age estimates from U.S. Forest Service ground inventory data and a novel data set from the North American Forest Dynamics project, which provides a dense temporal record (1984-2005) of forest canopy history across the United States, as well as ancillary geospatial data sets on forest change processes (wind, insect, fire, harvest, and conversion to suburban/urban land uses) across the CONUS. Forest area is estimated and causal processes of forest change are shown through time across multiple scales.

INTRODUCTION

For more than half a century, decadal snapshots of forest canopy characteristics have been available from the Forest Inventory and Analysis (FIA) Program. Annual FIA inventories and remote-sensing satellite imagery have recently begun to meet the need for data that are consistent across large spatial and temporal extents, at finer spatial and temporal grains (Cohen and Goward 2004, Gillespie 1999). However, we still lack data and understanding regarding the causal processes underlying observed forest canopy changes. It is important to know not just where and when forest canopy losses occur, but also the underlying process to help determine whether the losses are temporary or permanent and how the process influences other Earth systems across many scales (Reams et al. 2010).

Natural (fire, wind, insect) and human-managed (harvest) forest disturbances and forest land conversion affect millions of hectares of forest land, but the spatial and temporal trends of these phenomena are not well documented (Smith and Darr 2004). Although data are available on a single process for static points in time, there are few that focus on multiple processes through time (Birdsey and Lewis 2003). A current synthesis on the trends of specific forest canopy change processes including fire, insects, wind storms, harvests, and forest land conversion is lacking at fine spatial and temporal resolutions. This work demonstrates the need for this information below a coarse regional-decadal resolution and attempts to create an integrated geographic model of all these phenomena.

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METHODS

To synthesize data on forest canopy change and causal processes across different studies, common spatial boundaries must be used. We used the six historical FIA regions of the Northeast (NE), North Central (NC), Southeast (SE), South Central (SC), Intermountain West (IW), and Pacific (PAC) (see map insert, Fig. 2). These boundaries allow for comparison of newer data sets with historical data available only at coarse regional scales.

More than 20 years of forest age history data from FIA inventories and the North American Forest Dynamics (NAFD) project are discussed in the context of the underlying forest causal processes that they might have captured. NAFD provides a comprehensive look at forest disturbance rates for areas sampled biennially across the conterminous United States at a 30-m resolution from 1985 to 2005 (Goward et al. 2008). Forest age, often used as a proxy for disturbance history, has been collected by FIA on more than 125,000 ground plots (0.7 ha) laid out on a 5-km sampling grid across the conterminous United States. One-tenth of these plots are remeasured each year in the western United States. One-seventh to one-tenth of them are revisited each year in the eastern United States. However, measurement frequency and spatial sampling schemes varied through time and across regions prior to 1999 (Gillespie 1999).

To interpret the regional forest change estimates in the context of possible underlying causal processes, we compiled tabular data of forest area affected by each process to illustrate their trends through time. To judge the need for finer spatial and temporal resolution data we utilize NAFD forest history maps and geospatial data on recent insect infestations, harvests, forest fires, wind storms, and suburban/urban conversion of forest land (Table 1). These data are assembled into a single geographic information system geodatabase to enable multi-scale analysis on the patterns of forest change processes and forest canopy changes, and their overlap through time and space.

RESULTS

The more than 20 years of forest history captured in both FIA and NAFD data show some similarities across regions (Fig. 1). In general, NAFD disturbance rates are higher than FIA estimates within regions, with the exception of the SE region.

Regional trends for forest fire, insect infestations, suburbanization, harvest, and canopy cover changes vary by decade and region (Fig. 2). Regional-decadal scale statistics on change processes were found to have limited utility in explaining similar-scale canopy change trends. Coarse-scale observations and reporting confounded the signatures of localized canopy change events that overlap in space and time. Data inconsistencies through time and space raised questions on the reliability of the data. Comparing different data sources for both forest fires and suburbanization revealed large differences in area estimates that may have implications for end users.

Assembling available geospatial data into a single geodatabase produced a better integrated geographic model providing insights into the frequency and overlap of multiple forest change processes across the CONUS (Fig. 3). Mapping each change process individually revealed a unique signature of local spatio-temporal variability, suggesting that no one sampling scheme will adequately capture the canopy change resulting from all of the processes. Overlay analysis suggests that because of the limited number and location of NAFD samples, the benefit of the NAFD data occurs not in aggregate calculations but in the new perspective they offer on forest history events at the scale of landscapes and individual patches. Data gaps and inconsistencies through space and time in the various data on forest change processes make quantitative linkages with NAFD maps and wall-to-wall analysis difficult. For example, data on harvest area suggest harvesting affects more forest area in the CONUS than any other process; however, its spatial and temporal characteristics were found to be the most poorly characterized.

Table 1.—Data used to build an integrated geodatabase of forest change processes

Change process	Measurement method	Data source	Spatial		Temporal	
			Grain	Extent	Grain	Extent
Fires	Landsat, NDVI change	MTBS http://MTBS.gov	30-m grid	national	annual	1984-2007
Hurricanes and tornadoes	Ground measurements-wind speed	U.S. National Hurricane Center http://www.nhc.noaa.gov/pastall.html	lines	national	annual	1851-2008
Suburbanization/ urbanization	Decadal census – number of new housing units	Theobald 2005	100-m grid	national	decadal	1940-2030
Suburbanization/ urbanization	Landsat, Land use change	NLCD Retrofit Change Data http://www.mrlc.gov/changeproduct.php	30-m grid	national	decadal	1992-2001
Suburbanization/ urbanization	Landsat, Land use change	NLCD 2001/2006 Land cover change http://www.mrlc.gov/nlcd2006_downloads.php	30-m grid	national	5 years	2001-2006
Harvests	Timber Product Output Surveys	USFS FIA http://srsfia2.fs.fed.us/php/tpo_2009/tpo_rpa_int2.php	county polygons or >	sampled -national	5- to 10- year cycles	1997-2007
Pests and pathogens	Digitized aerial sketches of insect damage	U.S. Forest Health Program http://www.fs.fed.us/r3/resources/health/fid_surveys.shtml	polygon <1 ha	sampled -national	annual	WA and OR: 1984-2005; CA: 1994-2008; AZ: 2000-2009; NM: 1998-2009; states in the NC and NE regions: 1997-2009; NV, UT, and southern ID: 1991-2008; Northern ID, MT, ND: 2000-2008; most of Wyoming, CO, SD, NE, KS: 1994-2009
Southern Pine Beetle	Aerial Spot Detection Surveys	Williams and Birdsey 2003	county polygons	SE and SC states (except OK)	annual	1987-2004

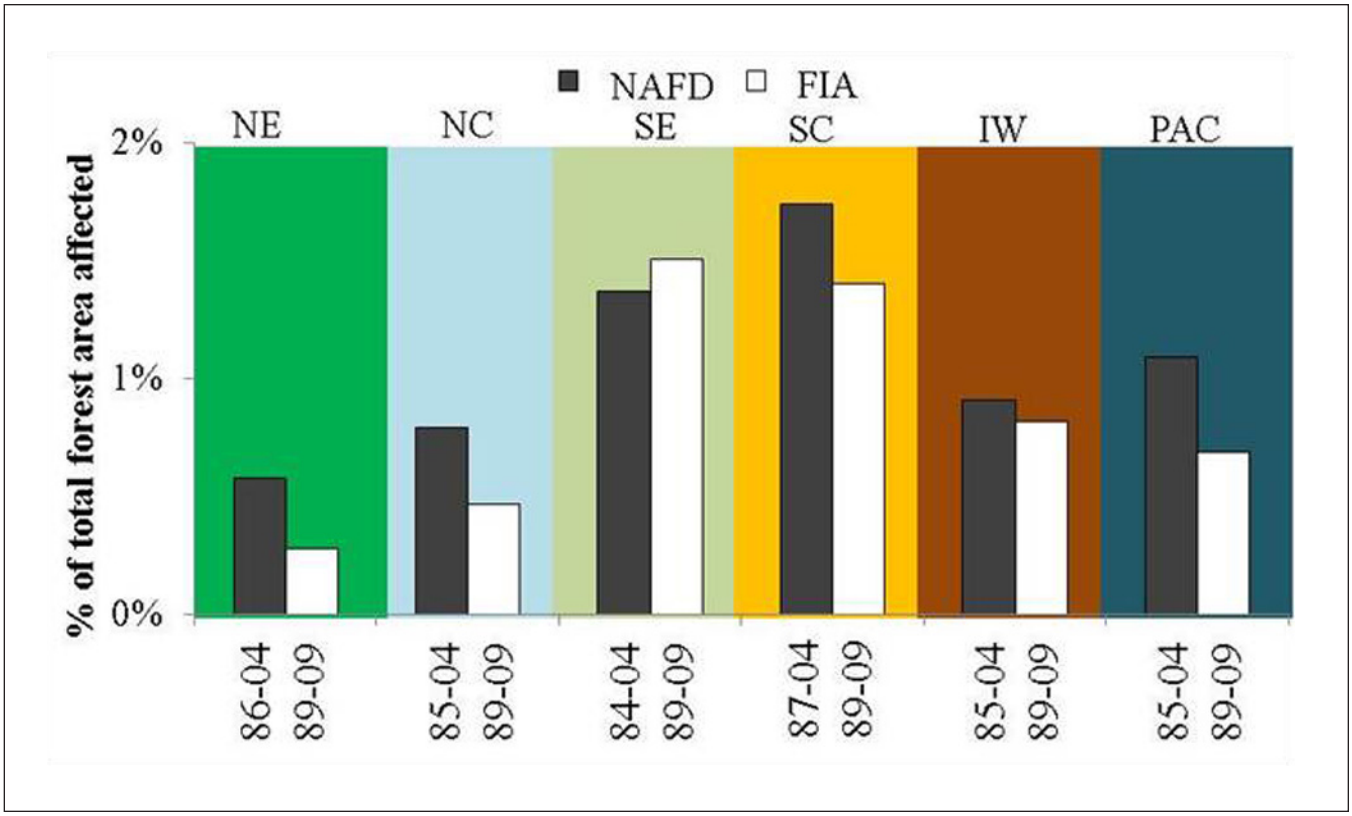


Figure 1.—Averaged annual forest change rates from FIA stand age, reported in the most recent inventory data and NAFD forest history maps over two decades for six regions of CONUS.

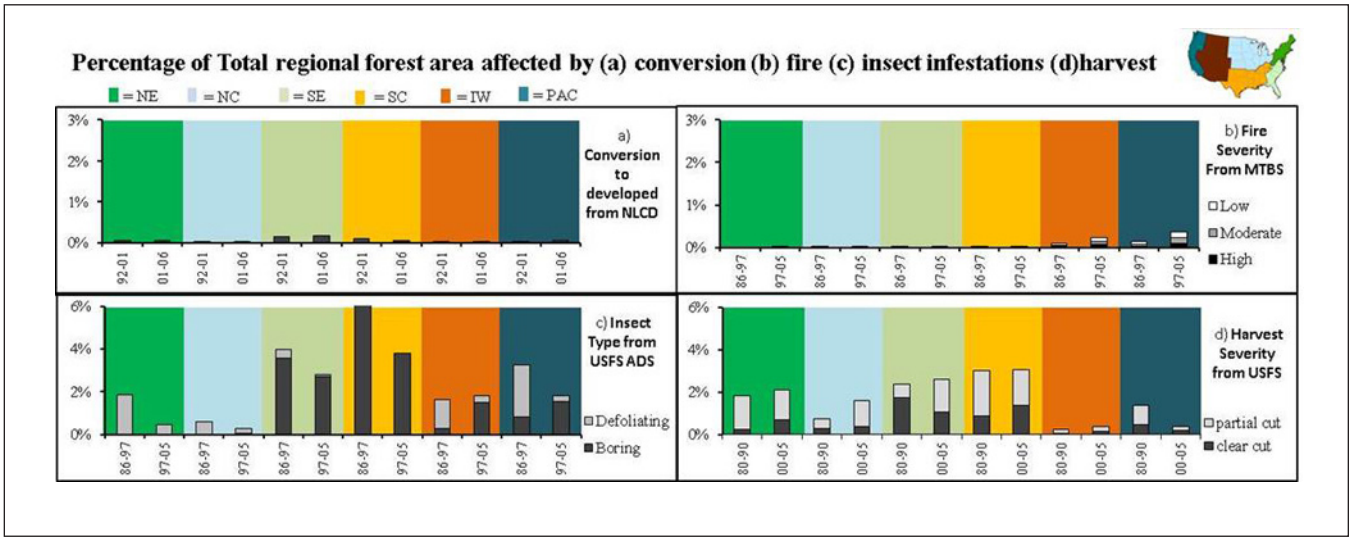


Figure 2.—Averaged annual rates calculated as a percentage of total forest area in the region using total forest area per region from Smith et al. (2009). Reported areas for individual disturbance processes are not mutually exclusive and can lead to double counting.

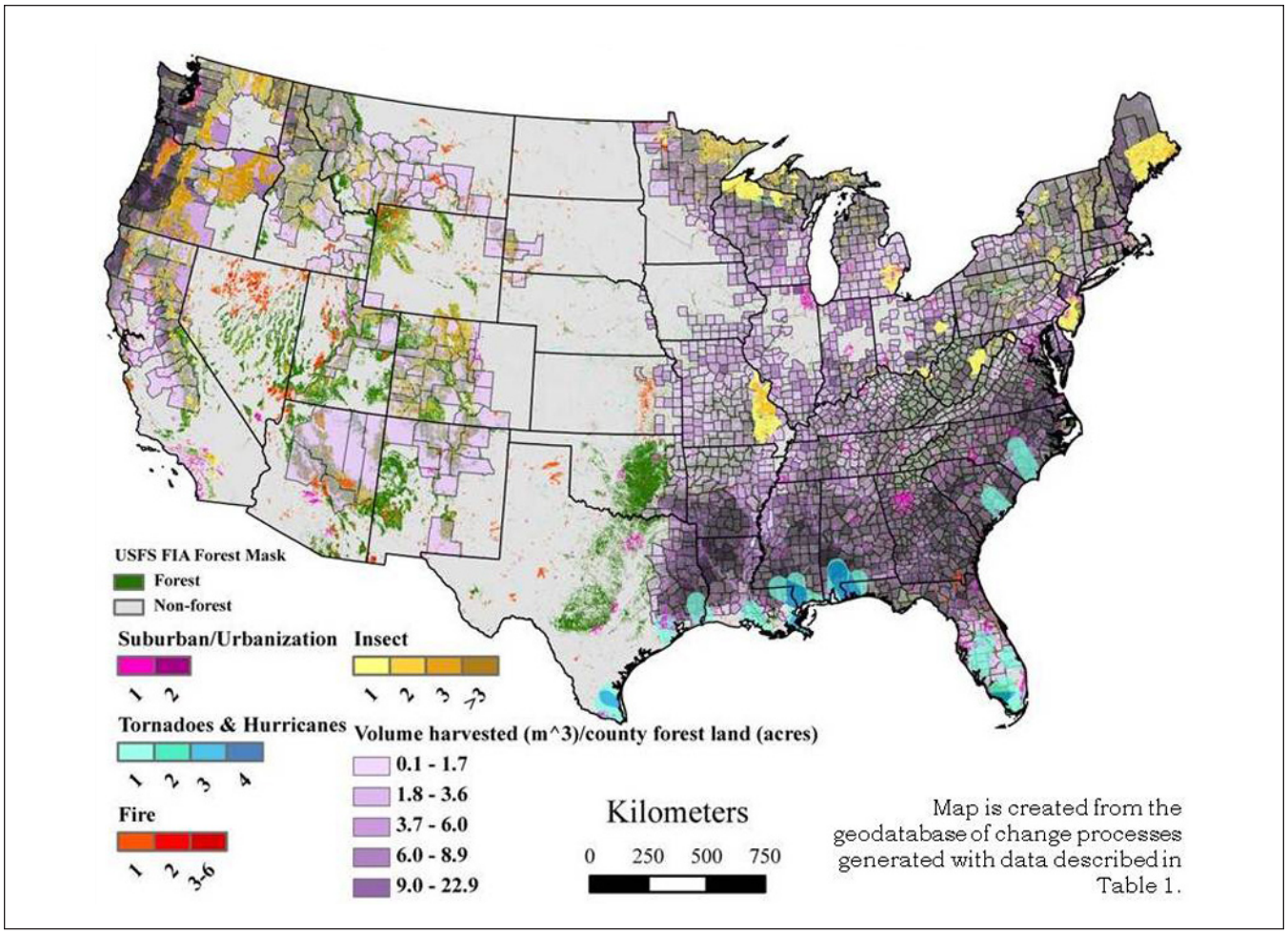


Figure 3.—Overlap of five forest change processes (fire, harvest, insects, windstorms, and suburbanization) over roughly two decades. Specifics on temporal and spatial characteristics of data vary with each change process and are available in Table 1.

DISCUSSION

Rates of forest canopy disturbance vary with differing underlying causal processes. This work found estimated disturbance rates from FIA and NAFD observations of forest stand age differ. The differing estimates may be related to the different methodologies used by FIA and NAFD and their capability to capture different underlying causal processes. The spatial and temporal patterns of the underlying causal processes are necessary to interpret rates of forest canopy from different remote sensing and ground inventory data products.

Estimates of canopy change and change processes have traditionally been available at decadal-regional scales, which hinder analyses of smaller-scale ecological processes and canopy observations within a landscape matrix. Estimates of forest area affected by individual change process, assembled from tabular data, revealed trends that vary both within and across regions through time. However, the coarse resolution of these data made linkages with regional-scale canopy change observations from FIA and NAFD problematic.

Consolidating the many data on forest change processes into one geospatial database allowed for both aggregate calculations and preservation of information on local patterns. Finer-scale observations of canopy change and causal processes revealed new insights into these dynamic processes. However, data gaps and inconsistencies preclude robust quantitative analysis. This work represents a first step towards a more integrated geographic model of forest change processes and canopy change observations.

ACKNOWLEDGMENTS

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IMPROVING AUTOMATED DISTURBANCE MAPS USING SNOW-COVERED LANDSAT TIME SERIES STACKS

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Abstract.—Snow-covered winter Landsat time series stacks are used to develop a nonforest mask to enhance automated disturbance maps produced by the Vegetation Change Tracker (VCT). This method exploits the enhanced spectral separability between forested and nonforested areas that occurs with sufficient snow cover. This method resulted in significant improvements in Vegetation Change Tracker outputs at the 95 percent confidence interval. An estimated 34 percent of the world's forests receive sufficient snowfall to use this method.

NOTE: A longer version of this paper with additional tables, figures, and a full literature cited section was published in Remote Sensing of Environment, Vol. 115, Issue 12, in December 2011.

INTRODUCTION

The extensive Landsat archive is increasingly being leveraged to gain an understanding of land cover/land use change dynamics by offering insight into the spatial and temporal aspects of forest disturbances. The Vegetation Change Tracker (VCT) is an automated change detection method that uses growing season Landsat time series stacks (LTSSs) to detect forest disturbances (Huang et al. 2010a). Its efficacy is highly dependent on forest density, abruptness of the onset of disturbance, and presence of agricultural and wetland areas (Thomas et al. 2011).

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STUDY AREA

VCT was applied to quantify landscape-level patterns of forest disturbances from 1985 to 2008 in the Lake Michigan and Lake Superior basins. This study area was chosen to gain an understanding of the impacts of forest disturbances on the water quality of the Great Lakes. These basins are primarily composed of forests (intact and disturbed), cropland, pastureland, wetlands, and urban areas. The level of forest fragmentation generally decreases along a south-to-north gradient. A variety of anthropogenic as well as natural disturbances occur throughout the study area. These disturbances include harvest, urban development, insect mortality, storm damage, and fire (Schulte et al. 2007, Stueve et al. 2011).

METHODS

In the course of this study, it was observed that VCT often incorrectly classified nonforested wetlands and agricultural areas as disturbances due to their dense vegetation cover and high inter-annual variability. To mitigate this error, a modified VCT workflow was developed and employed that incorporates winter Landsat imagery. This version of VCT is referred to as VCTw due to its utilization of snow-covered winter Landsat time series stacks (LTSSw) for the creation of a nonforest mask. The VCTw approach uses the VCT cloud masking method (Huang et al. 2010b). Due to similarities of clouds and snow cover in the spectral/temperature data space, the VCT cloud masking method consistently identifies nonforested snow-covered areas as clouds (Fig. 1). Areas that are consistently identified as clouds and that do not show a long-term recovery trend throughout an LTSSw are included in a nonforest mask. Forested and disturbed pixels from the standard VCT product that fall within the nonforest mask are recoded to nonforest (Fig. 2). The full VCTw flowchart can be found in Figure 3.

We produced standard VCT and VCTw change products for nearly 25 million hectares within the Lake Superior and Lake Michigan drainage basins. An accuracy assessment of the VCT and VCTw change products was conducted through a two-stage sampling design across three geographic regions using techniques discussed by Nusser and Klass (2003), as well as Stehman et al. (2003). Due to the variability in typical disturbance type and size throughout the basins, the study area was divided into three regions. The three accuracy assessment regions were the lower Lake Michigan basin (LLMB), upper Lake Michigan basin (ULMB), and the lower Lake Superior basin (LLSB). (The upper Lake Superior basin (ULSB) made up the Canadian portion of the Lake Superior basin. The ULSB could not be included in this validation due to a lack of consistent aerial reference imagery.) Aerial photography spanning the analysis period served as the reference imagery. The standard VCT year of disturbance classes were binned into two disturbance classes to match the temporal resolution of the reference imagery. These classes were disturbed early (1985-1999) (D1) and disturbed late (2000-2008) (D2). The remaining classes were persisting forest (PF), nonforest (PNF), and water (PW).

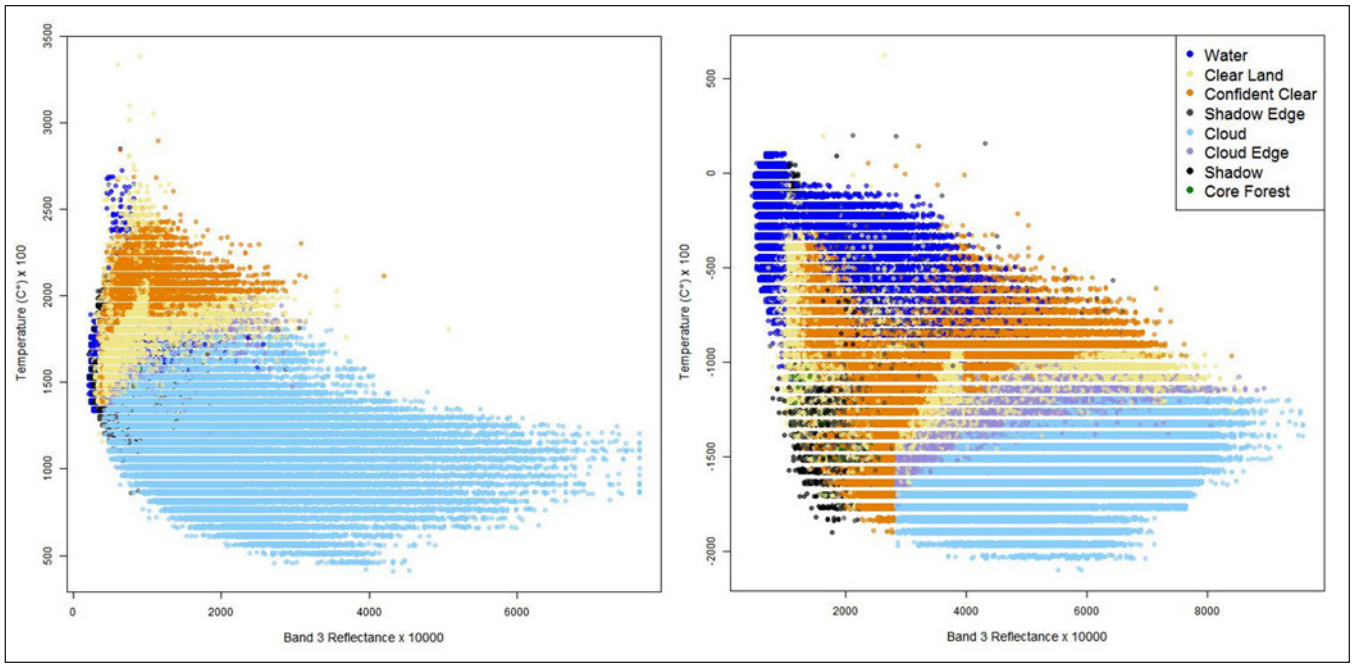


Figure 1.—Spectral-temperature space for a summer Landsat TM scene with clouds (left plot), and a cloud-free snow-covered winter scene (right plot). The cloud masking model misclassifies snow as clouds due to their similar bright/cold spectral/thermal signature.

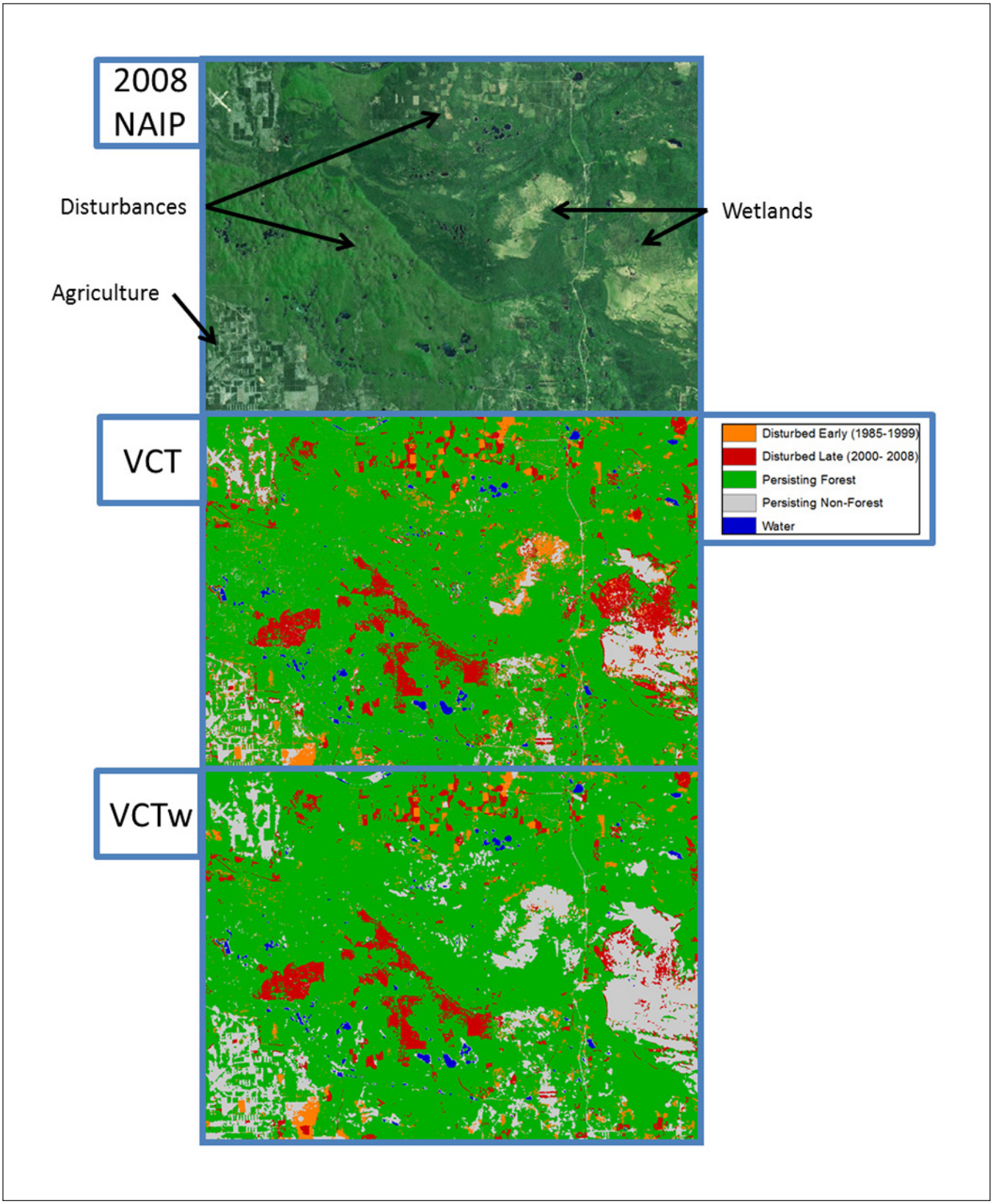


Figure 2.—Example of commission of wetland (right center of panels) and agricultural areas (lower left portion of panels) by VCT. VCT initially classified these areas as persisting forest/forest disturbance. They were then recoded to nonforest.

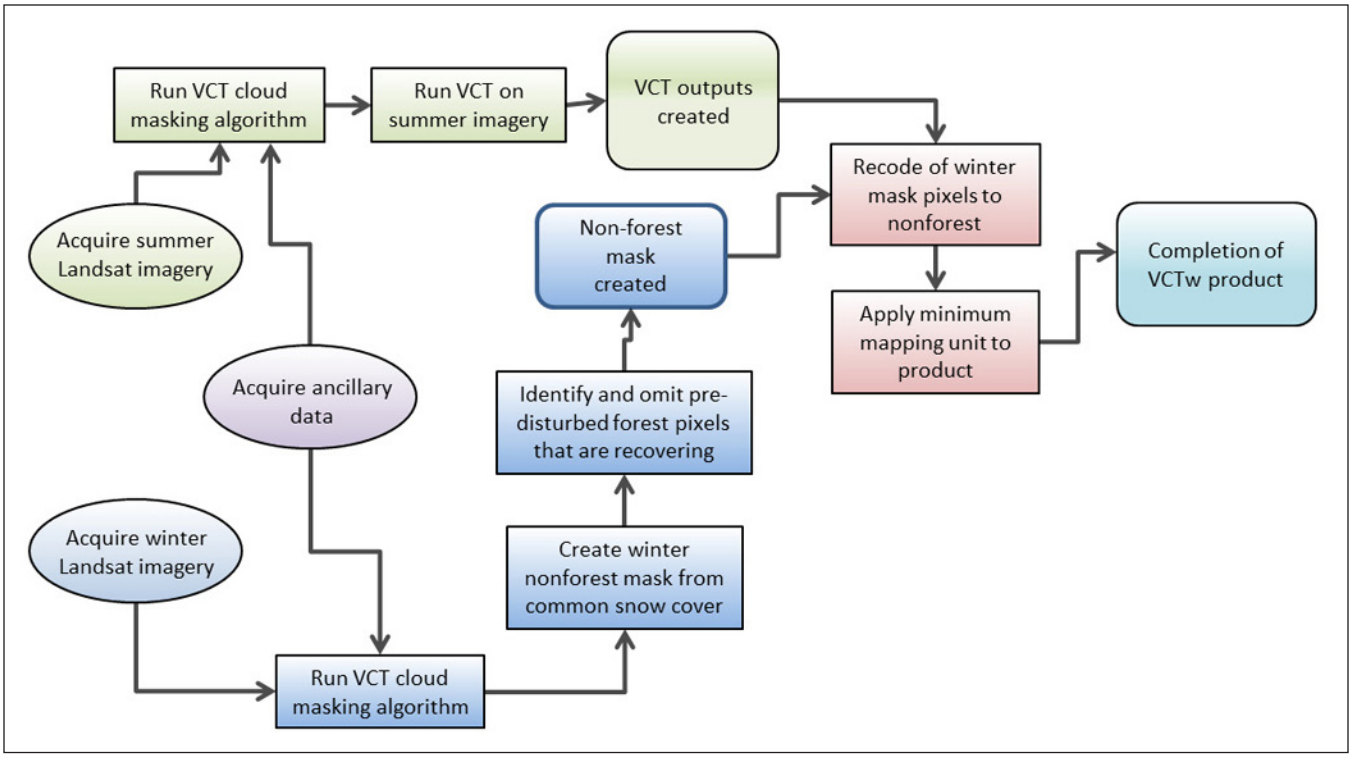


Figure 3.—Flowchart of all major steps of the VCTw workflow. Larger components depicted as different colors are running VCT using the standard protocol (green), creating a nonforest mask using VCT's cloud masking algorithm (blue), and applying nonforest mask and minimum mapping unit (red) to create the final VCTw product.

Because the aerial imagery had to be manually geo-referenced, the first stage of the sample design was intended to optimize our reference image preparation time. Therefore, the primary sampling unit (PSU) corresponded with the footprint of a 7.5-arc minute quadrangle. A simple random sample of 7.5-minute quadrangles that fell entirely within the basin was taken based on approximate region area. Thirty-five PSUs were selected in the LLMB and ULMB, and 17 were selected in the LLSB. The secondary sampling unit (SSU) corresponded to individual pixels. A stratified random sample was taken using the five VCTw classes as strata. The number of SSUs varied between strata and region (Table 1). Each SSU was photo-interpreted to determine the proper disturbance or persisting land cover class.

Table 1.—Number of SSUs from each stratum within each region

	PNF	PF	PW	D1	D2
LLSB	9	9	2	10	10
ULMB	5	5	2	6	6
LLMB	7	7	2	8	8

RESULTS

The binned VCT disturbance year product obtained an overall accuracy of 86.3 percent, while the binned VCTw disturbance year product yielded a statistically significant improvement at the 95 percent confidence interval with an overall accuracy of 91.2 percent. The difference between VCT and VCTw varied across the study regions (Fig. 4). The most pronounced improvement occurred in the LLMB, likely because the LLMB contains the largest proportion of the agricultural nonforested areas in which standard VCT erred while VCTw was able to discern. The proportion of agricultural areas in the ULMB and LLSB is lower than in the LLMB.

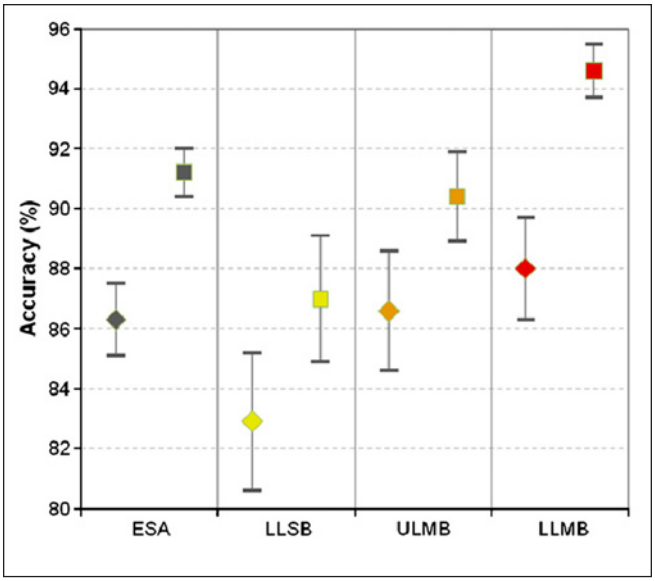


Figure 4.—Overall accuracy of VCT (diamonds) and VCTw (squares) with 95 percent confidence interval bars.

DISCUSSION

In this study, VCTw was used to create a significantly improved landscape-level forest disturbance map using LTSSw. VCTw is a robust, practical approach for mitigating misclassification of wetlands and agricultural areas as forest/forest disturbance in any area with sufficient snowfall. Because this method uses the VCT cloud masking method, it easily fits into the standard VCT workflow. Alternate approaches have proved effective, but generally require substantial model calibration data (Walterman et al. 2008). VCTw requires no calibration data and minimal additional time to implement. An estimated 34 percent of the world's forests receive sufficient snow to implement VCTw. Forested regions that do not receive reliable yearly snowfall would require an alternate approach.

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ADDING VALUE TO THE FIA INVENTORY: COMBINING FIA DATA AND SATELLITE OBSERVATIONS TO ESTIMATE FOREST DISTURBANCE

Todd A. Schroeder, Gretchen G. Moisen, Sean P. Healey, and Warren B. Cohen[1]

Abstract.—In addition to being one of the primary drivers of the net terrestrial carbon budget, forest disturbance also plays a critical role in regulating the surface energy balance, promoting biodiversity, and creating wildlife habitat. With climate change and an ever growing human population poised to alter the frequency and severity of disturbance regimes across the globe, improved monitoring of forest disturbance, especially at the landscape scale has taken on renewed importance. Because forest disturbance manifests at a variety of spatial and temporal scales and has varying impacts which affect the canopy, understory, and forest floor, effective monitoring will likely require a composite approach where localized field data collected by the Forest Inventory and Analysis (FIA) Program are combined with repeat observations from remote sensing satellites such as Landsat. As Landsat offers nearly 40 years of well calibrated and systematically collected imagery at no cost, it is now economically feasible to monitor year to year trends in forest disturbance over large areas. In addition to its use in mapping forest change, Landsat data can also serve as a valuable backdrop for collecting detailed human interpretations of disturbance. When collected over a design-based sample such as FIA plots, these manually derived interpretations offer a wealth of potential uses ranging from map validation to estimation of new disturbance-related attributes. Here satellite observations and FIA data are used to estimate the area impacted by several types of forest disturbance occurring in the Uinta Mountains of northern Utah. This study aims to evaluate two types of satellite observations in the context of FIA's estimation procedure, including the use of human interpretations as an augmented response variable and the use of disturbance maps for stratified variance reduction.

INTRODUCTION

The U.S. Forest Service Forest Inventory and Analysis (FIA) Program is required to produce timely and accurate estimates of a wide range of forest attributes. These attributes, which often include forest area and volume, are used to provide information on the current status and health of forests over varying geographical extents. Typically, areal estimates derived from inventory plots are used to quantify how much forest there is while maps derived from remote sensing imagery are used to delineate forest location and extent. Reporting population estimates which describe a forests current condition has long been a primary function of FIA. With climate change and population growth poised to alter the rate and severity with which forests are disturbed, a renewed emphasis has been placed on determining how much forest is changing, where it's changing, and what's changing it. Monitoring the status and trends of forest disturbance can be challenging for inventory programs as they typically have long temporal gaps between plot remeasurements (e.g., FIA remeasures plots every 5 years in the east and every 10 years in the west) likely resulting in missed disturbance events. But because small amounts of disturbance occur each

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year it is also important that measurements be made frequently and over large areas. Thus there is potential for national forest inventories to improve their change-monitoring capabilities by incorporating more frequent measurements of disturbance from remote sensing satellites such as Landsat.

MONITORING FOREST DISTURBANCE WITH LANDSAT IMAGERY

With a 40+ year historical archive and a 16-day repeat cycle, Landsat imagery offers an excellent platform for monitoring forest disturbance over large areas. The 30 m spatial grain and 7 spectral bands are capable of capturing many types of forest disturbance, especially those that impact the upper canopy. With the entire Landsat archive now freely available, it is now economically feasible to monitor disturbance through time using dense stacks of images. The free availability of images has also resulted in the development of several new algorithms which are capable of producing maps of disturbance in an automated manner. Two of these algorithms, the Vegetation Change Tracker or VCT (Huang et al. 2010) and the Landsat-based detections of trends in disturbance and recovery, or LandTrendr (Kennedy et al. 2010), are being tested and applied over large regions. For example, the North American Forest Dynamics (NAFD) project is currently using VCT to produce a wall-to-wall, seamless forest disturbance map for the conterminous United States. Given the increased availability and seamless coverage of these maps, it is important to determine if these national products can help FIA improve the timeliness and accuracy with which they monitor and estimate forest disturbance. Early attempts at using disturbance maps to stratify FIA variables have been met with mixed results, although it is possible this has more to do with variable definition and lack of remeasured data than poor map quality. Thus, a more comprehensively-defined disturbance response variable (e.g., one that is measured annually and includes all disturbance types) which is more in tune with the satellite perspective might yield improved stratification results.

One new strategy for collecting measurements of disturbance comes through the use of a human interpreter to analyze yearly time series of Landsat images (Cohen et al. 2010). When analyzed with periodic, high resolution imagery from Google Earth, these human interpretations yield highly accurate records of timing and cause of most natural and anthropogenic disturbance events. If these human-interpreted measurements of disturbance are made over a statistically based set of sample locations, such as FIA plots, they can be used for estimation purposes just like any other FIA variable. The objective of this study is to explore the utility of augmenting FIA plots with these human-interpreted measurements for the purpose of estimating the area impacted by several different types of disturbance. In testing potential improvements to the disturbance response variable, we will also test whether maps from VCT and LandTrendr can be used to improve the precision of the derived disturbance estimates.

STUDY AREA

The study area consists of the non-overlapping portion (or Thiessen scene area, TSA) of Landsat scene path 37 row 32, which covers the Uinta Mountains of northern Utah (Fig. 1). Approximately 56 percent of the study area is forested and includes broad expanses of conifer, mixed deciduous and pure aspen stands at high elevations, and sparse pinyon-juniper woodlands on drier, lower elevation slopes. According to the U.S. Forest Service forest type map (Ruefenacht et al. 2008) the majority of forest within the study area falls in five major group types. These include pinyon-juniper (18 percent), aspen/birch (12 percent), fir/spruce/hemlock (12 percent), lodgepole pine (10 percent) and Douglas-fir (3 percent). The diversity of forest types and land management objectives in this region have led to a number of known disturbance events including harvests, fires, insects, and mechanical treatments such as chaining. The broad array of disturbances, along with the presence of both dense and sparse forest types, makes this area an excellent location for evaluating FIA's potential use of satellite observations of disturbance.

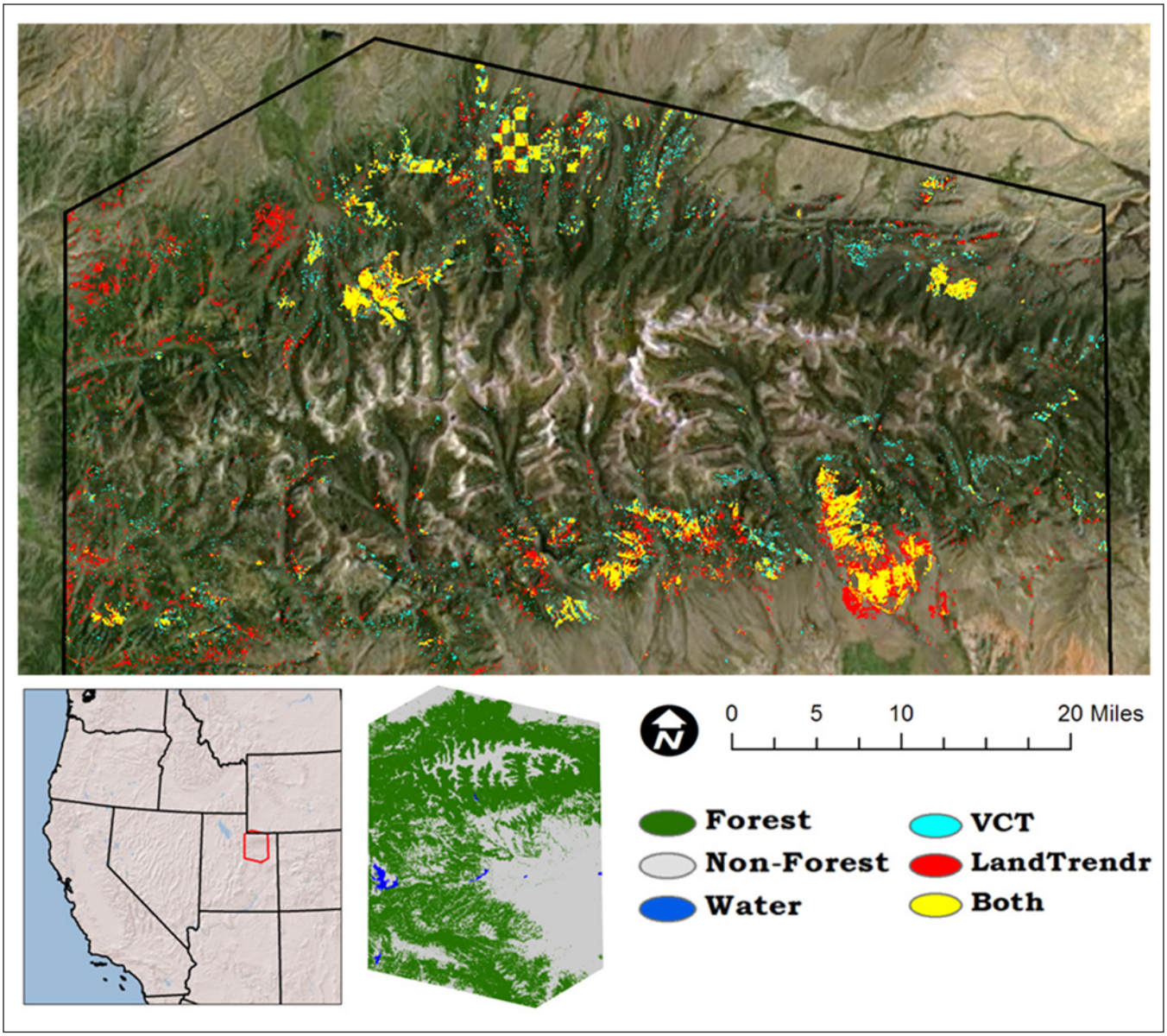


Figure 1.—Uinta Mountains study area with Vegetation Change Tracker (VCT) and LandTrendr forest disturbance.

METHODS

Satellite Disturbance Observations

The annual FIA plots (n=802) falling within the boundary of the study area were queried and loaded into a GIS for analysis. The plots containing at least one forest condition class (n=478) were identified so that a human interpreter could analyze and record the disturbance history of each plot. The interpretation process, similar to the one outlined in Cohen et al. (2010), entailed simultaneously viewing the full time series of Landsat images (acquired annually between 1987 and 2010) so that both the immediate plot area and its surrounding neighborhood could be easily surveyed for changes and supporting context. In a separate window, spectral trajectories for the plot were displayed using a number of different bands and indices. To aid the interpretation of the Landsat data, the interpreter used the high resolution, multi-date images found in Google Earth. These high resolution images covered several dates and were instrumental in detecting the first signs of stress-related crown mortality, such as from disease, insects, and drought.

Taken together, the multi-scale information from Landsat and Google Earth allowed the interpreter to accurately record the year and type of disturbances found on the FIA plots.

Satellite Disturbance Maps

Both VCT and LandTrendr have been successfully used to map disturbances across a broad range of forested ecosystems. Although the goal of both algorithms is to infer change on the ground from changes in the spectral signal captured by multiple Landsat images, both do so in different ways. For example, VCT is designed to locate abrupt forest disturbances such as fire and harvesting, whereas LandTrendr is designed to detect both abrupt events as well as slower, longer-term changes across all lands. Here we used each algorithm to generate maps of disturbance for the study area using Landsat images acquired annually between 1987 and 2009. Because LandTrendr maps disturbance across all lands, a forest cover map (Ruefenacht et al. 2008; see inset map Fig. 1) was used to remove disturbance from nonforested areas. For consistency, the VCT map was also merged with this forest cover map. Additionally, the time period of mapped disturbance was restricted to 1995-2009 to better coincide with the measurement window of the annual FIA plots.

RESULTS

Satellite and FIA Disturbance Observations

The image interpretation process identified a total of 129 disturbance events between 1995 and 2009. These 129 satellite disturbances were grouped into 10 categories as shown by the blue bars in Figure 2. The most prevalent disturbance types were insect and insect/disease which together accounted for more than 75 percent of the total observations. From the satellite perspective, these two classes represent distinct patterns of crown mortality which were distinguishable in the air photos. The insect label indicates the visible presence of red attack damage likely caused by mountain pine beetle, whereas the insect/disease label reflects conditions where dead gray crowns were observed, but the exact cause of death could not be inferred. The importance of the high resolution air photos was apparent, as more than half of these chronic stress related disturbances were only detectible in Google Earth. Fires were the next most abundant (11 percent) disturbance type, followed by harvesting (7 percent) and mechanical treatments such as chaining and brush saw (2 percent). Not surprisingly, the types and frequency of disturbances detected by FIA were similar to those observed by satellite interpretation (see red bars in Fig. 2). In total, FIA detected 86 disturbance events, of which the majority (72 percent) belonged to the insect and disease categories. Since FIA plots are field measured, we expect their insect and disease classes to be more accurate than those derived by satellite interpretation. Additionally, FIA was also able to detect smaller-scale impacts such as from animal grazing and weather, which could not be picked up from the satellite perspective. Over the 14-year period of observation (1995-2009), both the satellite and FIA measurements showed a noticeable trend of increasing disturbance with time as seen in Figure 3a and 3b (note different y axes). Despite the temporal similarities, it is important to note that in most cases FIA and the satellite captured different disturbance events. This results in considerably more disturbance when the data sets are combined than was found only by FIA (Fig. 3c).

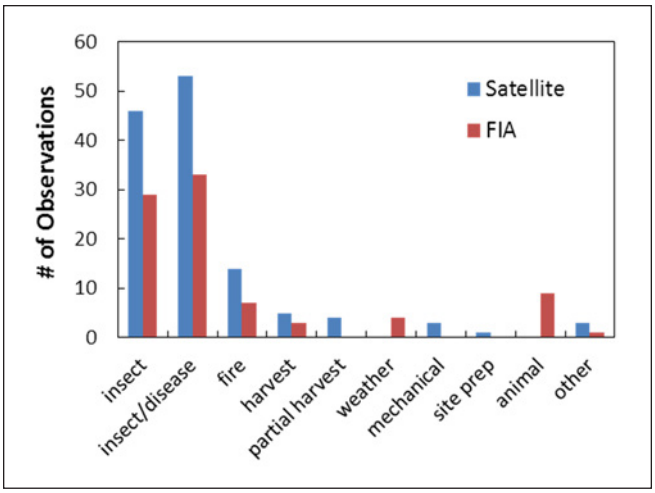


Figure 2.—Frequency of disturbance types observed by FIA and satellite interpretation.

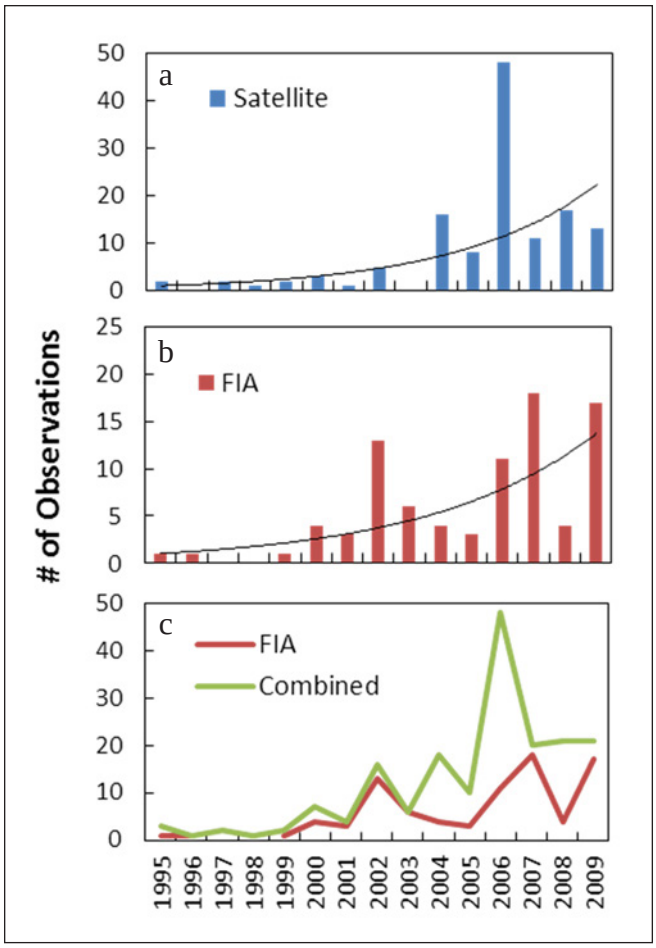


Figure 3.—Frequency of disturbance observed by (a) FIA interpretation, (b) satellite interpretation, and (c) FIA and satellite combined.

Satellite Disturbance Maps

Both the VCT and LandTrendr algorithms were used to derive forest disturbance maps for the study area. The algorithms produced noticeably different spatial (Fig. 1) and temporal (Fig. 4) patterns, with LandTrendr finding nearly twice as much disturbance as VCT. Despite these differences, both maps resulted in similar accuracy metrics when compared with the satellite interpretations of disturbance (VCT overall accuracy 87 percent, kappa = 0.42; LandTrendr overall accuracy 86 percent, kappa = 0.38). Unfortunately, combining the two disturbance maps did little to improve accuracy (combined overall accuracy 86 percent, kappa = 0.43).

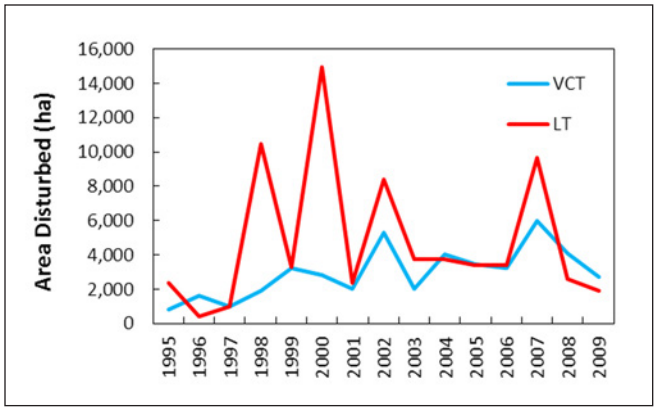


Figure 4.—Area of disturbance (in hectares) mapped by Vegetation Change Tracker (VCT) and LandTrendr.

CONCLUSION

The estimation and stratification results are currently being finalized and will be presented at the FIA Science Symposium in December 2012. Nonetheless, we believe the data gathered so far highlights the potential importance of augmenting FIA measurements with satellite observations of disturbance. Undoubtedly, the combination of these data sets will lead to larger estimates of disturbance than would otherwise be obtained from FIA data alone. In addition to improving estimates of disturbance, we also believe better disturbance histories will help enhance the overall analysis capability of the FIA plot data.

ACKNOWLEDGMENTS

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SPECIES DIVERSITY, SPECIES DISTRIBUTIONS, AND VEGETATION CLASSIFICATION

USING FOREST INVENTORY DATA ALONG WITH SPATIAL LAG AND SPATIAL ERROR REGRESSION TO DETERMINE THE IMPACT OF SOUTHERN PINE PLANTATIONS ON SPECIES DIVERSITY AND RICHNESS IN THE CENTRAL GULF COASTAL PLAIN

Andrew J. Hartsell[1]

Abstract.—This study investigates the impacts of southern yellow pine plantations on species evenness and richness in the gulf coastal plain. This process involves using spatial lag and spatial error regression techniques using GeoDa software and U.S. Forest Service's Forest Inventory and Analysis data. The results indicate that increasing plantation area is negatively correlated to species evenness and richness. Preliminary results indicate that for every 10 percent increment increase in southern yellow pine plantation area, Shannon's E decreases by 0.02 and species richness declines by 1.6 species. However, these models account for less than 50 percent of the data's variance, an indication that the models are incomplete and more research is needed.

INTRODUCTION

Biodiversity, synonymous with biological diversity, can be defined as "the variety and variability among living organisms and the ecological complexes in which they occur" (OTA 1987). Humans perceive regions with a multitude of diverse species to have more value than those that don't (Ehrlich 1991, Wilson 1993). Possible reasons that species diversity is valued by humans are: larger number of plant species means a greater variety of crops and life; greater species diversity helps assure natural sustainability for all life forms; diverse ecosystems can better withstand and recover from a variety of disasters; and finally the planets complex systems, ecological networks, and energy flows are dependent upon numerous organisms and interactions (Gaston 1996, SCBD 2006, Wilson 1993).

However, global biodiversity may be threatened by anthropogenic sources. The main factors responsible for potential biodiversity loss include: land use change; habitat change such as forest fragmentation and conversion; invasive alien species; overexploitation; and pollution. Plantations, which are artificially regenerated forests that are often composed of genetically modified or alien species, satisfy two of these factors. It is important that science ascertains the positive and negative impacts of this management regime to facilitate public discourse and planning.

STUDY AREA

The initial study area was limited to the states of Texas, Louisiana, Mississippi, and Alabama. Only counties in those states having the majority of their area in the gulf coastal plain, as defined by Bailey (1998), were considered. This population was thinned further by two more factors. First, the Mississippi River and its associated alluvial basin bisect the study area. Counties in this region were removed. Second, any county with less than 200,000 acres of forest land was removed from the dataset due to FIA's sampling intensity. This assures that at least 30 forested plots are in each county, providing a reasonable estimate of species diversity and richness at the county level. Additionally, any "island" counties that were isolated

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and not attached to the larger study area were also removed. The final dataset was composed of data from 158 counties (Fig. 1).

DEFINITIONS AND CONCEPTS

Measuring Biodiversity

Shannon-Wiener (Shannon's) evenness index (E) and diversity index (H) come from information theory and measure the order and disorder within a population (Shannon and Weaver 1971). Shannon's diversity index is derived by calculating the proportion of species *i* relative to the total number of species (p_i), and then multiplying by the natural logarithm of this proportion ($\ln p_i$). The result is summed across species, and multiplied by −1:

$$H = -\sum_{i=1}^{R} p_i \ln p_i$$

Species richness (R) is the number of different species found in a region or study area. For this study, species richness is a count of all tree species found in each county. Species richness does not take into account the relative abundance distributions of species.

Spatial Statistics

Detecting Spatial Autocorrelation

One of the most common ways of detecting spatial autocorrelation in group-level data is the Moran's I statistic. Moran's I is a weighted correlation coefficient used to detect departures from randomness such as clusters. The formula for Moran's I is:

$$I = \sum_i \sum_j w_{ij} (x_i - \mu)(x_j - \mu) / \sum_i (x_i - \mu)^2$$

where: μ is the mean of the x variable

w_{ij} are the elements of the spatial weights matrix.

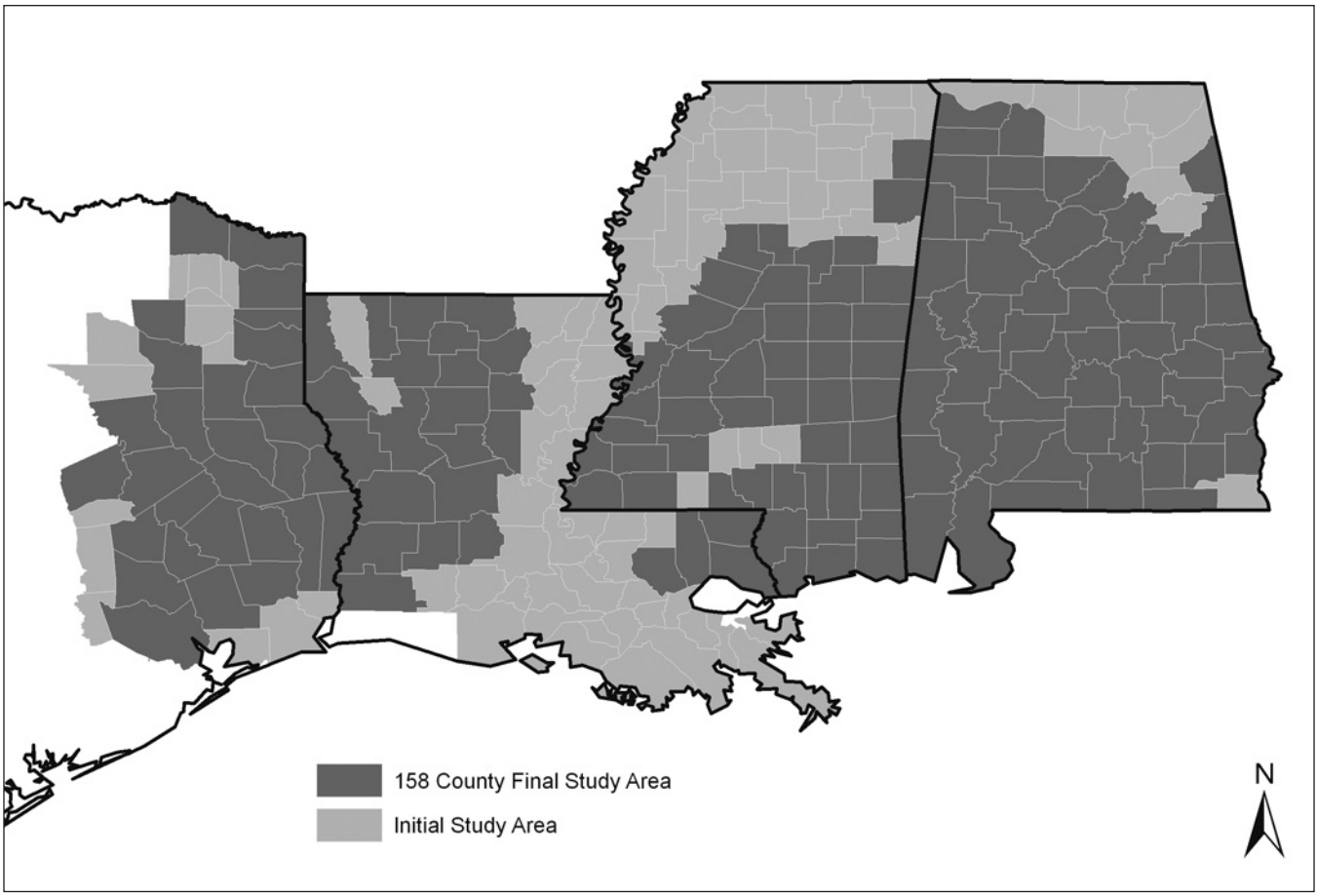


Figure 1.—Study area.

Geographically Weighted Regression: Spatial Lag and Spatial Error Models

Geographically weighted regression (GWR) can be performed in the presence of spatial autocorrelation. GWR accounts for distinctions between spatial similarity between the dependent and independent variables. Ordinary least squares (OLS) and other simple statistics do not do this. The basic formula for GWR is:

$$y = \chi\beta + e_i$$

where: χ is an n×p matrix of regressors
β is a p×1 vector of unknown parameters
e is unobserved scalar random variables (errors).

Spatial lag models (SLM) and spatial error models (SEM) are two types of GWR. Spatial lag models produce a spatially lagged variable on the right hand side of a regression equation. A spatial error model (SEM) considers the estimation of maximum likelihood of a spatial regression model that includes a spatial autoregressive error term on the right hand side of the regression equation.

METHODS

Species richness, Shannon's E, total forest area, and percent of forest area in southern yellow pine plantations (SYP) were computed for each county in the study area. Ordinary least squares (OLS) analysis was performed on the both Shannon's E and species richness using GeoDa version 0.95 software (OpenGeoDa version 1.2 is now available from the GeoDa Center at Arizona State University). Moran's I was calculated to determine if spatial dependence was an issue. If the data was determined to be spatially autocorrelated, then a series of LaGrange multiplier (LM) test statistics were computed. The results of the LM would then indicate which GWR model, spatial lag model or spatial error model, would be used in the final analysis.

RESULTS

Shannon's evenness index (E) was the first dependent variable investigated. The OLS regression of Shannon's E was performed using percent of forest land per county in southern yellow pine plantations (PCT_SYP_PL) as one independent variable, and a dummy variable that indicated if a county was on the east side of the Mississippi River. The average Shannon's evenness index was 0.695 (Table 1). The R^2 and adjusted R^2 were 0.368 and 0.360, respectively. The F-statistic and associated p-value indicated that the model was statistically significant. All three predictor variables, the intercept and two independent variables, were significant as well.

Table 1.—Results of ordinary least squares analysis on species evenness index using percent southern yellow pine plantations per county and location flag

Dependent Variable:	**SHANNONS_E**	Number of Observations:	158
Mean dependent var:	0.694942	Number of Variables:	3
S.D. dependent var:	0.0565841	Degrees of Freedom:	155
R-squared:	0.368228	F-statistic:	45.1709
Adjusted R-squared:	0.360076	Prob(F-statistic):	3.49482e-016
Sum squared residual:	0.319599	Log likelihood:	265.867
Sigma-square:	0.00206193	Akaike info criterion:	-525.734
S.E. of regression:	0.0454085	Schwarz criterion:	-516.546
Sigma-square ML:	0.00202278		
S.E. of regression ML:	0.0449753		

Variable	Coefficient	Std. Error	t-Statistic	Probability
CONSTANT	0.7422254	0.01048335	70.80043	0.0000000
PCT_SYP_PL	-0.002851605	0.0003366784	-8.469818	0.0000000
EAST_FLAG	0.03198344	0.007769342	4.116622	0.0000623

Tests for multicollinearity, normality, and heteroskedasticity proved to be insignificant (Table 2). However, Moran's I proved to be highly significant (p value =0.000000) indicating that spatial autocorrelation was an issue with the data. The first two tests (LM-error and LM-lag) were both significant, indicating that the robust models are more appropriate. The robust versions were to be considered only if the standard versions were significant. In this instance, both LM-lag and LM-error were significant, so the robust versions were then used. The Robust LM-error statistic was not significant (p value=0.8675), but the Robust LM-lag statistic was (p value=0.0087). Therefore, a spatial lag model is needed to remove any spatial autocorrelation. Table 3 shows the results of the spatial lag regression model on Shannon's evenness.

Table 2.—Regression diagnostics on ordinary least squares analysis of Shannon's species evenness index

REGRESSION DIAGNOSTICS			
MULTICOLLINEARITY CONDITION NUMBER		5.998419	
TEST ON NORMALITY OF ERRORS			
TEST	DF	VALUE	PROB
Jarque-Bera	2	0.2463868	0.8840927
DIAGNOSTICS FOR HETEROSKEDASTICITY			
RANDOM COEFFICIENTS			
TEST	DF	VALUE	PROB
Breusch-Pagan test	2	1.014434	0.6021692
Koenker-Bassett test	2	1.02169	0.5999884
SPECIFICATION ROBUST TEST			
TEST	DF	VALUE	PROB
White	5	N/A	N/A
DIAGNOSTICS FOR SPATIAL DEPENDENCE			
FOR WEIGHT MATRIX: **Queen** (row-standardized weights)			
TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.277114	5.5791937	0.0000000
Lagrange Multiplier (lag)	1	33.2970224	0.0000000
Robust LM (lag)	1	6.8814084	0.0087097
Lagrange Multiplier (error)	1	26.4434443	0.0000003
Robust LM (error)	1	0.0278303	0.8675084
Lagrange Multiplier (SARMA)	2	33.3248527	0.0000001

Table 3.—Spatial lag regression model on Shannon's species evenness index

Spatial Weight:	**Queen**		
Dependent Variable:	**SHANNONS_E**	Number of Observations:	158
Mean dependent var:	0.694942	Number of Variables:	4
S.D. dependent var:	0.0565841	Degrees of Freedom:	154
Lag coeff. (Rho):	0.510154		
R-squared:	0.518880	Log likelihood:	282.131
Sq. Correlation:	-	Akaike info criterion:	-556.262
Sigma-square:	0.00154043	Schwarz criterion:	-544.012
S.E. of regression:	0.0392483		

Variable	Coefficient	Std. Error	z-value	Probability
W_SHANNONS_E	0.5101542	0.07463184	6.83561	0.0000000
CONSTANT	0.3820561	0.05341811	7.152183	0.0000000
PCT_SYP_PL	-0.002135705	0.0003113954	-6.8585	0.0000000
EAST_FLAG	0.01523912	0.007230402	2.107645	0.0350616

The same process was repeated for species richness (R). The OLS regression on species richness included another independent variable, the amount of forest land in a county. This variable was labeled Forest_K, as each whole unit represents 1,000 acres of forest land. The average species richness for the study area was 50.5 (Table 4), indicating that each county in the study area has an average of 50 distinct tree species greater than 1.0 inch diameter at breast height (d.b.h.). The R^2 was 0.298 and the adjusted R^2 was 0.284, indicating that less than 30 percent of the dataset's variation was captured in the model. However, the model and all variables were statistically significant.

Tests for multicollinearity and normality indicated that neither was a problem. However, both tests for heteroskedasticity revealed that variances may not be equal. Furthermore, Moran's I shows that the data are spatially dependent (Table 5). The LM statistics indicated that the Robust LM-lag was insignificant.

Table 4.—Results of ordinary least squares analysis on Shannon's species richness using percent southern yellow pine plantations per county, amount of forested acres per county, and location flag

Dependent Variable:	**RICHNESS**	Number of Observations:	158
Mean dependent var:	50.5506	Number of Variables:	4
S.D. dependent var:	8.09715	Degrees of Freedom:	154
R-squared:	0.297692	F-statistic:	21.759
Adjusted R-squared:	0.284011	Prob(F-statistic):	8.38957e-012
Sum squared residual:	7275.27	Log likelihood:	-526.734
Sigma-square:	47.242	Akaike info criterion:	1061.47
S.E. of regression:	6.87328	Schwarz criterion:	1073.72
Sigma-square ML:	46.046		
S.E. of regression ML:	6.78572		

Variable	Coefficient	Std. Error	t-Statistic	Probability
CONSTANT	36.267	2.222544	16.31779	0.0000000
PCT_SYP_PL	-0.1072605	0.05378244	-1.994341	0.0478798
EAST_FLAG	3.60517	1.195587	3.015397	0.0030027
FOREST_K	0.04105437	0.005197799	7.898414	0.0000000

Table 5.—Regression diagnostics on ordinary least squares analysis of Shannon's species richness index

REGRESSION DIAGNOSTICS			
MULTICOLLINEARITY CONDITION NUMBER	9.475663		
TEST ON NORMALITY OF ERRORS			
TEST	DF	VALUE	PROB
Jarque-Bera	2	3.64542	0.1615873
DIAGNOSTICS FOR HETEROSKEDASTICITY			
RANDOM COEFFICIENTS			
TEST	DF	VALUE	PROB
Breusch-Pagan test	3	11.23643	0.0105138
Koenker-Bassett test	3	13.29254	0.0040448
SPECIFICATION ROBUST TEST			
TEST	DF	VALUE	PROB
White	9	N/A	N/A
DIAGNOSTICS FOR SPATIAL DEPENDENCE			
FOR WEIGHT MATRIX: **Queen** (row-standardized weights)			
TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.432723	8.6153092	0.0000000
Lagrange Multiplier (lag)	1	51.3552467	0.0000000
Robust LM (lag)	1	0.0432789	0.8352011
Lagrange Multiplier (error)	1	64.4791145	0.0000000
Robust LM (error)	1	13.1671467	0.0002849
Lagrange Multiplier (SARMA)	2	64.5223934	0.0000000

Therefore, a spatial error model must be created to counter these issues. Anselin notes that the spatial error model is also useful for reducing heteroskedasticity as well (Anselin 1992, 2005). A spatial error regression was performed to correct for these issues (Table 6).

The R^2 improved to 0.56, but as with the SLM model, this is a pseudo statistic and probably not directly comparable to OLS R^2. The best way to determine an improvement of goodness of fit over the OLS model is to compare LL, AIC, and SC. For the SLE model on species richness, all three improved.

DISCUSSION

The results of this study indicate that the area of southern yellow pine plantations in a county has a negative impact on species evenness and richness. Based on the spatially lagged regressions, Shannon's evenness (E) will decrease by 0.02 for every 10 percent increment increase in SYP plantation area. Likewise, species richness will drop by 1.6 species for the same change in plantation area.

However, while both models are statistically significant, they fail to account for over half of the variation in the dataset. This indicates that there are explanatory variables not accounted for. Further research needs to be performed to determine what these variables may be. Possible sources are: population estimates, road densities, land fragmentation patterns, or other socioeconomic factors.

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Table 6.—Spatial error regression model on Shannon's species evenness index

Spatial Weight:	**Queen**		
Dependent Variable:	**RICHNESS**	Number of Observations:	158
Mean dependent var:	50.550633	Number of Variables:	3
S.D. dependent var:	8.097153	Degree of Freedom:	155
Lag coeff. (Lambda):	0.675756		
R-squared:	0.559861	R-squared (BUSE):	-
Sq. Correlation:	-	Log likelihood:	-500.089426
Sigma-square:	28.857203	Akaike info criterion:	1006.18
S.E. of regression:	5.37189	Schwarz criterion:	1015.366637

Variable	Coefficient	Std. Error	z-value	Probability
CONSTANT	39.73594	2.177353	18.24966	0.0000000
PCT_SYP_PL	-0.1636192	0.04842778	-3.378622	0.0007286
FOREST_K	0.04129515	0.004798334	8.606143	0.0000000
LAMBDA	0.6757558	0.06527036	10.35318	0.0000000

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INCORPORATING EVOLUTIONARY RELATIONSHIPS INTO REGIONAL ASSESSMENTS OF FOREST BIODIVERSITY ACROSS FOREST INVENTORY AND ANALYSIS PLOTS

Kevin M. Potter and Christopher W. Woodall[1]

Abstract.—Evolutionary diversity metrics may be more biologically meaningful indicators of forest biodiversity than traditional measures such as species richness, which treat all species as equally important. This is because measures that account for evolutionary relationships among species should be better surrogates of functional diversity within forest communities, given that taxonomically distinct species should contribute more to the diversity present within a community. One measure, phylogenetic diversity, has been linked to a variety of plant ecosystem processes, goods and services, supporting the argument that it is a more useful conservation criterion for management decisions. To investigate patterns of forest functional biodiversity across the United States, we calculated plot-level evolutionary diversity measures on approximately 125,000 Forest Inventory and Analysis plots. Most measures were not well-correlated with species richness, while others were decoupled with it at small and medium scales. Phylogenetic diversity was consistently better correlated than species richness with most plot-level measures of forest productivity, including trees per acre and relative density, although the results varied by region. Using data remeasured over time on a subset of the forest inventory plots, we detected broad-scale patterns of phylogenetic diversity change that were consistent with the expected early effects of climate change. Specifically, phylogenetic diversity change was greater among seedlings than trees, was associated in some locations with latitude and elevation, and was greater among species with high dispersal capacity. These findings demonstrate that demographic indicators of evolutionary diversity can refine our understanding of climate change impacts on forest community biodiversity and function across broad regions. The importance, statistical power, and geographic extent of such indicators will increase as repeated measurements occur on all 125,000 inventory plots across the United States.

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RECENT TRENDS IN MAPLE AND OAK-HICKORY DISTRIBUTION FOR THE UNITED STATES

Michael Farrell[1]

Abstract.—Many researchers predict that climate change will cause maple-dominated forests to move northward and be replaced with oaks and hickories throughout much of their current range. Whereas there is strong evidence that the climate has been changing and will continue to do so, the current trends in these species abundance and distribution over the past 30 years are in direct contrast with many stated predictions. To date, human management has played a much larger role than climate in shaping the distribution of these tree species throughout the northeast. This presentation utilizes Forest Inventory and Analysis (FIA) data for 25 states in the eastern United States to examine the diameter distributions for sugar and red maples, oaks, and hickories since the 1980s. Oaks and hickories have had trouble regenerating throughout their established range whereas shade-tolerant sugar and red maples have been rapidly invading oak-hickory forest types. In fact, both sugar and red maples are becoming established much more rapidly along the southern and central states than they are in the northeast. Red maple is becoming even more dominant than sugar maple in almost every state, especially those along the southern and western ranges of sugar maple. This presentation explores the FIA data for the past 30 years on a state-level to determine what the future composition of maples, oaks, and hickories could be in the eastern United States if these trends continue. Implications for the maple syrup industry are explored, including where and what kind of trees will be tapped in the future.

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ANALYSIS OF URBAN AND NATURAL FOREST COMPOSITION ACROSS THE UNITED STATES

Mark J. Ambrose[1]

Abstract.—It has been suggested that urban forestry tree planting practices are creating a homogenous urban forest, with the same limited number of species dominating urban landscapes across North America. There is also concern about urban forests as pathways for invasive pests and pathogens to adjacent natural forests. However, to date urban forest inventory data have been limited and data collected from different cities were often incompatible. To begin to address the issue of urban forest composition, tree species data were obtained 150 U.S. and Canadian cities which had conducted inventories for use with the i-Tree Eco (UFORE) or i-Tree Streets (STRATUM) models or which maintained comprehensive street tree databases. Relative basal area of each tree species was calculated by city and land use class and (where possible) for each city as a whole. Those data were combined with data from nearby natural forests from the U.S. Forest Service Forest Inventory and Analysis (FIA) Program. The data were then analyzed using PC-ORD to determine which cities' urban forests were most similar to one another (using cluster analysis) and how species composition related to large-scale environmental variables (using non-metric multi-dimensional scaling). Environmental and geographic explanatory variables used included latitude, longitude, elevation, total annual precipitation, and plant hardiness zone.

Preliminary analysis of urban forest data alone showed that urban forests as a whole clustered by species composition data along rough geographic and climatic lines. More intensively managed portions of the urban forest (e.g., street trees) tended to cluster in ways less closely related to geography and climate. Analyses of the urban data together with natural forest data indicate that urban forests are generally more similar to one another than they are to nearby natural forests. Street tree populations were most similar in their species compositions while other components of the urban forest showed greater variation. The more intensively managed segments of the urban forest were also less similar to adjacent natural forests. Urban forests also tend to resemble the natural forests of the eastern United States more than they resemble western forests.

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FOREST CARBON: ACCOUNTING AND SCIENCE

TECHNICAL ASPECTS OF THE FOREST CARBON INVENTORY OF THE UNITED STATES: RECENT PAST AND NEAR FUTURE

Christopher W. Woodall, James E. Smith, Grant M. Domke, Sean P. Healey, John W. Coulston, and Andrew N. Gray[1]

Abstract.—The Forest Inventory and Analysis program of the U.S. Forest Service has explicitly assumed responsibility for providing an inventory of the U.S. forests' carbon stocks and stock change to the U.S. Environmental Protection Agency for numerous years to meet obligations to the United Nations Framework Convention on Climate Change. Recent improvements, plans for the future, and implications regarding use of the U.S. inventory both nationally and at the project scale are discussed.

It appears unlikely that the 112th Congress of the United States will approve incentives for the commoditization of biogenic carbon (C) (i.e., "cap and trade"), so where should the science of forest C accounting head in the near future? Initial versions of the 2012 Farm Bill coupled with the National Forest System Climate Change Performance Scorecard highlight areas of current and future research in C accounting. The Forest Inventory and Analysis (FIA) Program of the U.S. Forest Service has adopted several areas of priority research in the area of carbon: reduction of the uncertainty associated with FIA's C estimates; downscaling of national C estimates to the national forest or mid-level; and refinement of biomass estimation procedures. This represents a substantive course of action to improve the science of C accounting and to meet user demands.

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Over the past year (2011-2012), the major changes to the accounting of U.S. forest C involved adoption of the Component Ratio Method (CRM) approach (Domke et al. 2012) to biomass/C estimation and incorporating standing dead tree measurements in the national inventory (i.e., annual Phase 2) (Woodall 2012). Incorporating standing dead tree measurements greatly improved the sensitivity of the national inventory to stand-level dynamics (Woodall et al. 2012a). FIA is encouraged that incorporating a national downed dead wood inventory (Woodall et al. 2008) in the 2012 National Greenhouse Gas Inventory (NGHGI) may impart the same positive effect. In 2013 and beyond, it is hoped that many aspects of the FIA national inventory of forest health indicators (Woodall et al. 2011) may refine C estimation. Sometimes the casting of a forest health indicator in a different light can greatly inform the estimation of a C stock such as found with components of the forest floor (Woodall et al. 2012c). This process of "stepping through" each forest C pool with the objective to increase estimate precision and linking the estimates to recently derived empirical information (i.e., Phase 3 inventory) is a tremendous benefit to C and biomass accounting.

Refined C stock estimates at the national scale may benefit the NGHGI, but can this be downscaled to our national forests and other comparable

scales? Estimates of National Forest System C stocks (Heath et al. 2011) are now a requirement of climate change scorecard reporting for national forests in the United States. Because an intention of the scorecard is to understand and consider the effects of management activities on carbon budgets at the scale of a national forest, the uncertainty (sometimes > 5 percent sampling error) associated with a "downscaled" NGHGI may not appropriately inform such management activities. Ongoing research into "downscaling" NGHGI to inform mid-level activities (Wilson et al. in review, Coulston et al. this proceedings) may improve the statistical power (Westfall et al., in review) to detect management/disturbance effects on C budgets. Whereas the techniques used to develop the NGHGI satisfy requirements under United Nations Framework Convention on Climate Change (U.S. EPA 2012), new areas of research are needed to downscale NGHGI to empower land managers interested in mitigating climate change.

As renewable biomass is an emerging topic in regards to energy and economic development (Woodall et al. 2012b), the draft 2012 Farm Bill language requests more information on the supply of renewable forest biomass in the United States. In addition to C accounting, it should be recognized that forest C accountants are also biomass experts. The FIA program has already initiated a national effort to improve the modeling of individual tree biomass/C attributes (Coulston et al. this proceedings). This same drive should be reflected in non-live tree pools. Refining the estimations of standing dead tree, downed dead, and understory components should benefit more comprehensive biomass assessments. Domke et al. (2011) found that biomass estimates could be improved by refining the decay reductions and structural deductions for standing dead trees. Such a research approach across the many diverse pools associated with C accounting will benefit renewable biomass estimation.

Finally, all of these technical improvements do not occur in isolation within the FIA program. State and university partners in concert with an array of federal partners (e.g., USGS and NASA) are critical to the development and application of C/biomass accounting. Only through partnership can FIA's refined approaches to C/biomass monitoring be leveraged to meet the expectations of our diverse user community.

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RECENT CHANGES IN THE ESTIMATION OF STANDING DEAD TREE BIOMASS AND CARBON STOCKS IN THE U.S. FOREST INVENTORY

Grant M. Domke, Christopher W. Woodall, and James E. Smith[1]

Abstract.—Until recently, standing dead tree biomass and carbon (C) has been estimated as a function of live tree growing stock volume in the U.S. Forest Service, Forest Inventory and Analysis (FIA) Program. Traditional estimates of standing dead tree biomass/C attributes were based on merchantability standards that did not reflect density reductions or structural loss due to decomposition common in standing dead trees. In 1999, the FIA program began consistent nationwide sampling of standing dead trees. That data may now be used to supplant previous approaches to standing dead biomass and C stock estimation. The objective of this study was to incorporate density reductions and structural loss adjustments into standing dead tree biomass/C estimation procedures and assess differences in estimates at multiple spatial scales. The results suggest that accounting for density reductions and structural loss in standing dead trees substantially decreases estimates of standing dead tree biomass and C at tree, plot, and regional scales. Incorporating density reductions and structural loss adjustments may improve the accuracy of standing dead tree biomass and C estimates in the U.S. forest inventory as well as the consistency with FIA field methods and documentation.

INTRODUCTION

Standing dead tree carbon (C) is part of the dead wood C pool recognized in the Land Use, Land Use Change, and Forestry (LULUCF) section of the U.S. National Greenhouse Gas Inventory produced annually by the U.S. Environmental Protection Agency. Forest ecosystem C estimates in the LULUCF are based on the national forest inventory conducted by the U.S. Forest Service, Forest Inventory and Analysis (FIA) Program. Until recently, standing live and dead tree (SDT) biomass and C estimates were calculated by FIA using the same procedures. It has been recognized that the density of dead wood generally decreases with each stage of biomass decay (Krankina and Harmon 1995, Sandstrom et al. 2005) and that structural losses (e.g., sloughing and breakage) occur throughout the decomposition process (Aakala et al. 2008, Cline et al. 1980, Raphael and Morrison 1987). This paper briefly describes the process of incorporating density reduction factors (DRFs) and structural loss adjustments (SLAs) into standing dead tree biomass and C estimates (for a complete description, see Domke et al. 2011). The study objectives were: 1) examine the distribution of SDTs across decay classes in the FIA database; 2) test the differences between unadjusted and adjusted standing dead tree biomass and C estimates (i.e., incorporation of DRFs and SLAs); and 3) suggest refinements of proposed SDT biomass and C estimation procedures and future research directions.

METHODS

DRFs for SDTs were developed using standing and down dead wood samples categorized by decay class and divided into subsections where wood disks were cut from each end and volume and weight measurements (wet and dry) were taken to determine the density of wood and bark (Harmon et al. 2011).

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DRFs were calculated as the ratio of the average current decayed density (current mass/volume) of the piece of dead wood to average undecayed (live tree mass/volume) density for each species and decay class (Table 1).

Preliminary SLAs for tops and branches and belowground biomass were estimated using qualitative descriptions from the FIA field guide (USDA Forest Service 2010) and other studies documenting structural loss by decay class and tree component (Cline et al. 1980, Krankina and Harmon 1995, Vanderwel et al. 2006). Preliminary SLAs for bark biomass were estimated from data collected as part of Harmon et al.'s (2011) study. Merchantable stem deductions due to rough, rotten, or missing cull were accounted for in the conversion from gross to sound volume (Woudenberg et al. 2010) so no additional SLAs—with the exception of bark biomass—were estimated for bole or stump components (Table 1).

Regional Case Study

The most abundant SDT species in the Lake States (Michigan, Minnesota, and Wisconsin) and Pacific Northwest (Oregon and Washington) were selected to compare differences in unadjusted and adjusted biomass and C stock estimates. While the two species selected (quaking aspen [*Populus tremuloides* Michx.] and Douglas-fir [*Psuedotsuga menziesii* (Mirb.) Franco], respectively) may not be representative of all species in their respective regions, they are both extremely common in the FIA database and provide a sound starting point for consideration.

Field data for each region and species were taken from the FIA database. All standing dead (SD) aspen and Douglas-fir trees with a diameter at breast height ≥ 12.7 cm were included in the analysis. A total of 9,369 SD aspen trees were sampled on 3,975 plots in the Lake States from 2005-2009, and 10,144 SD Douglas-fir trees were sampled on 2,825 plots in the Pacific Northwest from 2001-2009.

Mean differences in tree-level biomass estimates for the component ratio method (CRM), CRM+DRFs, and CRM+DRFs+SLAs were compared by diameter class for each tree species. Mean differences of tree level biomass estimates for each approach were not tested for statistical significance for two reasons. First, information was not available to estimate the uncertainty of the tree level biomass predictions. Second, differences between estimates for individual trees on the same plot were expected to be highly correlated. Techniques for accommodating these correlations, particularly with different numbers of trees per plot, are beyond the scope of this study.

Estimates of plot-level SDT biomass were calculated using the three approaches and compared for the two species and regions. The uncertainty of mean plot-level estimates can be attributed to two sources, the uncertainty of individual tree-level estimates and plot-to-plot sampling variability. The uncertainty of the tree-level estimates is generally regarded by national forest inventory programs as negligible relative to the sampling variability and, therefore, was ignored for these analyses. Mean differences in

Table 1.—Density reduction factors by species and preliminary SLA for each decay class by tree component for all tree species in the FIA database; table adapted from Domke et al. (2011)

	Density Reduction Factors		Structural Loss Adjustment Factors				
Decay Class	Quaking aspen	Douglas-fir	Top	Bark	Bole	Stump	Roots
1	0.970	0.892	1.00	0.92	1.00	1.00	1.00
2	0.750	0.831	0.50	0.66	1.00	1.00	0.95
3	0.540	0.591	0.20	0.39	1.00	1.00	0.80
4	0.613	0.433	0.10	0.21	1.00	1.00	0.65
5	0.613	0.433	0.00	0.00	1.00	1.00	0.50

plot-level estimates were calculated in three steps. First, the estimate for each tree was calculated using each approach. Second, plot level differences were calculated as the difference between the CRM estimate of the plot total and the CRM+DRFs and CRM+DRFs+SLAs estimates of the plot total. Mean plot-level differences were calculated as the mean over all plots of the previously calculated plot-level differences. A t-test was used to determine the statistical significance in the mean differences; in effect, the test was a paired t-test because it focused on mean differences rather than differences of means. The null hypotheses were that the mean differences between estimates of C stocks were not significantly different from zero ($\alpha = 0.01$).

RESULTS

The distributions of SD aspen and Douglas-fir trees tended toward a normal distribution centered around the third decay class (see Domke et al. 2011). Nearly 29 percent of SD aspen were missing branches and an additional 16 percent lacked top and branch biomass. For Douglas-fir stems in the Pacific Northwest, only 5 percent of sample trees had missing tops and branches and more than 73 percent of stems had at least some top, branch, and bark biomass present.

The difference in individual tree biomass estimates was compared by diameter class in Figure 1. Bole and stump biomass estimates were quite similar for the CRM+DRFs and CRM+DRFs+SLAs for both study species across diameter classes (differences were due to SLAs for bark biomass in each component), but substantially less than the CRM estimates. The CRM+DRFs+SLAs produced an almost uniform trend for top and branch biomass across diameter classes, while belowground biomass trends increased more or less consistently with the other two methods.

Mean plot-level differences in tree component biomass for the three estimation procedures were statistically significantly different for both species across the two regions. The CRM+DRFs and CRM+DRFs+SLAs decreased plot-level SD bole biomass estimates for aspen by 35 percent (65.8 kg) and 42 percent (78.1 kg), respectively across the Lake States (Table 2). In the Pacific Northwest, the CRM+DRFs reduced plot-level SD Douglas-fir bole biomass by 32 percent (595.0 kg) and the CRM+DRFs+SLAs reduced bole biomass by 36 percent (672.7 kg) (Table 2). For results on individual trees and regional population estimates, see Domke et al. (2011).

DISCUSSION

Forest inventories in the United States have transitioned from a timber focus toward a more holistic sampling of forest ecosystem attributes such as C stocks of standing dead trees. Likewise, the estimation procedures associated with the changing inventory need to be inclusive of tree attributes beyond those required by the forest products industry. Developing SDT biomass and C stock estimates within the construct of an inventory system traditionally designed to estimate growing stock volume requires: 1) the development of a SDT decay class system which is both qualitative for ease of use in the field and quantitative to account for structural loss by tree component and species; 2) the development of DRFs for SDT species in each decay class, with specific emphasis on advanced decay classes; and 3) the development of a flexible SDT estimation procedure which incorporates initial SLAs and DRFs and allows for continual refinement.

SDTs are an important part of the dead wood forest ecosystem C pool recognized by the international community. In an effort to improve the accuracy of biomass and C stock estimates that are used in various facets of the national forest inventory, preliminary DRFs and SLAs have been developed for SDTs. These adjustments reflect the current state of the science on SDT biomass/C estimation and result in significantly lower plot-level biomass estimates, and thus, substantial differences in regional SDT biomass and C stock estimates. The results from this study suggest that incorporation of the SDT adjustments will

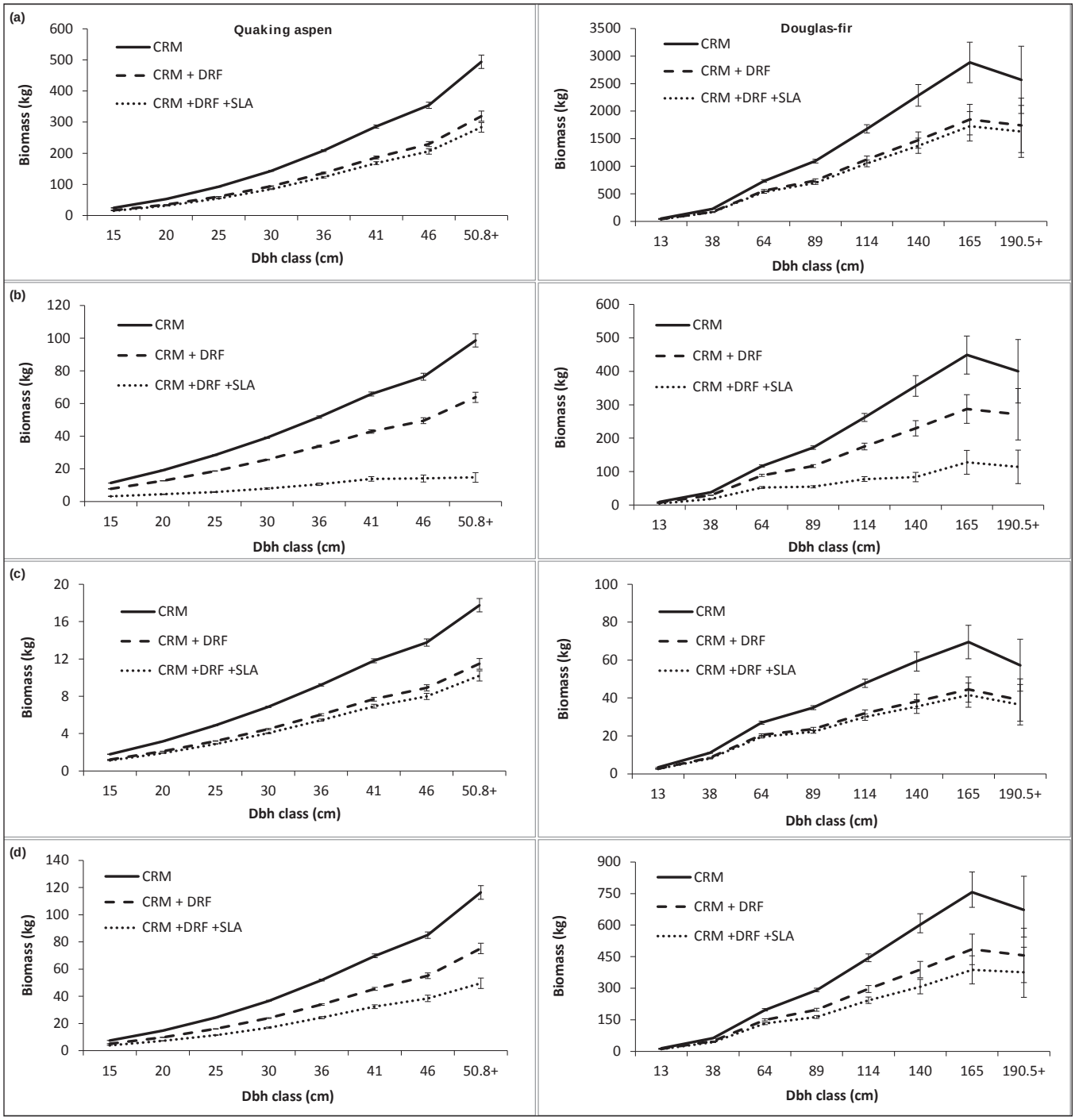


Figure 1.—Mean (with standard errors) SD biomass (oven-dry kg) by tree species (quaking aspen on left, Douglas-fir on right; note the y-axis scale differs by species), estimation method, and d.b.h. class for: a) bole, b) top and branches, c) stump, and d) belowground components; adapted from Domke et al. (2011).

Table 2.—Mean plot-level difference (d) in standing dead biomass (oven-dry kg) by tree component and estimation method (1 = CRM vs. CRM+DRF and 2 = CRM vs. CRM+DRF+SLA) for quaking aspen in the Lake States (2005-2009) and Douglas-fir in the Pacific Northwest (2001-2009); table adapted from Domke et al. (2011)

Component	Comparison	Quaking aspen				Douglas-fir			
		t	*df*	*p*	*d*	*t*	*df*	*p*	*d*
Top and branches	1	56.4	3966	<0.001	19.6	21.4	2823	<0.001	94.1
	2	56.8	3966	<0.001	45.1	21.2	2823	<0.001	203.1
Bole	1	48.1	3966	<0.001	65.8	21.2	2823	<0.001	595.0
	2	48.2	3966	<0.001	78.1	21.2	2823	<0.001	672.7
Stump	1	55.0	3966	<0.001	3.4	23.4	2823	<0.001	19.0
	2	55.2	3966	<0.001	4.0	23.5	2823	<0.001	21.5
Belowground	1	50.6	3966	<0.001	17.2	21.3	2823	<0.001	158.4
	2	49.9	3966	<0.001	26.6	21.2	2823	<0.001	216.5

substantially reduce estimates of dead wood biomass and C stocks across spatial-scales and tree species of the United States. While the preliminary estimates offer a sound starting point for SDT biomass and C estimation, more work is necessary to refine SLAs (perhaps by species and region) for each decay class used in national inventory field sampling.

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THE CLIMATE CHANGE PERFORMANCE SCORECARD AND CARBON ESTIMATES FOR NATIONAL FORESTS

John W. Coulston, Kellen Nelson, Christopher W. Woodall, David Meriwether, and Gregory A. Reams[1]

Abstract.—The U.S. Forest Service manages 20 percent of the forest land in the United States. Both the Climate Change Performance Scorecard and the revised National Forest Management Act require the assessment of carbon stocks on these lands. We present circa 2010 estimates of carbon stocks for each national forest and recommendations to improve these estimates.

INTRODUCTION

The climate change performance scorecard is the mechanism through which the U.S. Forest Service seeks to increase its capacity to respond to climate change (U.S. Forest Service 2011). Under this paradigm, there are four dimensions (organizational capacity, engagement, adaptation, and mitigation) that span a range of important components relevant to climate change (Fig. 1). Here we focus on the mitigation and sustainable consumption dimension with particular focus on carbon (C) assessment and stewardship in support of the climate change performance scorecard.

The revised regulations (Code of Federal Regulations: 36 CFR 219, 2012) for implementing the National Forest Management Act also include requirements for assessments of C stocks for each new national forest plan or plan revision. Long-term C storage is described as a "regulating" ecosystem service of forests, rangelands, and grasslands. Plans must include components that provide for social and economic sustainability, taking into account the ecosystem services and reasonably foreseeable risks. Responsible officials should use the assessment of C stocks to understand (1) how the plan area plays a role in sequestering and storing C and (2) how disturbances, management, and resource uses influenced C stocks in the past and may affect them in the future.

Quantifying and tracking changes in C stocks are key objectives for the U.S. Forest Service on National Forest System (NFS) lands, which account for 20 percent of U.S. forest land. The Forest Inventory and Analysis (FIA) Program provides a consistent monitoring and assessment framework across all lands and ownerships, which can be used to consistently estimate C stocks across landscapes. Through regional or local partnerships between FIA and NFS, the base FIA sample can be intensified to increase the precision of estimates at the NFS administrative forest level.

Several studies have provided C estimates for national forests at the region, state, and individual forest spatial scales (e.g., Heath et al. 2011). In some cases, these approaches have relied on estimating the areal extent of each national forest (the population of interest) and therefore can be improved by (1) explicitly defining the areal extent of the populations of interest, and (2)

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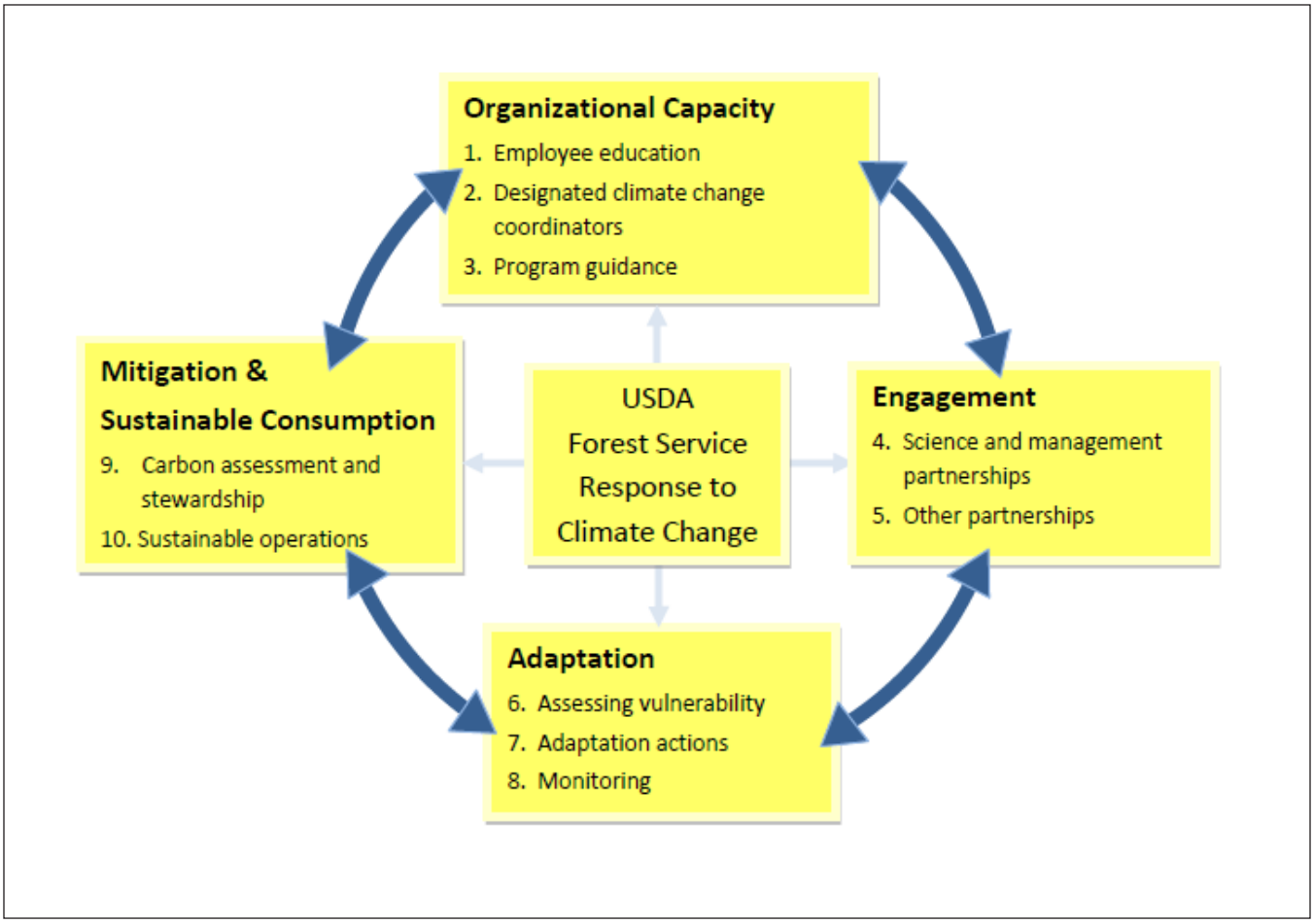


Figure 1.—The four dimensions and ten elements of the U.S. Forest Service climate change performance scorecard (source U.S. Forest Service 2011).

including inventory plot intensifications on NFS lands. Our goal here is to incorporate these improvements and identify additional areas for improvement in support of C estimates for the climate change performance scorecard, for forest planning, and for monitoring

METHODS

To construct C estimates for each national forest, we used field-based observations from FIA and intensified national forest data collected using FIA protocols (Southern and Eastern NFS regions). Most national forest intensifications were either 2x or 3x the intensity of the standard FIA sample. The area of each national forest was obtained from the Automated Lands Project (ALP) geospatial database available through the corporate U.S. Forest Service Citrix environment. The 2001 NLCD percent tree canopy cover data (Homer et al. 2007) were obtained from the Multi-Resolution Land Characteristics consortium.

The standard FIA post-stratified estimator was used to estimate population totals and the standard error of the estimates (Bechtold and Patterson 2005). The population total was $\hat{Y} = A_t \sum_h^H W_h \bar{Y}_h$ where A_t was the population area as defined by the ALP database, W_h was the weight of each h stratum, and $\bar{Y}_h$ was the within strata average from the plot level observations. The strata weights were developed from the NLCD percent tree canopy cover data using an automated

stratification routine. $W_h = A_h/A_t$ where A_h is the area of the population in stratum h. The standard error of the estimate was then $S.E(\hat{Y}) =$

$$\sqrt{\frac{A_t^2}{n}\left[\sum_h^H W_h n_h v(\bar{Y}_h) + \sum_h^H (1 - W_h)\frac{n_h}{n} v(\bar{Y}_h)\right]}$$

where n was the total number of plots in the population, n_h was the number of plots in each stratum, and $v(\bar{Y}_h)$ was the variance of the plot level values within each h stratum. Estimates of the following C pools were made for each administrative forest: down dead wood, litter, overstory trees above ground, overstory trees below ground, standing dead wood, soil organic carbon, understory story trees above ground, and understory trees below ground. Plot level estimates of forest C stocks were a combination of empirically measured tree/site attributes combined with a series of individual tree/site models (see USEPA 2012 for methods). To estimate stocks at aggregate levels (NFS administrative region and for all NFS lands), basic error propagation techniques were used.

RESULTS

Across all pools there are approximately 10.88 billion tons (0.4 percent sampling error) of C stored on NFS lands. The majority of the C is stored in national forests in the western United States (Fig. 2). This finding is primarily due to the larger areal extents of these forests. For example, the Tongass National Forest in southern Alaska stores 1.17 billion tons

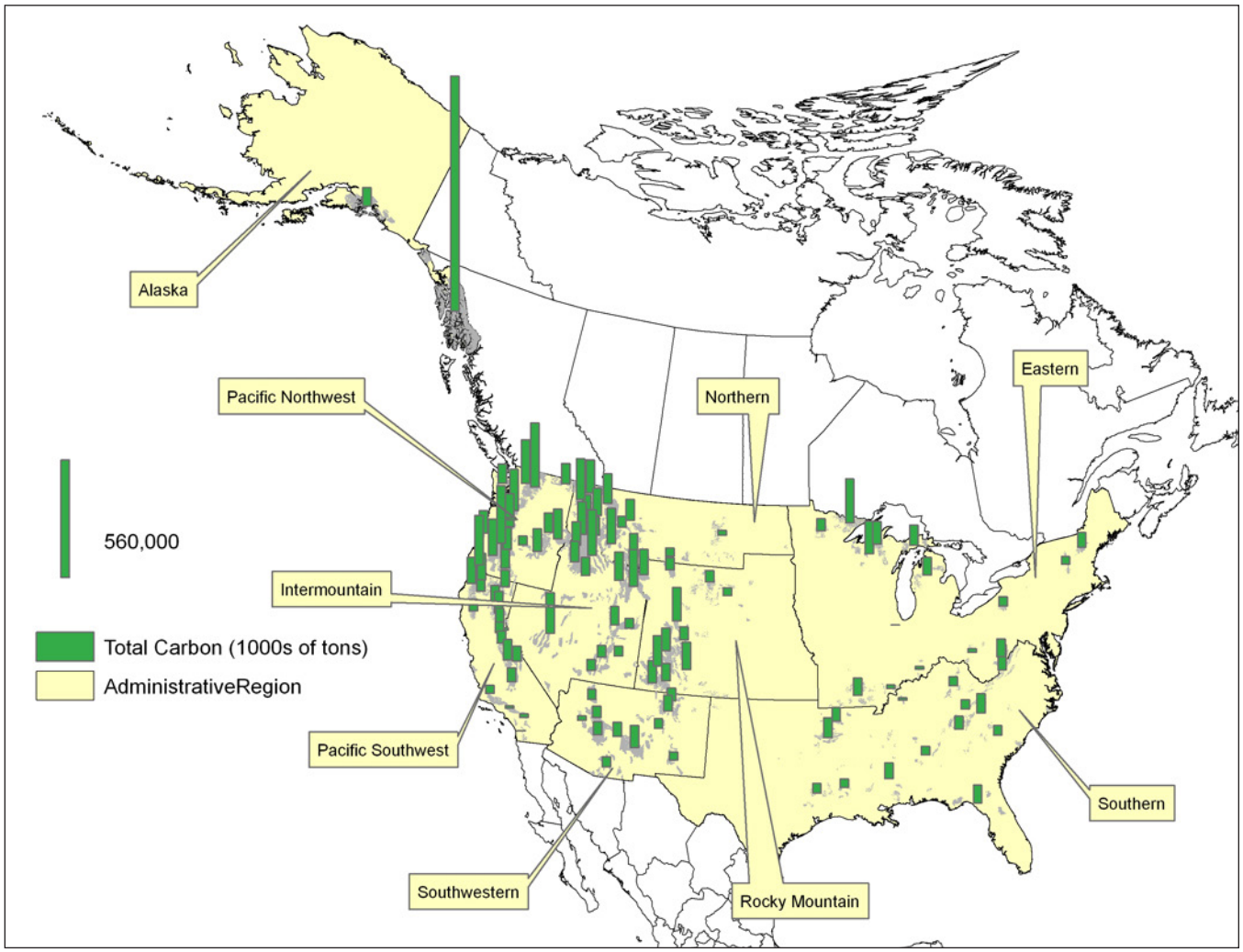


Figure 2.—Estimates of total C stocks (i.e., all pools) in thousands of tons for each administrative forest.

(1.9 percent sampling error) of C and occupies about 16.8 million acres. On a per acre basis, NFS lands on average have a C density of 57 tons per acre; the lowest density occurs in southern California and the highest density occurs in the Pacific Northwest region (Fig 3).

The Pacific Northwest region has an average total C density of approximately 103 tons per acre (1.06 percent sampling error) (Table 1). These substantial stocks are primarily driven by highly productive forests (e.g., large overstory trees) combined with considerable input to detrital forest components with concomitantly slow decay rates (e.g., C in soil organic carbon and dead wood). The Eastern region has the second highest C densities (87 tons per acre, 0.56 percent sampling error) primary driven by storage in organic soils (50 tons per acre, 0.68 percent sampling error).

DISCUSSION

The intent of the climate change performance scorecard is to increase the capacity of the U.S. Forest Service to respond and adapt to climate change (U.S. Forest Service 2011). The revised planning regulations include requirements to assess and sustain C in forest, rangeland, and grassland management. Monitoring C stocks and fluxes is a fundamental step toward

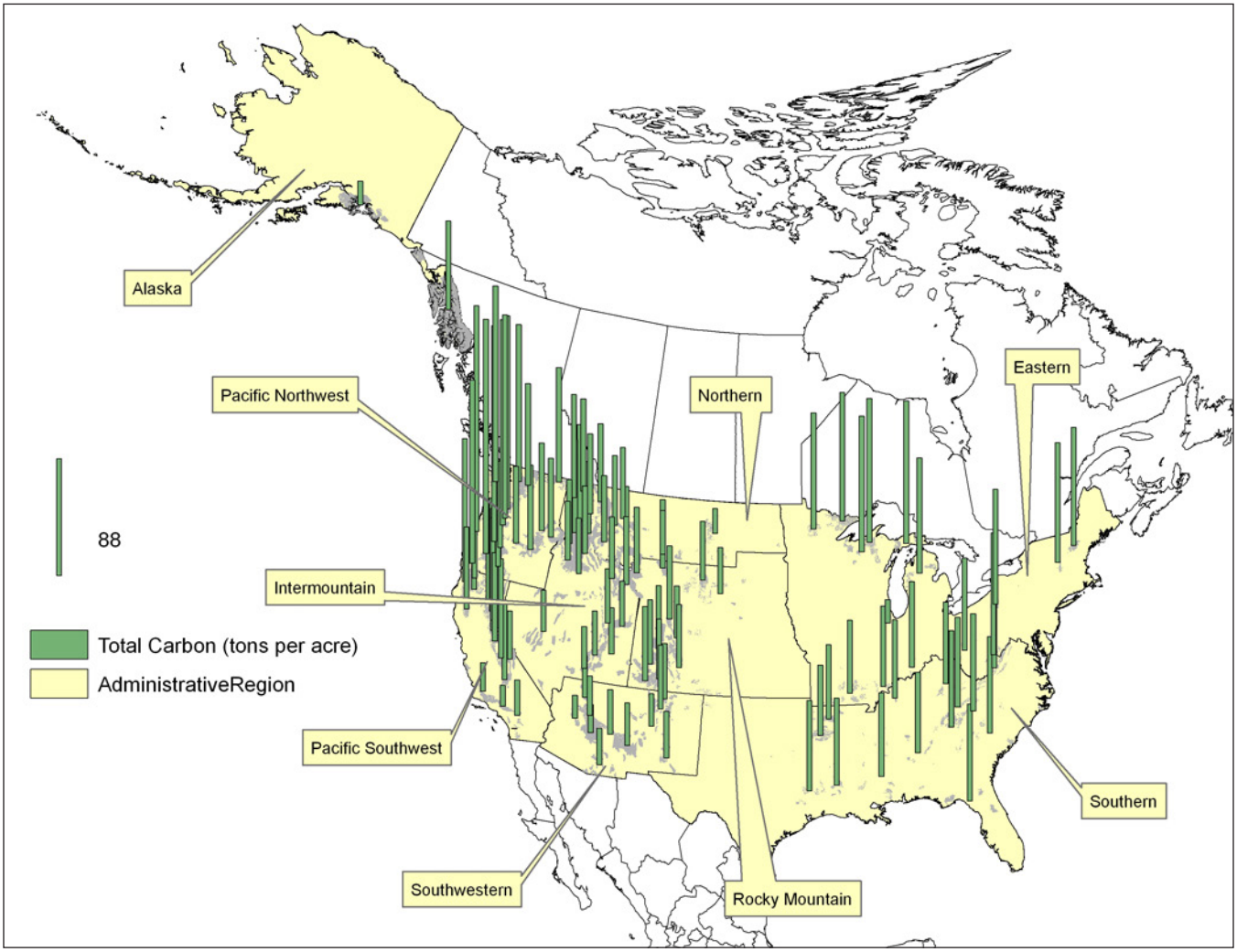


Figure 3.—Estimates of total C density (i.e., all pools) in tons C per acre for each administrative forest.

Table 1.—Carbon density estimates (tons C/acre) and sampling errors (percent, in parentheses) for each carbon pool and administrative region

National Forest System Region	Carbon Pool								
	Down dead wood	Litter	Overstory trees above ground	Overstory trees below ground	Standing dead wood	Soil organic Carbon	Understory trees above ground	Understory trees below ground	Total Carbon
Northern	2.51 (1.22%)	12.25 (0.69%)	17.91 (1.47%)	4.1 (1.46%)	2.97 (3.08%)	15.09 (3.08%)	0.8 (1.01%)	0.09 (1.01%)	55.71 (0.78%)
Rocky Mountain	1.88 (1.17%)	9.38 (0.87%)	12.35 (1.52%)	2.77 (1.51%)	1.87 (3.06%)	10.65 (0.98%)	0.61 (1.6%)	0.07 (1.6%)	39.59 (0.91%)
Southwestern	1.02 (1.87%)	8.33 (0.89%)	7.71 (1.76%)	1.74 (1.74%)	1.04 (3.98%)	8.02 (0.89%)	0.79 (1.24%)	0.09 (1.24%)	28.73 (1.02%)
Intermountain	1.52 (1.85%)	9.29 (1.01%)	8.94 (1.88%)	2.02 (1.87%)	1.8 (3.34%)	10.84 (1.07%)	0.79 (1.39%)	0.09 (1.39%)	35.3 (1.08%)
Pacific Southwest	4.03 (1.61%)	10.99 (0.87%)	23.57 (1.79%)	5.19 (1.79%)	1.77 (4.72%)	13.94 (0.84%)	0.92 (1.53%)	0.1 (1.53%)	60.5 (1.14%)
Pacific Northwest	6.26 (1.09%)	14.02 (0.76%)	37.56 (1.8%)	8.45 (1.79%)	3.28 (3.23%)	31.76 (0.69%)	1.12 (0.71%)	0.12 (0.71%)	102.58 (1.06%)
Southern	2.71 (0.76%)	4.33 (0.57%)	22.81 (1.28%)	4.69 (1.27%)	0.53 (5.28%)	22.68 (0.64%)	1.13 (0.4%)	0.13 (0.4%)	59.01 (0.7%)
Eastern	2.81 (0.72%)	7.91 (0.97%)	21 (1.01%)	4.27 (0.97%)	0.66 (3.05%)	49.7 (0.68%)	0.67 (0.43%)	0.07 (0.43%)	87.11 (0.56%)
Alaska	3.02 (2.43%)	10.58 (1.67%)	17.49 (2.94%)	3.96 (2.91%)	1.9 (5.26%)	20.09 (1.8%)	0.59 (2.06%)	0.07 (2.06%)	57.69 (1.89%)

these goals. Here we provide baseline estimates of C stocks by national forest. However, for brevity, we have presented summarized results by NFS region. Regardless, all pool estimates (circa 2010) are available by national forest. Continued monitoring of C stocks will allow the U.S. Forest Service to track the changes in individual pools in response to disturbance and management. FIA provides a consistent framework for providing these estimates in support of the climate change performance scorecard and forest planning.

In this paper we presented solutions to two shortcomings in FIA-based carbon estimates for national forests. These solutions included explicitly defining the areal extent of the populations of interest and including NFS intensified data in the eastern United States. We also incorporated improvements in estimating C in the standing dead pool. The standing dead C estimates available through FIA's database were model based and developed by Smith et al. (2003) and are not based on direct summaries of observed standing dead tree measurements. The alternative used here was to estimate standing dead C from observed data on standing dead trees and incorporating appropriate decay reduction factors (Domke et al. 2011); however, this approach, although now a part of the national greenhouse gas inventory (USEPA 2012), is not slated to be fully incorporated in the FIA compilation procedures until early in 2013. We incorporated the Domke et al. (2011) methods for this analysis for each plot where standing dead tree data were available. An effort is underway to revisit each C pool delineated within FIA's inventory system to improve the accuracy and precision of estimates (Woodall 2012). This investment should yield reductions in total uncertainty when coupled with other efforts described subsequently.

The second area of improvement is in the ALP geospatial database, which was used to define the populations and their areal extents. As described in the methods section, population totals and sampling

errors are developed by multiplying per acre estimates of each pool by the total area and the total area squared, respectively. However, reported acreages in the ALP database often differ from reported acreages in the Land Area Report of areal extent (U.S. Forest Service 2012). The total calculated area from the ALP data is approximately 880,000 acres lower than the acreages reported in the Land Area Report. Given the magnitude of this discrepancy, the total C stored on national forests may be 50 million tons larger than reported here just because of the accuracy of the boundary layer. Also note that the ALP boundary layer is used in part to determine strata weights. Clearly, if the boundary is not correctly reflected, the strata weights may be incorrect because they are determined by spatial overlay of the ALP layer and the NLCD percent tree canopy cover layer. Errors from incorrectly specifying the population are not reflected in the reported sampling errors. Typically one assumes that the population is defined without error. Increased precision of national forest boundaries and geographic extents will make this assumption more tenable.

The third area of improvement is to ensure that the NFS funded intensified data are incorporated into the public FIA database and state-level estimates. Several NFS regions have invested in these intensifications so that the precision of estimates will meet their individual requirements. Typically, intensifications have been either 2x or 3x the base FIA sample. The basic rule of thumb is that a 4x intensification will reduce the width of the 95 percent confidence interval of an estimate by half. Clearly, these intensifications will have a substantial influence on the sampling errors. However, to date the Northern Research Station FIA unit is the only program that incorporates intensified national forest data into state-level estimates and treats each national forest as an individual population. Other FIA units should take the opportunity to incorporate these intensified data into state-level estimates and treat national forests as individual populations, which will increase the precision of both FIA's traditional state-level estimates and estimates for national forests.

In conclusion, the FIA program is a foundational component of Forest Service research, and data collected as part of the FIA program can be used to estimate C storage on NFS lands. Providing these estimates in a consistent way to our NFS partners will allow for timely reporting of C storage in support of the climate change performance scorecard and forest planning. We have identified three areas of improvement in support of this effort. These improvements require efforts from both FIA and the NFS regions, but will foster more accurate, more comprehensive, and timelier estimates of C.

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ASSESSING ESTIMATION TECHNIQUES FOR MISSING PLOT OBSERVATIONS IN THE U.S. FOREST INVENTORY

Grant M. Domke, Christopher W. Woodall, Ronald E. McRoberts, James E. Smith, and Mark A. Hatfield[1]

Abstract.—The U.S. Forest Service, Forest Inventory and Analysis Program made a transition from state-by-state periodic forest inventories—with reporting standards largely tailored to regional requirements—to a nationally consistent, annual inventory tailored to large-scale strategic requirements. Lack of measurements on all forest land during the periodic inventory, along with access issues and misidentification of forest plots as nonforest, have resulted in plot-level data gaps spread in the FIA database. In this study, we examined several approaches that compensate for missing observations with respect to the deviation and precision of stratified estimates of carbon stocks per unit area using data from the FIA database. Preliminary estimates of live tree carbon stocks per unit area calculated using all missing data approaches were well within one standard error of the baseline estimates for the Lake States study region.

INTRODUCTION

Forest ecosystem carbon (C) stocks and stock change have been documented by the Intergovernmental Panel on Climate Change (IPCC) using 1990 as a baseline reference for all IPCC reports. In the United States, estimates of forest C stocks and stock change are obtained from data collected and maintained by the U.S. Forest Service, Forest Inventory and Analysis (FIA) program. Over the course of the IPCC monitoring period, the FIA program made a transition from state-by-state periodic inventories—with reporting standards largely tailored to regional requirements—to nationally consistent, annual inventories tailored to large-scale strategic requirements (Bechtold and Patterson 2005). Lack of measurements on all forest land during the periodic inventory, along with access issues and misidentification of forest plots as nonforest due to poor aerial imagery, have resulted in plot-level data gaps throughout the FIA database. These data gaps contribute to large differences in estimates of carbon stock change between periodic and annual inventories. In this study, we examined several approaches that compensate for missing observations with respect to the accuracy and precision of stratified estimates of carbon stocks per unit area using data from the FIA database. The objectives of the study were to: 1) identify patterns of missingness in the FIA data; 2) examine approaches for replacement; 3) assess approaches under increasing levels of missingness; and 4) document strategies for replacement in periodic and annual forest inventory data within the context of National Greenhouse Gas Inventory.

METHODS

Data

Data came from base intensity FIA plots measured in each of the two most recent annual inventory cycles (2002-2006 and 2007-2011) in the Lake States region (Michigan, Minnesota, and Wisconsin). These plots are quasi-systematically distributed approximately every

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2,428 hectares across the 48 conterminous states of the U.S. Each plot comprises a series of smaller plots (i.e., subplots) where tree- and site-level attributes—such as diameter at breast height (d.b.h.) and tree height—are measured at regular temporal intervals (Bechtold and Patterson 2005).

Because the precision standards established by the FIA program are rarely satisfied with the base intensity plot sample size, the estimation process is enhanced through stratification. Stratification is used to reduce the variance of attributes, such as C stocks, by portioning the population into strata (Bechtold and Patterson 2005). Each FIA plot is assigned to a stratum using the National Land Cover Database (Homer et al. 2004) or other Forest Service databases (Ruefenacht et al. 2008). In the Lake States region, strata are assigned based on percent canopy cover (i.e., 0-5, 6-50, 51-65, 66-80, and 81-100 percent). Strata are typically grouped into estimation units which are determined by a combination of sampling intensity (i.e., number of plots) and geographical boundaries (Woudenberg et al. 2010).

Stratified estimates of aboveground live tree (≥12.7 cm d.b.h.) C per unit area, $\overline{C}$, and variance, $Var(\overline{C})$, were calculated following Cochran (1977):

$$\overline{C} = \sum_{j=1}^{J} w_j \overline{C}_j$$

and

$$Var(\overline{C}) = \sum_{j=1}^{J} w_j^2 \frac{\hat{\sigma}_j^2}{n_j}$$

where $j = 1,\ldots, J$ denoted stratum, w_j was the weight for the jth stratum, calculated as the proportion of pixels assigned to the stratum, $\overline{C}_j$ was the mean carbon per unit area for plots assigned to the jth stratum, and $\hat{\sigma}_j^2$ was the within-stratum variance for the jth stratum.

Missing Data Strategies

Strategies used to compensate for missing plot observations in forest inventory estimation generally fell into two categories, ignoring plots with missing observations or replacing missing observations. In this study, we examined five approaches: 1) treat plots with missing observations as if they had not been selected for the sample (IGNORE); 2) replace missing plot observations with the observation for the same plot from the previous inventory (PREVIOUS); 3) replace missing observations with the stratum mean (STRATUM); 4) randomly draw from a pool (nearest neighbors) of observed plots most similar to the plot with the missing observation (NEAREST); and 5) compute the expected values for missing plot observations by repeatedly updating maximum-likelihood parameter estimates and imputing expected values until convergence is achieved (EM). Each approach was further divided (beyond strata) by ownership domain to account for differences in forest land management which may result in different C estimates. This subdivision also accounts for bias in instances when all missing plot observations fall on a particular ownership (e.g., denied access on private forest land).

Analysis and Comparisons

The C estimates generated by each missing data approach were compared to the base estimates (BASE) by stratum and stratum+ownership (i.e., public and private). Stratified base estimates of $\overline{C}$ and $Var(\overline{C})$ were calculated using observations for all base intensity plots across the five canopy-cover strata. This BASE estimate served as the standard for comparison for estimates obtained with the techniques that compensate for missing plot observations. Estimates were first compared visually by generating a graph of the distribution for the BASE estimates and the distributions of the different missing data approaches. Estimates for the missing data approaches were then compared with the BASE estimates and each other for proportions of missing plot observations ranging from 0 to 25 percent, which encompassed the range

of nonresponse in the FIA program reported by Patterson et al. (2012). Specifically, the proportion was calculated as the ratio of the number of plots classified as missing (i.e., hazardous, denied access, skipped) to the total number of plots selected for measurement. A Monte Carlo procedure (McRoberts 2003) was used to simulate random denied access on private forest lands to compare the deviation and precision of the mean values produced by each missing data approach at each level of missingness (0-25 percent) against the BASE estimates of $\bar{C}$. In the initial analysis, standard errors of the mean estimates produced by the missing data approaches at each missingness level were used to compare with the BASE estimates. Mean estimates greater than one standard error from the BASE mean were consider significantly different from the BASE estimate. All analyses were conducted using R statistical software (R Development Core Team 2012)

RESULTS

Preliminary analyses were restricted to 12,323 base intensity plots where at least one accessible forest land condition (i.e., area classification on each plot such as forest type or ownership group used for analytical purposes) was present during the annual inventory period. The proportion of missing base intensity plots for the most recent inventory was 5 percent in Minnesota, 6 percent in Wisconsin, and more than 11 percent in Michigan. Nearly all missing observations (94 percent) were due to private landowners denying field crews access to lands with the remaining plots deemed hazardous by field crews (3 percent) or skipped due to seasonal access (3 percent). The distribution of missing plot observations by county suggests that denied access areas are not uniformly distributed throughout the study region (Fig. 1).

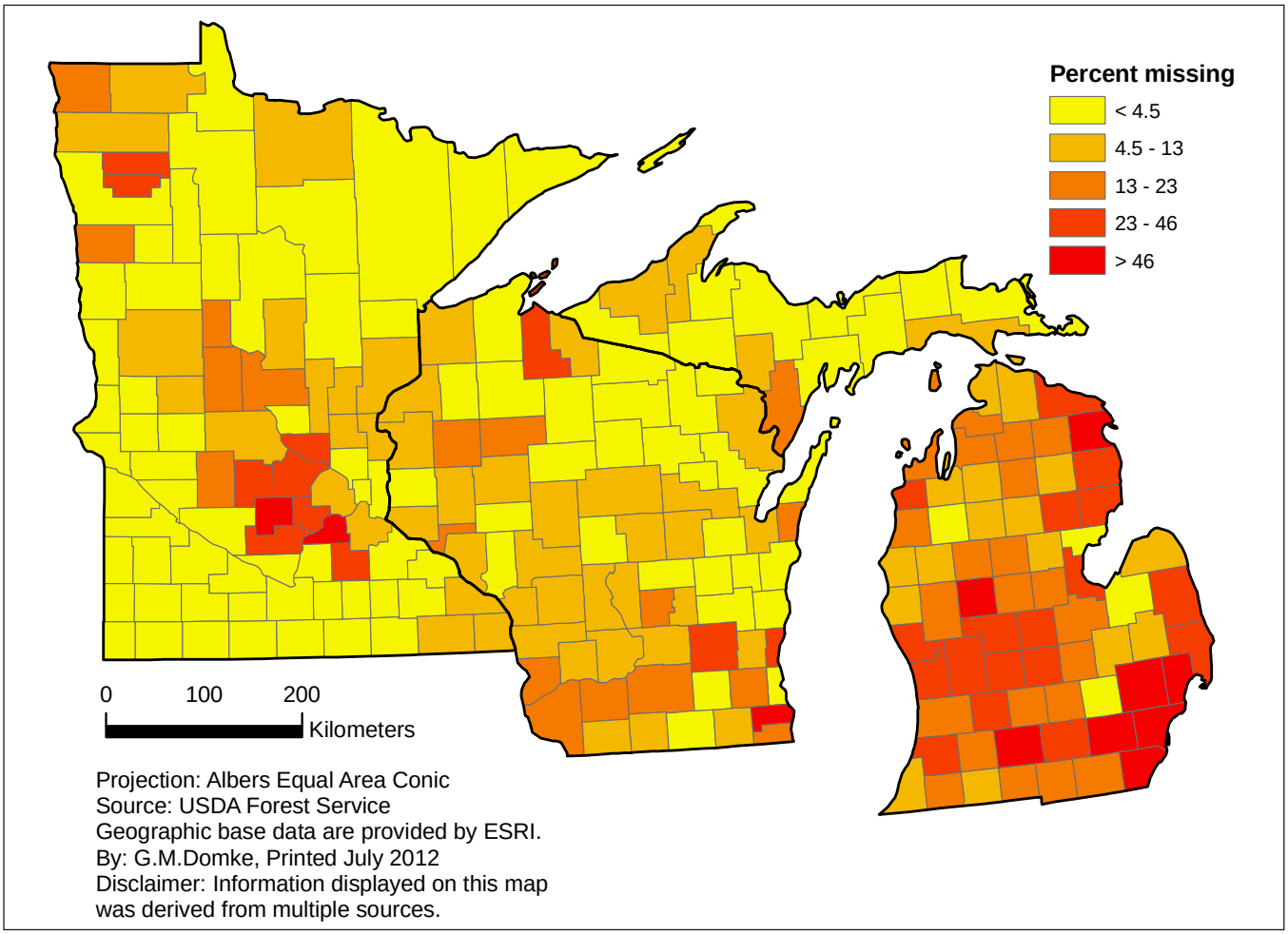


Figure 1.—Proportion of missing plot observations due to denied access by county in the Lake States region of the U.S. for the most recent FIA inventory period, 2007-2011.

Stratified base estimates of $\bar{C}$ increased with increasing canopy cover for the most recent inventory period in each of the three Lake States (Table 1). Preliminary estimates calculated using the IGNORE, STRATUM, NEAREST approaches, at current missingness levels, were within one standard error of the BASE estimate of $\bar{C}$ using observations for all plots. This suggests there were no statistically significant differences among estimates obtained using the missing data approaches initially investigated in the study. That said, the IGNORE approach was computationally more efficient than the STRATUM approach, which was more efficient than the NEAREST approach.

DISCUSSION

Early results suggest there are a number of strategies for dealing with missing plot observations in annual forest inventory data. The IGNORE approach at current nonresponse levels was computationally more efficient than the other two approaches initially evaluated. Assuming the PREVIOUS and EM approaches perform comparably to the STRATUM and NEAREST techniques, the likely outcome of the initial phase of this study will be that the IGNORE approach is optimal for dealing with missing plot observations (at current nonresponse levels in the study area) due to denied access in annual forest inventory data. This approach has merit assuming the distribution of missing plot observations is random. If not, an alternative approach and/or subdivision of strata or domain may be necessary to account for bias from missing plot observations due to denied access. Furthermore, all missing data approaches must be examined across the range of potential nonresponse in order to evaluate which approach or approaches may be useful at the national level. Assessing the distribution of missing plot observations and the range of nonresponse is important since it is likely there are patterns of missingness in the periodic inventory, albeit for a variety of different reasons, which may

Table 1.—Stratum statistics for the most recent FIA inventory (2007-2011) in the Lake States

			Live tree C per unit area (Mg ha^{-1})		
			2006	2011	
State and Stratum	Weight	Number of plots	Mean	Mean	Standard Error
Michigan	1.00	4,454	28.36	28.80	0.42
Canopy cover 0 - 5	0.64	391	9.77	12.42	0.90
Canopy cover 6 - 50	0.07	600	11.66	12.24	0.65
Canopy cover 51 - 65	0.04	415	20.03	20.50	1.02
Canopy cover 66 - 80	0.10	1,264	26.63	27.46	0.66
Canopy cover 81 - 100	0.15	1,784	41.22	40.85	0.74
Minnesota	1.00	3,966	17.24	18.04	0.32
Canopy cover 0 - 5	0.63	370	8.85	10.59	0.82
Canopy cover 6 - 50	0.03	97	9.45	11.05	1.36
Canopy cover 51 - 65	0.03	202	11.42	13.42	1.01
Canopy cover 66 - 80	0.12	1,231	16.29	17.15	0.56
Canopy cover 81 - 100	0.19	2,082	20.21	20.53	0.47
Wisconsin	1.00	3,903	23.51	25.23	0.39
Canopy cover 0 - 5	0.60	686	10.25	11.86	0.56
Canopy cover 6 - 50	0.02	135	11.53	12.44	1.32
Canopy cover 51 - 65	0.03	182	10.98	15.31	1.22
Canopy cover 66 - 80	0.08	619	19.88	21.31	0.82
Canopy cover 81 - 100	0.27	2,281	30.19	31.86	0.55
Lake States	1.00	12,323	23.24	24.21	0.22

require similar subdivisions to account for bias. While the initial analyses focused on a few approaches using annual inventory data, the full suite of missing data approaches will be evaluated using the annual inventory and then applied to the periodic inventory to assess whether any of the missing data approaches better align estimates for forest C stocks and stock change between periodic and annual inventories in the United States.

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GAIN-LOSS ESTIMATION OF COMPONENTS OF CHANGE IN FOREST CARBON: AN EXAMPLE FROM OREGON

Andrew N. Gray, Thomas R. Whittier, and David L. Azuma[1]

Abstract.—Increases in carbon dioxide in the atmosphere are thought to be a main cause of changes in global temperature and sea level. There is thought to be a large carbon (C) sink on lands in the Northern Hemisphere, but the amounts and causes are not well known. Forests are a focus of efforts to understand changes in carbon storage over time because they accumulate larger amounts of carbon than other terrestrial ecosystems. Current "stock-change" estimates of forest carbon flux are based on a combination of field measurements, surveys, remote sensing classifications, and models. The goal of this study was to attempt to improve on existing carbon accounting methods by using the "gain-loss" method and directly tracking components of change in tree carbon across a large region with strong environmental gradients using field measurements. We used repeated Forest Inventory and Analysis (FIA) measurements on permanent plots to quantify tree carbon flux due to land use change, disturbance, and harvest on 1,067 plots across Oregon. Land use change resulted in a net increase of 1.1×10^5 ha of forest land in Oregon between 1986 and 1997. However, there was a net loss of 3.4 Tg of live tree C because most of the losses were on productive west-side forests and most of the gains were on east-side juniper woodlands. Live woody C decreased significantly in eastern Oregon (-14.4 Tg), with mortality and harvest exceeding growth. Much of the mortality and subsequent harvest was associated with severe defoliation by western spruce budworm. However, C stores increased significantly in western Oregon (19.2 Tg) due to large accumulations from growth on public lands, and harvest being balanced by growth on private lands. Patterns of C density associated with stand age differed by site productivity class and forest type. The increase in C density with stand age was greater on more productive sites due to higher growth rates in young stands, but contribution of those sites to growth decreased as harvest rates increased with stand age. We demonstrate that gain-loss accounting from a probabilistic field sample can produce detailed estimates of carbon flux that identify causes and components of change, and have the potential to produce more consistent estimates than combining alternative approaches.

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MANAGING FOR CLIMATE BENEFITS IN DRY MIXED-CONIFER FORESTS: TRACKING THE CARBON IMPLICATIONS OF FUEL TREATMENTS AT LANDSCAPE SCALE

Jeremy S. Fried, Theresa Jain, Jonathan Sandquist, and Larry D. Potts[1]

Abstract.—Building on the statistically representative sample of a complex of forest types, often described as dry mixed conifer, provided by over 5000 annual Forest Inventory and Analysis (FIA) plots in seven western states, we modeled multiple indices of existing fire hazard and the extent to which implementation of mechanically focused fuels management programs could substantially improve these indices with respect to a range of objectives. Design of the generic/stylized fuel treatments tested in this study was guided my multiple, sometimes conflicting objectives: 1) leave behind a healthy, resilient stand; 2) reduce surface fire intensity; and/or 3) reduce crown fire potential, though results varied by pretreatment stand structure and forest type. Fuel treatment costs, including costs of on-site activities and transportation of harvested materials, and yields and values of merchantable and energy wood resulting from treatments under alternative policy scenarios were modeled or calculated, allowing estimation, by forest type, ecoregion, landowner class, stand density and size class of: 1) the area over which fuel treatment is capable of achieving one or more objectives and at what cost [or net revenue]; 2) the amount of carbon that fuel treatment can move into long-term storage as harvested wood products or into utilization as fossil-carbon-emission offsetting bioenergy; 3) the amount of live tree carbon remaining at risk in treated stands and the likelihood of that carbon leaving the live-tree pool in the event of a fire; and 4) the potential carbon dynamics of post-fire recovery that includes salvage harvest in treated or untreated stands. Results reveal that less than half of the dry mixed-conifer forest would benefit from the kinds of fuel treatments simulated in this study; however, nearly all the acres with potential benefit are on federal lands, and most can be treated so as to generate net revenue, useful products and carbon benefits. Although markets for energy wood are essentially absent in some regions where these forest types occur, most of the value derived from effective treatments flows from the sale of merchantable wood products, so markets for energy wood are rarely the determining factor as to fuel treatment feasibility. While clearly linked to fire incidence and return interval, the extent to which fuel treatments produce net carbon benefits also depends on how post-treatment carbon accumulation capacity is impacted by stocking reduction, the reduction in mortality achieved in the event of fire, and assumptions about the feasibility of post-fire salvage harvest.

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ISSUE ANALYSIS

MAPPING FOREST SOIL ORGANIC MATTER ON NEW JERSEY'S COASTAL PLAIN

Brian J. Clough, Edwin J. Green, and Richard G. Lathrop[1]

Abstract.—Managing forest soil organic matter (SOM) stocks is a vital strategy for reducing the impact of anthropogenic carbon dioxide emissions. However, the SOM pool is highly variable, and developing accurate estimates to guide management decisions has remained a difficult task. We present the results of a spatial model designed to map soil organic matter for all forested land in the Coastal Plain physiographic province of New Jersey. SOM stocks from 60 sampling locations, distributed across the region in a stratified random design based on vegetation type and drainage class, were used in a kriging model that incorporated several indices derived from Landsat Thematic Mapper data as predictor variables. This model reduced mean squared error at validation plots (n=26) by 10 to 23 percent when compared to kriging models that did not use a predictor variable. Our results suggest that this approach, combining SOM inventory and remote sensing data in a geostatistical framework, is a useful method for reducing uncertainty in forest SOM estimates.

INTRODUCTION

Forest inventory data have been an important tool in estimating forest carbon (C) stocks (Birdsey 1992). The widespread availability of spatially explicit, plot-level forest inventory data has allowed landscape ecologists to employ a variety of spatial modeling techniques to calculate forest C stocks at the landscape scale. Much progress has been made in estimating aboveground carbon, but belowground carbon storage is still poorly documented.

Combining geostatistical analysis with plot inventory data and remotely sensed covariates may represent an effective method for mapping soil organic matter distribution. In geostatistics, the spatial covariance among estimates at sampling locations is quantified, and statistical approaches such as variogram analysis are used to model the spatial pattern of the variable of interest (Isaaks and Srivastava 1989). The creation of a spatially explicit model of covariance provides a quantitatively rigorous framework for interpolating values across response surfaces. The results of such interpolation models are "rasterized," making them ideal for up-scaling plot-level data to broad scales, and they avoid the issues introduced by spatial aggregation and *a priori* assumptions in other approaches to scaling SOM.

The development of metrics for inferring forest soil organic matter stocks from Landsat imagery presents a fruitful line of research, and a reliable methodology would be of considerable interest to biogeochemists and climate change policy-makers. Formation of forest soil organic matter (SOM) is controlled by a variety of factors, including forest cover type, topography, and disturbance (Chapin et al. 2002). The widespread availability of landscape-scale remote sensing data, largely funded by governmental agencies such as the U.S. Geological Survey (USGS), provides researchers with tools to collect data on such factors at broad scales.

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In this study, we report on a model to interpolate SOM across forests of the Coastal Plain region of New Jersey. The model incorporates soil inventory and normalized difference vegetation index (NDVI) data to map SOM across a grid covering the entire study region. Kriging with external drift (KED), also referred to as "kriging with a trend model" in the literature (Goovaerts 1999), was used as the framework for incorporating secondary information into the SOM interpolation. Our study has three objectives: (1) Establish a relationship between SOM and NDVI to validate the latter as a predictor variable for mapping SOM distribution, (2) Demonstrate that incorporating NDVI in an interpolation model reduces uncertainty of prediction estimates relative to a model that does not incorporate any secondary information, and (3) Apply our model to generate a map of SOM distribution for New Jersey's Coastal Plain physiographic province.

STUDY AREA

This study was conducted on the Coastal Plain physiographic province of New Jersey. Three major upland forest communities dominate the region: (1) *Pinus rigida* Mill. forest, (2) *Quercus* L. spp. forest, and (3) mixed communities that span a gradient between the two pure types. On the inner coastal plain, these communities mix with other hardwood species such as *Fagus grandifolia* Ehrh. and *Carya* Nutt. species. Forested wetlands are common along river courses or in low areas. Most of these wetlands are hardwood swamps dominated by *Acer rubrum* L., *Liquidambar styraciflua* L., and *Nyssa sylvatica* Marsh. However, forested *Sphagnum* bogs with pure stands of *Chamaecyparis thyoides* (L.) B.S.P. are also present across the landscape.

Soils in the region are largely typic Hapludults and Quartzisappamments of marine or alluvial origin (Tedrow 1986). Podzolization occurs in some soils, owing to litter inputs rich in tannins and other recalcitrant organic compounds (Tedrow 1998). Soils range from very poorly to excessively drained and are primarily sandy in texture. However, clayey and mucky soils are frequent in wet areas. Mean annual temperature is 54 °C and average annual rainfall is 1055 mm.

METHODS

Eighty-six plots were established throughout all forests on New Jersey's Coastal Plain, using a stratified random sampling design based on dominant forest type and drainage class. Soil was collected within each plot at three depths: 0-10 cm, 10-20 cm, and 20-30 cm. At each depth interval bulk density was sampled using the core method (Blake and Hartge 1986), and a second sample was taken for laboratory analysis. The analytical samples were air dried for at least 48 hours, while the bulk density samples were dried at 105 °C. Both were sieved to 2 mm, and the fine fraction material was ground into powder with a mortar and pestle and homogenized. Soil organic matter content was estimated using loss-on-ignition at 400 °C for 24 hours. Soil organic matter stock (t/ha) was then calculated for each plot using the calculated bulk density and gravimetric soil organic matter content data.

Cloud-free Landsat TM scenes (courtesy of USGS) were extracted for a single date during the study, July 14, 2011, and tiled into a mosaic of the study region. We generated raster files for two indices calculated from the Landsat data: NDVI and tasseled cap band 2 (TC2). Both are related to photosynthetic activity, and have been shown to correlate with net primary productivity (Asrar et al. 1984), so it was reasonable to expect a relationship with SOM. Values of NDVI were extracted for all 86 sampling plots, and the complete raster files were collated and retained to interpolate SOM across the study region.

The 86 plots were randomly divided into a prediction set (60 plots) and a validation set (26 plots). To test if incorporating remote sensing covariates as predictor variables reduces uncertainty, we compared two univariate models, universal kriging (UK) and ordinary kriging (OK) to three multivariate models:

NDVI only (NDVI), tasseled cap only (TC), and both NDVI and tasseled cap data (NDVI+TC). Multivariate interpolation of SOM was accomplished using a universal kriging procedure with a trend model that allows for dependency between the response variable and a chosen set of predictors. This approach, also referred to as "kriging with external drift" (KED), derives predictions of the response variable by extending the covariance matrix of the kriging system to incorporate the predictor variables (Goovaerts 1999). Each model was used to interpolate SOM on 26 validation plots, and the sum of squared error (SSE) between predicted and observed values of SOM was computed for each model from 50 simulations.

To ensure that the composition of the modeling data set did not overly influence model results, a new set of validation plots was randomly selected at the beginning of each trial. Model performance was assessed by comparing the mean SSE of each model for all 50 trials. The results of the best kriging model were used to interpolate values of SOM density for all cells in a 90 m^2 grid covering the full extent of forested land on New Jersey's Coastal Plain. All geostatistical analysis was accomplished in the R statistical computing environment (R Development Core Team 2008), using the gstat package (Pebesma 2004).

RESULTS

All three multivariate models (NDVI, TC, NDVI+TC) reduced mean sum of squared error by at least 5 percent when compared to the two univariate models. The model which used NDVI as the only predictor had the lowest mean SSE while the ordinary kriging model had the highest SSE (Table 1). NDVI reduced mean SSE by 17 and 22 percent, respectively, when compared to UK and OK. NDVI also outperformed TC, reducing mean SSE by 12 percent, and provided slight improvement when compared to the full model (NDVI+TC). These results are probably explained by the higher correlation of SOM stock with the normalized difference vegetation index data than with the tasseled cap index (Fig. 1). In general, our results demonstrate that incorporating remote sensing covariates as predictor variables reduces uncertainty in regional SOM estimates by at least 17 percent.

Table 1.—Mean sum of squared error (SSE) of each model, and percent reduction by the best performing model (NDVI).

	Mean SSE	Reduction in mean SSE when compared to "best" model (percent)
Univariate models		
Universal kriging (UK)	1984734	0.17
Ordinary kriging (OK)	2118974	0.22
Multivariate (KED) models		
NDVI only (NDVI)	1657018	0
TC only (TC)	1883040	0.12
Both predictors (NDVI+TC)	1686912	0.02

The modeling data set that produced the lowest squared error was used for generating a map of SOM distribution for the entire study region. Our fitted variogram suggests a range of spatial covariance among data points of approximately 12,500 m (Fig. 2). However, note that considerable variation is unaccounted for by this model. The spatial pattern, owing to the fairly small sample size in the modeling data set (n=60), is not well defined. Additionally, the large nugget effect of the variogram indicates significant microscale spatial variability below the resolution of our sampling regime. Due to the weakly fitting variogram model, we observed only weak correlation between observed and predicted results at the 26 validation plots (Fig. 3). Although this model performs better than either univariate model ($r = 0.15$ for UK and $r = 0.05$ for OK using the same data set), there is still significant uncertainty owing to the small sample size in the modeling data set.

The model tends to predict higher SOM density on the interior portions of the Coastal Plain and declining SOM stocks to the southeast (Fig. 4). These predictions are consistent with our knowledge of the region, where the inland soils tend to be more nutrient rich and less excessively drained.

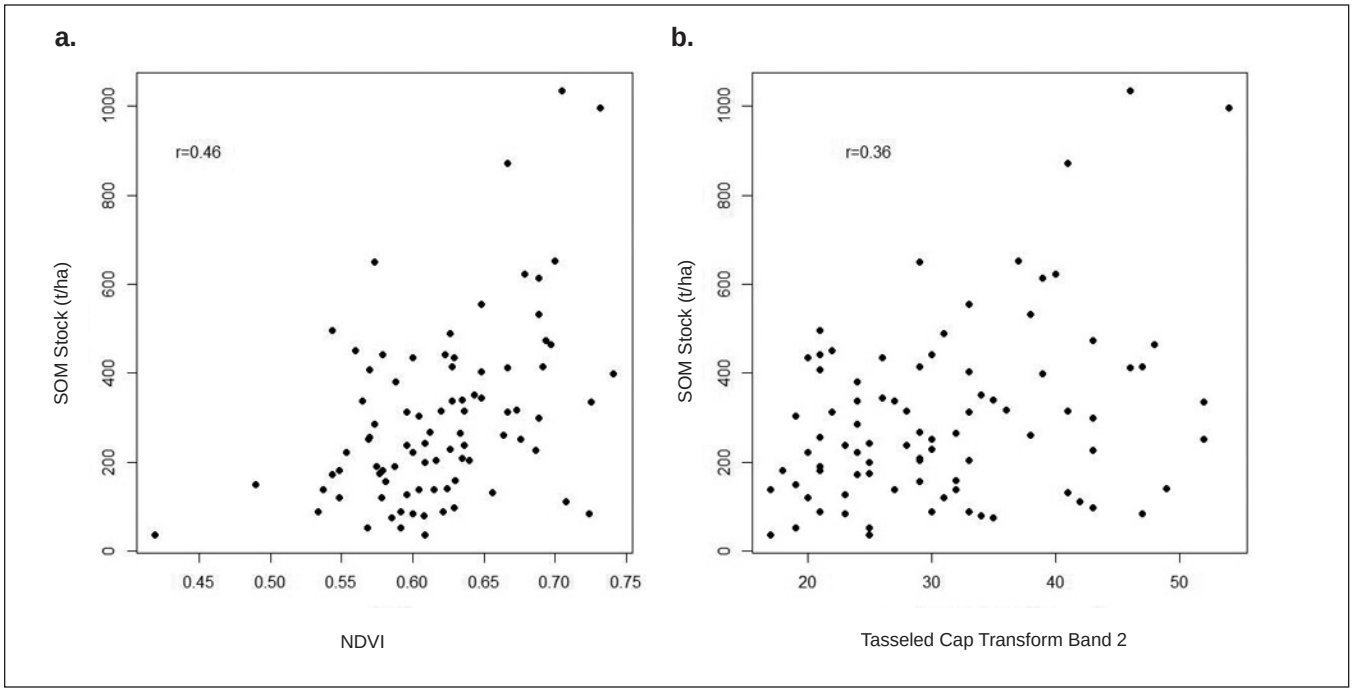


Figure 1.—Relationship between (a) soil organic matter stock (SOM) and normalized difference vegetation index (NDVI), and (b) SOM and tasseled cap band 2 (TC) at all 86 sampling locations.

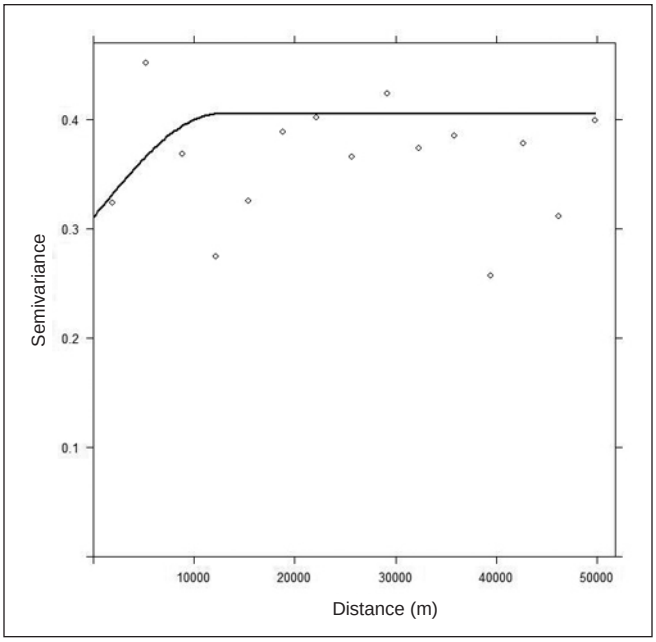


Figure 2.—Semivariogram for the 60 modeling plots. The open circles represent the binned empirical values of semivariance. The solid line is a spherical variogram model fitted with a restricted maximum likelihood optimization routine (partial sill = 0.09, range=12,500, nugget = 0.31).

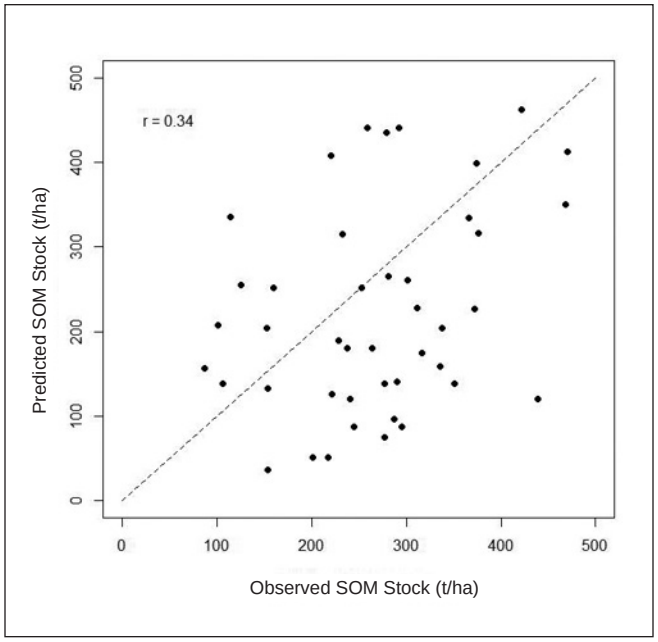


Figure 3.—Observed vs. predicted soil organic matter content at 26 independent validation plots. The dotted line represents a 1:1 relationship between the two variables.

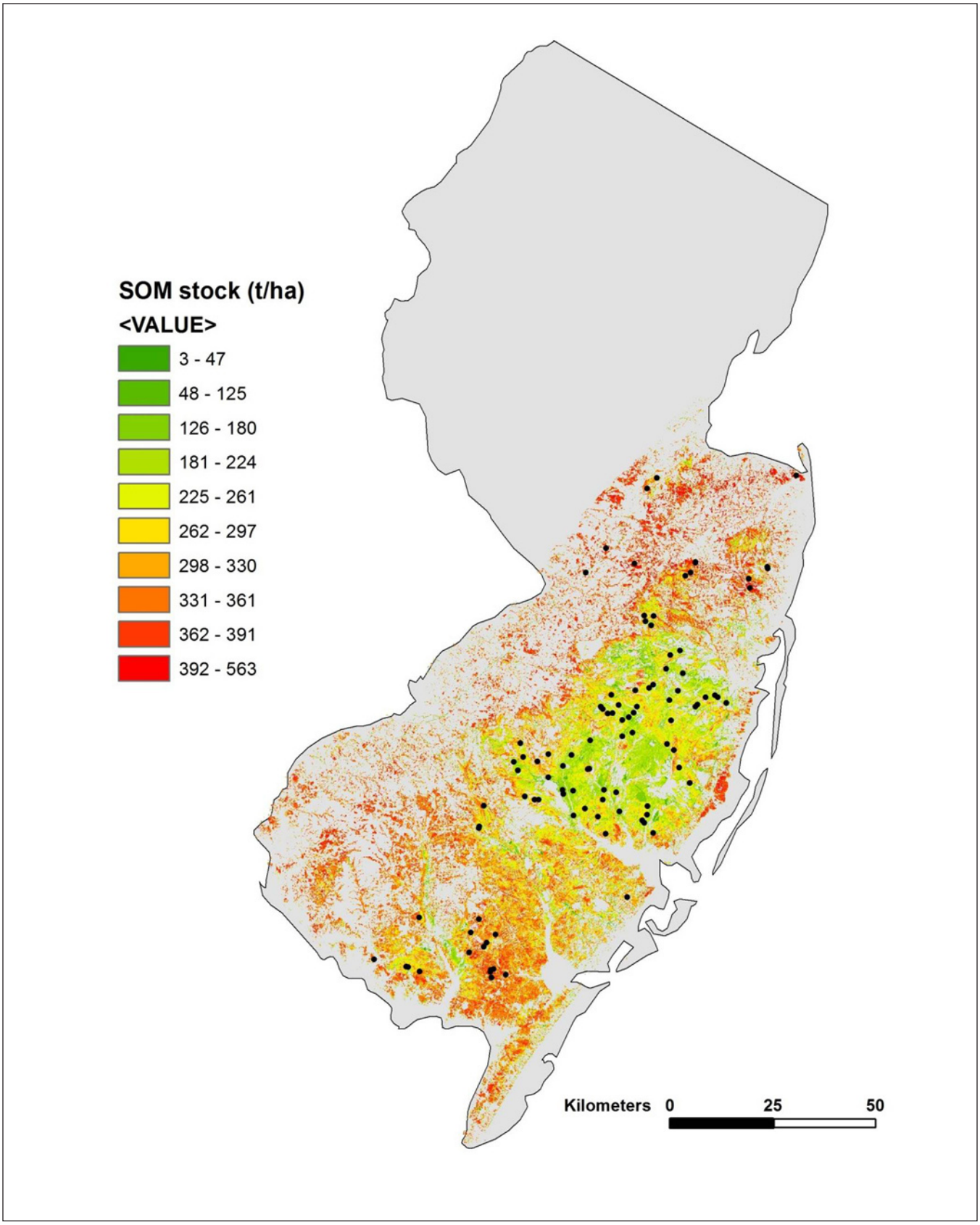


Figure 4.—Result of a KED interpolation for a 90-m^2 grid covering all forests in New Jersey's Coastal Plain. Our study region is defined by the outline. Note that the model predicts higher SOM stocks on the inner portion of the Coastal Plain, where soils tend to be less nutrient- poor.

DISCUSSION

Including soil sampling in large-scale forest inventories, such as the Forest Inventory and Analysis Program, will greatly increase the spatial coverage and availability of data on belowground carbon stocks. Incorporating NDVI reduced uncertainty in forest SOM estimates by 17 to 23 percent with a relatively small set of modeling plots (n=60) despite considerable error between measured and predicted values at the validation plots. Large coordinated efforts to sample forest SOM, where sampling density is increased and the range of variation in SOM can be better characterized by the data set, would provide improved performance. Our model framework will likely be an effective means for modeling SOM on a variety of forested landscapes, though appropriate predictor variables will have to be selected on a case-by-case basis. In general, predictor variables should be selected based on local knowledge of the environmental factors that are most likely to drive variation in SOM stocks.

Combining soil inventories with remotely sensed data and geostatistical analysis represents an effective framework for quantifying the SOM pool at broad spatial scales. Interpolation methods such as kriging, which provide a statistically rigorous framework for defining spatial patterns, provide an appealing alternative to traditional approaches for incorporating belowground C into landscape-scale forest carbon budgets. These methods are especially useful when predictor variables derived from rasterized remote sensing data sets are incorporated into the models. Our results confirm that such an approach constitutes an effective method for reducing uncertainty of soil organic matter stock estimates and would be a useful addition to forest inventory projects.

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BEECH STATUS IN NEW ENGLAND'S AFTERMATH FORESTS

George L. McCaskill and Randall S. Morin[1]

Abstract.—American beech (*Fagus grandifolia*) is one of the three most dominant tree species occupying the northern hardwoods forest of New England. We studied Maine, New Hampshire, Vermont, and New York to capture those areas with higher concentrations of beech. The status of beech in the northern hardwood forests is important because of the long-term impacts of beech bark disease (BBD) (*Neonectria* ssp.) on the composition and regeneration of aftermath forests within the region. We assessed the current conditions of beech trees at the stand level by comparing 2011 Forest Inventory and Analysis survey data with the previous survey conducted on the same set of plots (2006). To understand the current impacts of BBD on forests, we compared the number of growing-stock trees, number of rough cull trees, number of rotten cull trees, number of standing dead trees, and number of mortality trees with an important associative species, sugar maple (*Acer saccharum*). To evaluate the impacts of BBD on stand regeneration, we also assessed the number of sapling-size trees of American beech and three of its close associates, sugar maple, yellow birch (*Betula alleghaniensis*), and eastern hemlock (*Tsuga canadensis*). Beech trees had 40 percent of their stocking classified as defective or dead; sugar maple stocking had less than 15 percent. Mortality tree numbers for American beech were highest in the larger diameter trees (11.0 inches diameter at breast height and larger) where BBD had been detected for less than 37 years, but were more equally distributed in older aftermath forests where BBD had been present for more than 60 years. The number of beech saplings increased while the numbers of its three associate tree species did not change significantly. Net growth of beech was increasing as a proportion of net growth for sugar maple.

INTRODUCTION

American beech (*Fagus grandifolia* Ehrh.) is an important component of the northern hardwood forests of the Northeast. It is more shade tolerant than most of its associates and can quickly regenerate in the form of sprouts (Jones and Raynal 1987). Unlike its common associates, beech has been impacted by the beech bark disease (BBD). BBD is an insect-fungus complex involving the scale insect (*Cryptococcus fagisuga* Lindinger) and the exotic canker fungus *Neonectria faginata* (M.L. Lohman and A.M.J. Watson; Castlebury, Rossman and Hyten) or the native *Neonectria ditissima* (Tul. & C. Tul.). BBD has been spread by the scale insect throughout New England since the early 1930s (Ehrlich 1934). Three stages of BBD development have been identified (Shigo 1972). The stages are the advancing front where forests with concentrations of beech trees are degraded by the scale insect during bark feeding and subsequent infection of *Neonectria* spp., the killing front where forests have widespread beech mortality as a result of the effects of BBD accompanied by high populations of the scale insect, and finally the aftermath zone where BBD-related mortality and scale insect numbers have declined and greater numbers of smaller beech trees occupy the stand (Cale et al. 2012, Munck and Manlon 2006). This analysis has focused on forest conditions within the aftermath zone. As the fungal-insect complex progresses toward its southern and western limits, how can we analyze Forest Inventory and

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Analysis (FIA) data to identify the current conditions of maple-beech-birch (northern hardwood) aftermath forests for any given locale? Can these same data be used to project temporal changes to BBD aftermath forests and their important associate tree species?

DATA AND METHODS

This assessment focused on identifying FIA inventory attributes from the 2006 and 2011 surveys that can be used to determine the present stand-level conditions of BBD-infected beech forests within the northern hardwood region (Bechtold and Patterson 2005). BBD-infected stands were stratified by the number of years since first detection. County-level records of the year of initial scale insect establishment were provided by the U.S. Forest Service, Northeastern Area State and Private Forestry, and are available online (Jones et al. 2011). These county-level data were not based upon the FIA systematic survey; therefore, slight inconsistencies may exist between years and regions concerning scale insect detections. Two prior studies have used these data to examine the relationship between the spread of the scale insect and beech density (Morin et al. 2005, 2007). The northern New England region was studied because the BBD complex has been active there longer than anywhere else in the U.S. (Fig. 1). Areas in Maine, New Hampshire, New York, and Vermont were broken down into areas where scale had been detected for less than 37 years, areas where scale had been detected from 37 to 60 years, and areas where scale had been detected for longer than 60 years (Morin et al. 2007). We compared the number of growing-stock trees, number of rough (form defect) cull trees, number of rotten (decay defect) cull trees, number of standing dead trees, and mortality expressed as tree numbers to make comparisons between American beech and an important associative species, sugar maple (*Acer saccharum* Marsh.). We also compared net growth between these two species. On the landscape level, we compared these attributes as a whole within the northern New England region and by state (Maine, New Hampshire, New York, and Vermont). These data were stratified by two broad

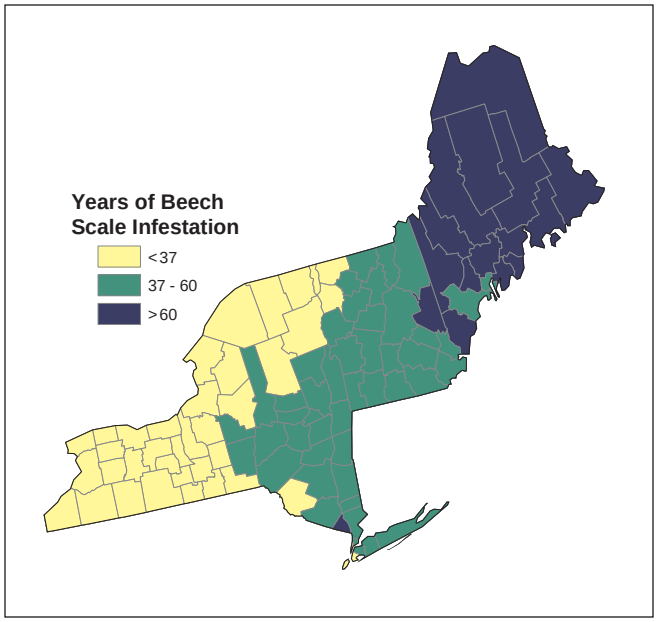


Figure 1.—Years of scale insect infestation by county in New England (ME, NH, NY, VT), 2011.

diameter classes: all trees greater than or equal to 7.0 inches diameter at breast height (d.b.h.) versus all trees greater than or equal to 11.0 inches d.b.h. Acreage was stratified by year of scale detection within a given county. All trees greater than 7.0 inches d.b.h. were chosen instead of 5.0 inches to reduce the influence of sprout stimulation caused by BBD on overall beech tree numbers. The number of saplings (all trees between 1.0 and 5.0 inches d.b.h.) was used to evaluate BBD impacts on regeneration while examining possible interactions between beech and three of its close associates, sugar maple, yellow birch (*Betula alleghaniensis* Britt.), and eastern hemlock (*Tsuga canadensis* Carr.).

RESULTS

Aftermath Forests

New England region: Beech inventory showed that 40 percent of all beech trees (5.0 inches d.b.h. and greater) are classified as rough and rotten cull trees or standing dead. By comparison, less than 15 percent of sugar maple trees are cull or dead (Fig. 2).

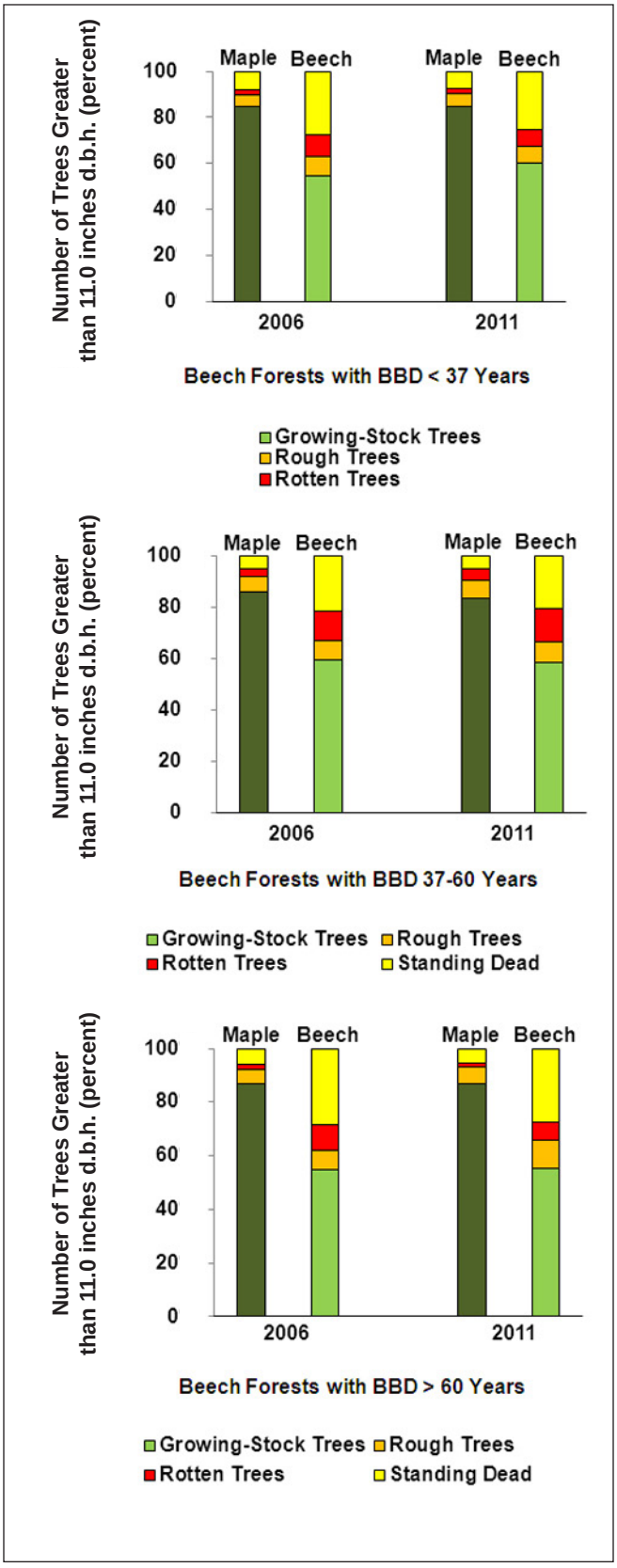


Figure 2.—Number of sugar maple versus beech trees 11.0 inches d.b.h. and greater in percent on forest land in New England (ME, NH, NY, VT), 2006 versus 2011.

Infection Classes

New York, and to a lesser degree, Vermont made up most of the areas infected for less than 37 years. New Hampshire, Vermont, and to a lesser degree, Maine contain acreages infected from 37 to 60 years. Finally, Maine, and to a lesser degree, New Hampshire make up most of the acreages infected for longer than 60 years. Below are the numbers of defected or dead trees as a percentage of total tree numbers, including growing-stock trees (Table 1).

Mortality and Standing Dead

Mortality trees differ from all standing dead trees because they represent only those trees that died since the last measurement (5 years). The mortality trees also include fallen trees or recently burned material. The greatest proportion of mortality beech trees were found in areas infected for less than 37 years when counting trees of 11.0 inches d.b.h. or greater. In those same areas, when the count included trees with diameters of 7.0 inches or greater, the mortality levels were lower, which was comparable to northern New England beech numbers as a whole (Fig. 3).

Table 1.—Numbers of rough, rotten, mortality, and standing dead beech trees as percentage of total trees; classified by years since first scale insect detection.

Infection Class	Attribute	Tree Count (%)
Infection <37 Years	Standing dead trees	25
	Mortality trees	6
	Rough cull trees	8
	Rotton cull trees	6
Infection ≥37 and ≤60 Years	Standing dead trees	21
	Mortality trees	1
	Rough cull trees	7
	Rotton cull trees	12
Infection >60 Years	Standing dead trees	28
	Mortality trees	3
	Rough cull trees	8
	Rotton cull trees	7

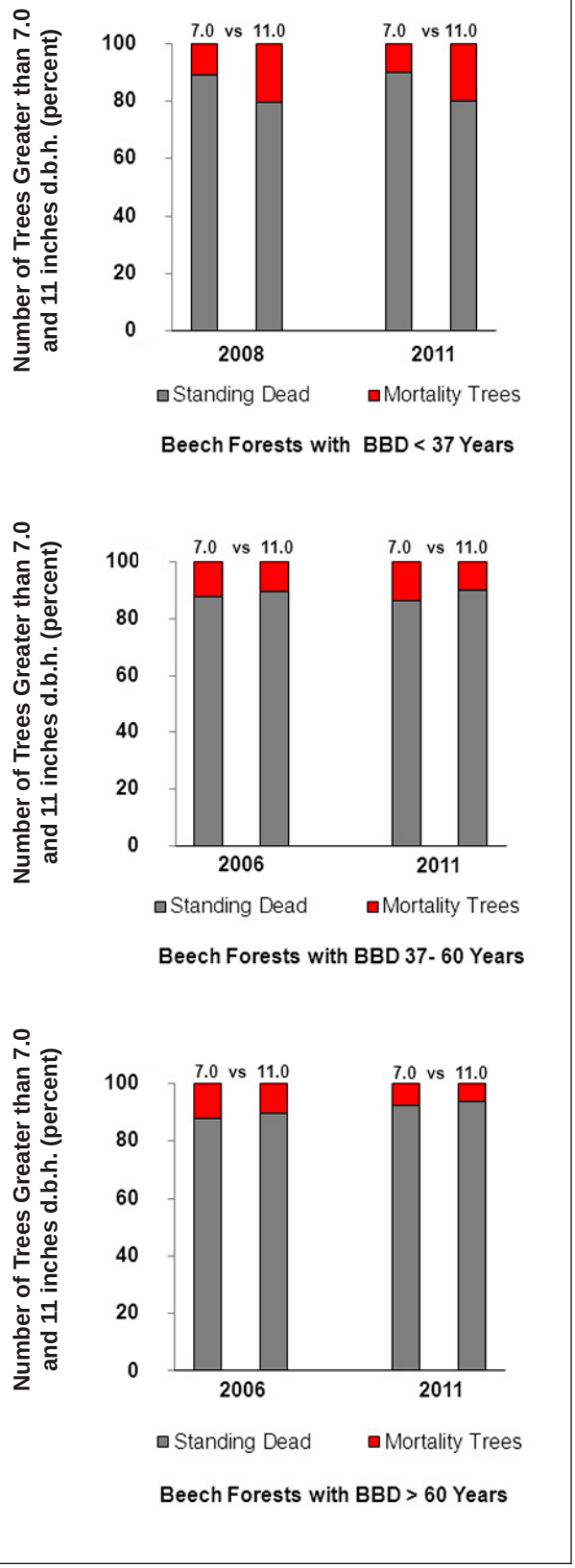


Figure 3.—Number of beech trees 7.0 and 11.0 inches d.b.h. and greater in percent on forest land in New England (ME, NH, NY, VT), 2006 versus 2011.

Regeneration

The number of saplings increased in BBD-infested acreage because beech sprouting was stimulated by the BBD complex. Sugar maple and hemlock numbers did not statistically change (Fig. 4). In Maine, beech regeneration had a lower proportion of the total sapling numbers where higher yellow birch and hemlock stock were growing.

Net Growth

The net growth of beech trees as a proportion of sugar maple growth is increasing. The largest proportions were found in the younger aftermath forests (Fig. 5).

DISCUSSION

With the killing front comes the beginning of the aftermath forests. The effects are first seen on the largest beech trees (d.b.h. >16 inches). Gaps are created when these larger beech trees fall (snap) as a result of wood defects created by BBD infection. The new openings are filled by beech saplings as a result of BBD-stimulated sprouting and by some released yellow birch and hemlock trees. The beech sprouts form “thickets” creating understory shading while crowding out sugar maple (Gravel et al. 2011). Some researchers believe sugar maple saplings are suppressed by possible toxic effects of higher levels of beech leaf leachate excreted from these dense thickets, coupled with focused deer browsing (Hane et al. 2003, Runkle 2007). Scale populations eventually decline as aftermath conditions become prevalent (Cale et al. 2012). The beech thickets grow and cause increased shading, creating a nursery environment for young hemlock trees. The aftermath stand will contain greater numbers of smaller, defective beech trees. These smaller diameter beech trees will produce fewer sprouts than the larger diameter beech trees exposed to the killing front (Jones and Raynal 1987). The impact of greater numbers of beech saplings on the regeneration of sugar maple, yellow birch, and hemlock in upper New England is not yet clear based upon current FIA inventory data. But in areas where

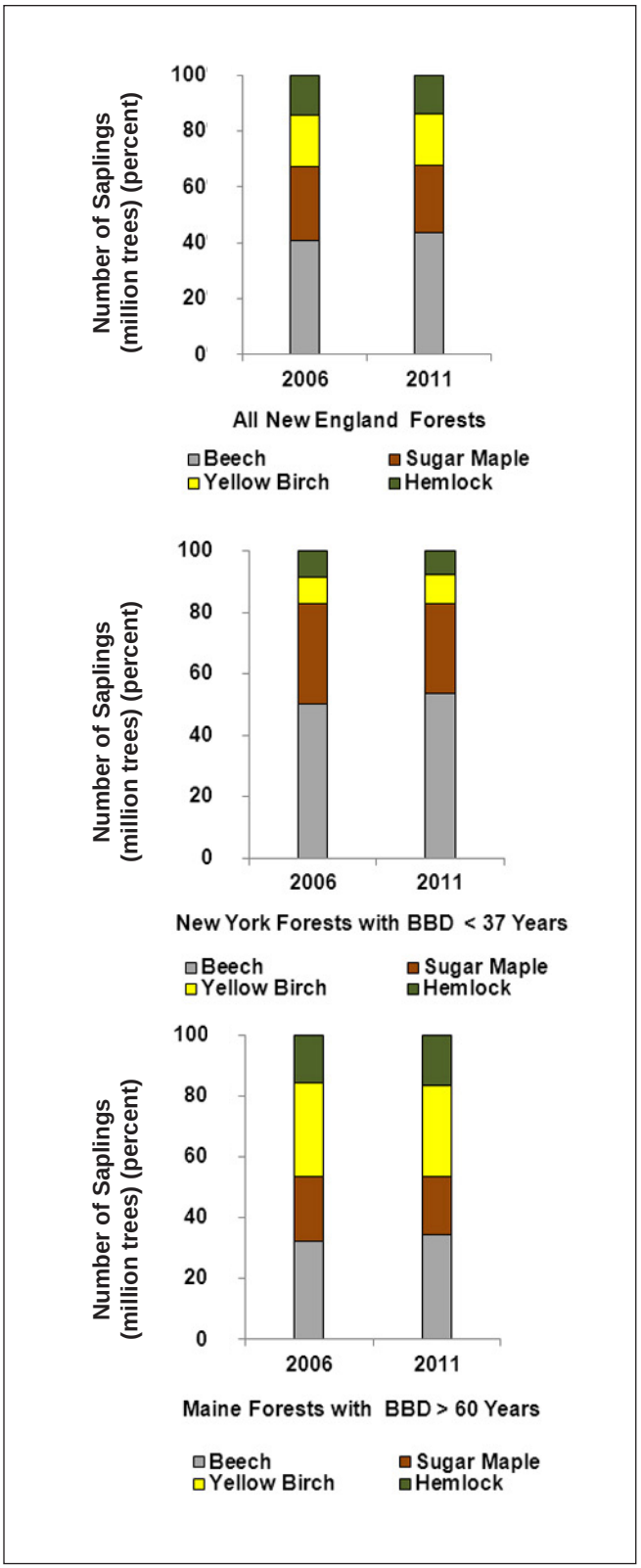


Figure 4.—Number of saplings (million trees) between 1.0 and 5.0 inches d.b.h. in percent on forest land in New England (ME, NH, NY, and VT), 2006 versus 2011.

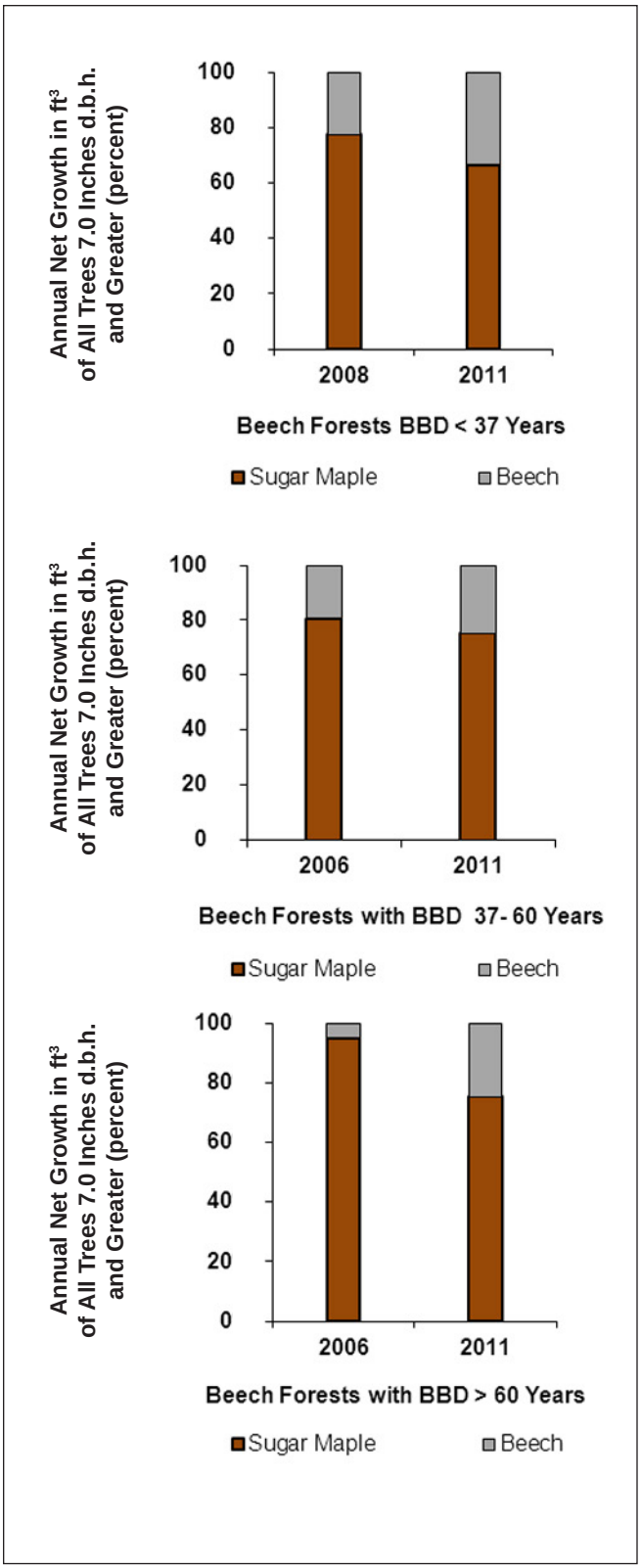


Figure 5.—Annual net growth of growing-stock trees 7.0 inches d.b.h. and greater (cubic feet) in percent by species (beech, sugar maple) on forest land in New England (ME, NH,NY,VT), 2006 versus 2011.

larger numbers of yellow birch and eastern hemlock saplings are growing, there may be a defense against stimulated beech sprouting through stiff competition for light and moisture.

CONCLUSIONS

The condition of the northern hardwood forest varies based upon the number of years BBD has been infecting an area. Forests that have been infested for less than 37 years tend to have higher numbers of standing dead trees within the larger diameter classes as a result of high tree mortality during the killing front phase. They also tend to have an equal number of rough and rotten cull trees. Sprout numbers are high as BBD-induced breakage prevails in the larger beech trees. Beech forests infected from 37 to 60 years had fewer standing dead, fewer rough cull trees, and greater numbers of rotten cull trees, resulting in down woody debris accumulation. Beech mortality is no longer concentrated in the larger diameter trees. Where BBD has been present for longer than 60 years, beech forests tend to have larger numbers of standing dead trees in the smaller diameter classes and fewer rotten cull trees as breakage occurs earlier. The BBD-generated sprouts initiated during the killing front are now infected pole-size trees, facing death at a much earlier age than their parents. Tree mortality occurs across the diameter classes, and the number of beech sprouts tends to be lower in these smaller diameter beech trees.

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The content of this paper reflects the views of the author(s), who are responsible for the facts and accuracy of the information presented herein.

ESTIMATING TREE CAVITY DISTRIBUTIONS FROM HISTORICAL FIA DATA

Mark D. Nelson and Charlotte Roy[1]

Abstract.—Tree cavities provide important habitat features for a variety of wildlife species. We describe an approach for using historical FIA data to estimate the number of trees containing cavities during the 1990s in seven states of the Upper Midwest. We estimated a total of 280 million cavity-containing trees. Iowa and Missouri had the highest percentages of cavity-containing trees; Michigan and Minnesota had the lowest. The percentage of trees containing cavities was higher for the hard hardwood species group and dead trees, and it generally increased with increasing diameter at breast height. Abundance of cavities decreased with increasing cavity entrance diameter and increasing aboveground cavity height.

INTRODUCTION

Forest Inventory and Analysis (FIA) data (Woudenberg et al. 2010) span several decades and are easily queried to estimate status and trends of coarse-scale habitat characteristics, such as area of young hardwood forest or old softwood forest. These data also include attributes of tree species and tree size (and, for some state inventories, cavity entrance diameters, and cavity heights above ground), which can provide finer scale habitat information for many forest-associated vertebrate species.

Cavity availability is thought to limit populations of many secondary cavity nesters. Although primary cavity nesters excavate their own cavities (e.g., woodpeckers, nuthatches, flickers, and chickadees), secondary cavity users depend upon existing cavities formed from tree injury or through excavation by primary cavity nesters. Secondary cavity users include wood duck (*Aix sponsa*), hooded merganser (*Lophodytes cucullatus*), common goldeneye (*Bucephala clangula*), American kestrel (*Falco sparverius*), eastern bluebird (*Sialia sialis*), prothonotary warbler (*Protonotaria citrea*), tree swallow (*Tachycineta bicolor*), great crested flycatcher (*Myiarchus crinitus*), boreal owl (*Aegolius funereus*), barred owl (*Strix varia*), house wren (*Troglodytes aedon*), flying squirrels (*Glaucomys* spp.), American deer mouse (*Peromyscus maniculatus*), weasels (*Mustela* spp.), fisher (*Martes pennant*), American marten (*Martes Americana*), and raccoon (*Procyon lotor*). The size and location of tree cavities determine their suitability for each wildlife species.

Cavity formation and presence is related to tree species, size (diameter at breast height-d.b.h., height), and status (live, dead). Such relationships have been used with FIA data to estimate tree cavity abundance for mature second-growth timberland in Missouri (Fan et al. 2003) and to develop models for cavity-nesting waterfowl in hardwood forests of the north central United States (Denton et al. 2012). However, strategic estimates of tree cavities are lacking for the majority of cavity-dependent wildlife species, across most forests in the Midwest.

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Attributes of tree cavity diameter and cavity height above ground historically were recorded in some states in the northern FIA region. We analyzed cavity data from seven contiguous Midwestern States to produce estimates of historical numbers of cavity trees, by tree species group, tree diameter, cavity size, and cavity position.

DATA AND METHODS

Tree cavity data were queried from historical North Central FIA periodic field inventory plots from seven Midwestern States during 1989-1998. The inventory years were 1998 for Illinois and Indiana, 1990 for Iowa and Minnesota, 1993 for Michigan, 1989 for Missouri, and 1996 for Wisconsin. Tree cavity data no longer are collected in this FIA region.

The following text from the 1998 FIA field manual describes data collection protocols:

> At each sample point, examine all live and standing-dead trees, > 5.0" D.B.H., for cavities that could be used for nesting, resting or storage by birds or mammals. To qualify as a cavity, an entrance hole must be 1.0" or larger in the main stem, fork, or large limb. (A limb must be greater than 8.0" DOB.)
>
> For the largest cavity record a two-digit code. [Only one cavity–the largest-was recorded for each cavity tree, regardless of the number of cavities present.] The first digit indicates the size of the cavity. Cavity size is the diameter of the largest ball that could fit through the entrance hole [by 1-inch categories, through 9+ inches (Table 1)]. The second digit indicates the location of the cavity on the tree [above-ground, in feet, aggregated into nine height categories (Table 1)].

We tabulated the total number of trees sampled and the number of those trees containing one or more cavities, by tree status (live, dead), tree d.b.h., and major species group: (1) pines; (2) other softwoods–spruce, fir, hemlock, etc.; (3) soft hardwoods-cottonwood, aspen, elm, basswood, soft maple, etc.; and (4) hard hardwoods–oak, hickory, beech, walnut, hard maple, etc. (Woudenberg et al. 2010: see Appendix F for complete list of species.). Tree records were omitted when status was absent or populated with unknown codes (n = 8,427; 1.1 percent), and when trees were down-dead (n = 10,915; 1.4 percent) or stumps (n = 39,772; 5.2 percent). For counts of trees with cavities, tree records were excluded when cavity codes did not reveal both cavity entrance diameter and cavity height above ground (n = 91; 0.01 percent).

Table 1.—Percentage of cavity-containing trees, by cavity entrance diameter and aboveground cavity height during the 1990s, Upper Midwest

Cavity Entrance Dia. (in.)	Aboveground cavity height (feet)									
	0-1	2-5	6-9	10-19	20-29	30-39	40-49	50-59	60+	Total
1	5.5	6.6	4.6	3.9	1.2	0.4	0.1	0.0	0.2	22.5
2	5.5	5.1	4.4	5.0	2.2	0.7	0.3	0.1	0.1	23.4
3	4.7	3.0	3.1	4.2	2.2	0.8	0.2	0.1	0.1	18.5
4	3.6	1.7	1.4	2.1	1.3	0.7	0.5	0.0	0.0	11.4
5	2.0	0.8	0.7	1.1	0.6	0.2	0.1	0.0	0.0	5.6
6	2.0	0.7	0.6	0.7	0.5	0.3	0.1	0.0	0.0	4.8
7	0.9	0.3	0.2	0.3	0.2	0.1	0.0	0.0	0.0	2.0
8	0.6	0.3	0.1	0.2	0.1	0.1	0.0	0.0	0.0	1.6
9+	4.5	1.6	1.2	1.5	0.9	0.3	0.1	0.0	0.1	10.2
Total	29.3	20.0	16.4	19.1	9.4	3.6	1.4	0.3	0.5	100.0

Numbers of all live and standing dead trees ≥ 5 inches d.b.h. on timberland were estimated using standard FIA estimators via FIA's online EVALIDator tool (http://apps.fs.fed.us/Evalidator/tmattribute.jsp). In brief, counts of trees on each sample plot, proportion of each plot in forest, and number of plots in each stratum were used in a stratified estimation procedure to produce estimates of total number of trees (Scott et al. 2005). Numbers of cavity trees were estimated by multiplying the estimates of numbers of live and standing dead trees times the proportion of sampled trees containing cavities, by combinations of tree diameter, major species group, and live/dead status. No estimates of uncertainty (e.g., standard errors) were computed for this preliminary study because population estimates of numbers of trees were weighted by the proportion of cavity trees in another database, with some mismatch in tree records.

RESULTS

A total of 709,638 trees were sampled in this study; one or more cavities were observed in 25,424 trees. Nearly half of all cavities were observed 0 to 5 feet above ground, one-third were 6 to 19 feet above ground, and the remainder were more than 20 feet above ground. Nearly two-thirds of cavities were 1 to 3 inches in diameter. Cavity abundance decreased with increasing cavity diameter (Table 1).

Percentage of cavity-containing trees varied by state, ranging from 1.7 percent and 2.8 percent in Michigan and Minnesota, respectively, to 6.5 percent and 7.8 percent in Missouri and Iowa, respectively. Standing dead trees made up 11 percent of all trees and 15 percent of cavity trees. The proportion of total trees containing cavities was 3.4 percent for live, 5.0 percent for dead, and 3.6 percent for live and dead trees combined. The largest absolute numbers of cavities in live trees were recorded in soft and hard hardwood tree species and in trees of 9.0 to 16.9 inches d.b.h. The hard hardwood major species group also contained the largest percentages of cavities relative to total number of live trees recorded for that group (4.9 percent). One or more tree cavities were recorded in more than 29 percent of the largest diameter live trees (41.0+ inches d.b.h.) (Fig. 1). Relative to the total number of trees by diameter class, cavity-containing trees were less abundant in small-diameter trees (<11 inches d.b.h.), similar in abundance for trees of 11 to 12.9 inches d.b.h., and more abundant for larger trees (13.0+ inches d.b.h.) (Fig. 1).

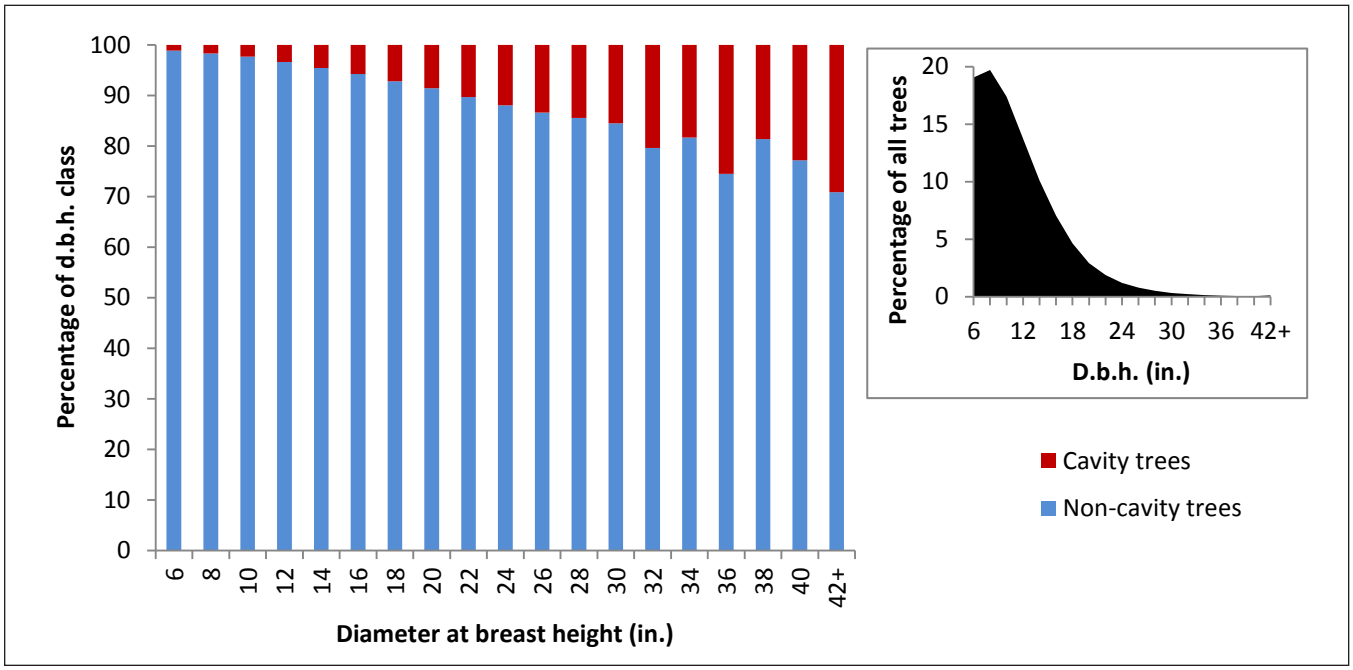


Figure 1.—Distribution of non-cavity and cavity-containing trees within each tree d.b.h. class during the 1990s, Upper Midwest.

Based on the sample, we estimated a total of 11.3 billion live trees and 1.6 billion dead trees ≥ 5 inches d.b.h. for the seven states during the 1990s, of which 225 million live trees (2.0 percent) and 55 million dead trees (3.4 percent) were estimated to contain one or more cavities.

DISCUSSION AND CONCLUSIONS

Using historical FIA data, we estimated a total of 280 million cavity-containing trees in the seven-state region during the 1990s. The number of cavity trees as a percentage of all trees generally increased with increasing d.b.h. Dead trees and live trees in the hard hardwood species group both contained higher percentages of cavities relative to total tree abundance of hard hardwoods, which may explain variability among states. The two states with the highest percentages of cavity-containing trees, Iowa and Missouri, both have <1 percent of all trees in softwoods; the two states with the lowest percentages of cavity-containing trees, Michigan and Minnesota, both have >20 percent of all trees in softwoods.

Almost half of all cavities had entrance diameters smaller than 3 inches; about half of all cavities were located less than 6 feet above ground. These characteristics are unsuitable for many wildlife species. We acknowledge that some entrances deemed cavities from the ground may not have been actual cavities (just knots or scars), and some cavities may not have been observed from the ground, despite their presence, especially at greater heights above ground: tree cavities on FIA plots in the Pacific Northwest are frequently missed by field crews (Tara Barrett, personal communication).

This study expands the geographic extent addressed in Fan et al. (2003) and introduces potential enhancements to the approach described in Denton et al. (2012): cavity probabilities were expanded to include both softwood and hardwood trees, both live and dead, for a wider range of tree diameters, and from a larger sample of trees.

Work is underway to estimate standard errors for historical tree cavity data and to refine models of tree cavity probabilities that can be applied to current and future FIA data for which cavity observations are no longer recorded. Ongoing collection of FIA tree cavity data could detect changes in cavity probabilities. Additional studies are being conducted to estimate abundance of cavities meeting species-specific wildlife habitat requirements.

ACKNOWLEDGMENTS

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The content of this paper reflects the views of the author(s), who are responsible for the facts and accuracy of the information presented herein.

BUILDING IMPROVED MODELS OF SUGAR MAPLE MORTALITY

Charles H. Perry and Patrick L. Zimmerman[1]

Abstract.—The decline of sugar maple (*Acer saccharum* Marsh.) in the northern United States is causing concern, and several studies have identified soil properties that are linked to the observation of dead/dying trees. Unfortunately, the sample of trees supporting these studies is purposive in nature; soil properties are assessed only on those plots where dead trees are observed. In this study, we used the U.S. Forest Service's Forest Inventory and Analysis database (FIADB) to conduct an exploratory analysis of a broader population of sugar maple (live and dead) across a wide range of soil types. This population of plots has a highly skewed, zero-inflated distribution: the number of plots in the sample without dead trees is an order of magnitude greater than the number of plots with dead trees. One effective method of analysis is a hurdle—or conditional—model approach. In the first phase, the response variable is the presence or absence of dead sugar maple and the inferential space is the entire population of plots with sugar maple trees. The second phase uses the relative abundance of dead sugar maple as the response variable; in this case, inference is restricted to those plots where dead sugar maple trees are observed. In both sets of models, basal area and geology are significant predictors of dead sugar maple, but the most significant soil variables vary between these two inferential spaces. Our study highlights important analytical considerations when using FIADB for analysis of forest health conditions and presents simple methods to create a more comprehensive space for statistical inference.

INTRODUCTION

Several studies of sugar maple (*Acer saccharum* Marsh.) mortality exist (e.g., Horsley et al. 2000, Long et al. 2009), but most evaluations focus on an area of known decline from Pennsylvania to New Hampshire. Sampling of sugar maple decline in these and related studies tends to be purposive in nature and evaluates only those plots with dead sugar maple.

The U.S. Forest Service Forest Inventory and Analysis Program (FIA) collects field data to describe the status and trends of forests across the United States. It focuses on live trees and live-tree observations vastly outnumber those of dead trees in the FIA database (FIADB). To wit, the ratio of live-tree to dead-tree observations for the complete 2011 5-year inventory of the Great Lakes states of Minnesota, Wisconsin, and Michigan was 5.8:1.[2] However, the inventory is not biased systematically against dead trees. Dead trees are recognized as particularly important ecologically (Woodall et al. 2009), and standing dead trees are the subject of specific reporting since Field Guide 2.0 was published in 2004 (USDA Forest Service 2004).

Joint observations of live and dead trees contain important ecological information and increasing the size of the sample population also increases the resulting inferential space. However, a joint analysis of live and dead trees in FIADB yields a zero-inflated population, and statistical inference which does not

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[2] Calculations may be made using FIA's online tools available at http://fiatools.fs.fed.us.

account for zero-inflation is likely to be erroneous (Martin et al. 2005). Zero-inflation often can be accommodated by hurdle and mixture models when the additional zeros are "true zeros" (Martin et al. 2005). Hurdle models (also known as conditional models) treat the problem in two stages: first, the analyst determines the probability of a species or property being present or absent in a binary outcome; second, and conditional on its presence, the relative abundance of said species/property is found (Cameron and Trivedi 1998). Mixture models attempt to answer the same two questions in one model, but the resulting parameters are more challenging to interpret (Martin et al. 2005).

In this paper, we outline the application of a hurdle model approach to sugar maple mortality in the northern United States. Twenty states were included in the analysis: Connecticut, Delaware, Illinois, Indiana, Iowa, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Vermont, West Virginia, and Wisconsin. Our study highlights important analytical considerations when using FIADB for analysis of forest health conditions and presents simple methods to create a more comprehensive space for statistical inference.

METHODS

Forest and soil inventory plots in the Northern United States were joined and extracted from the FIADB (Woudenberg et al. 2010). These data were collected between 2000 and 2006. Plots were included in the analysis if at least three sugar maple trees with d.b.h. greater than 5 inches were measured on the plot.

Plot information included state and county, and latitude, and longitude. Plot latitude and longitude were used to link plots to spatially explicit geologic databases describing the origin of surface material (Fullerton et al. 2003). Forest-level attributes included the basal area of live and dead sugar maple, ecological subsection, forest-type group, stand age, stand-size code (a classification of the predominant diameter class of live trees), slope, aspect, physiographic class (e.g., xeric, mesic, or hydric), and the presence/absence of disturbance on the plot. Soil plot information focused on the suite of soil chemistry variables extracted from mineral soil samples (O'Neill et al. 2005, Woodall et al. 2010) and their derivatives.

Statistical analyses were conducted in three stages: (0) ordinary linear regression on all plots to demonstrate the impact zero-inflation; 1) logistic regression on the presence and absence of dead sugar maple; and 2) ordinary linear regression of those plots with dead sugar maple. Given the exploratory nature of our investigation using the suite of variables available in FIADB, analyses were completed using stepwise techniques in R (R Development Core Team 2011). Appropriate variable transformations were suggested by Box-Cox analyses. Zeroes cannot be log transformed, so a very small number (0.001) was added to variables as required.

RESULTS

Stage 0

A total of 219 plots were selected that met the defined criteria of at least three sugar maple trees and the collection of soil chemistry data. A number of terms were available as predictors (Table 1). Our first effort was directed at modeling the fraction of dead sugar maple basal area as the response in a multiple regression model. If successful, this would be a simple and complete model of sugar maple mortality. This investigation collapsed because of the zero-inflated distribution; too many plots had zero dead sugar maple (Fig. 1).

Stage 1

Given our trouble with the zero-inflated fraction of dead sugar maple basal area in stage 0, we adopted hurdle modeling. Using the hurdle model, we modeled the data in two stages. In stage 1, we modeled the presence or absence of dead sugar maple using logistic

Table 1.—Variables available to predict sugar maple death across the northern United States

Site characteristics	Soil characteristics
Latitude, Longitude {lat, lon}	pH
Drought index {di}	sqrt(ECEC) {secec}
Ecoprovince {eco}	log(Ca:Al ratio) {lca.al}
Forest-type group {forest}	log(Mg:Al ratio) {lmg.al}
Basal area {ba}	log(Mg:Mn ratio) {lmg.mn}
Stand age {age}	log(Exchg. K percentage) {lekp}
Stand-size class {size}	log(Exchg. Na percentage) {lesp}
Site class {site.class}	log(Exchg. Ca percentage) {lecp}
Slope {slope}	log(Exchg. Mg percentage) {lemp}
Aspect {aspect}	log(Exchg. Al percentage) {leap}
Disturbance {dist}	
Geology {geo}	

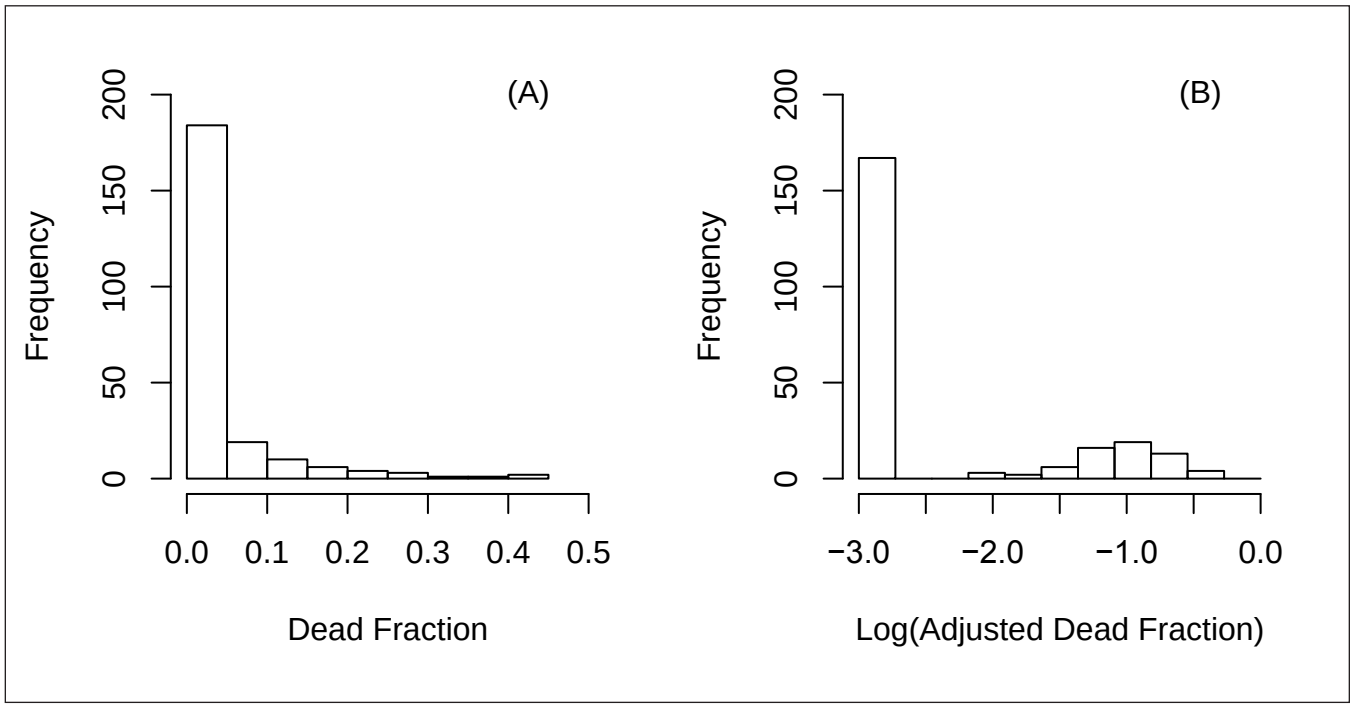


Figure 1.—Histograms of the observed dead fraction of sugar maple basal area on all plots (A) before and (B) after logarithmic transformations.

regression. In stage 2 (below), we modeled abundance given dead trees were present. Modeling presence or absence was accomplished using the binomial family of `glm()`. As before, 219 plots were available to parameterize the model, and the same terms were used as predictors (Table 1).

Exploratory binomial models were built using two starting points: 1) intercept only; and 2) a full model. Stepwise regression found the best model using AIC as the selection criteria. Similar models were selected from different starting points. The coefficients of the most plausible stage 1 model are included in Table 2.

Table 2.—Parameters for the most plausible model of sugar maple death using logistic regression with all plots

Variable Coefficient	Estimate	Std. Error	Z	Pr(>|z|)
ba	0.0197	0.0057	3.47	0.0005
lmg.mn	-0.5959	0.2198	-2.71	0.0067
geo:glacial	-0.3715	0.5001	-0.74	0.4576
geo:till	-1.0628	0.3698	-2.87	0.0041
geo:non-glacial	-2.5894	0.5593	-4.63	3.67e-06

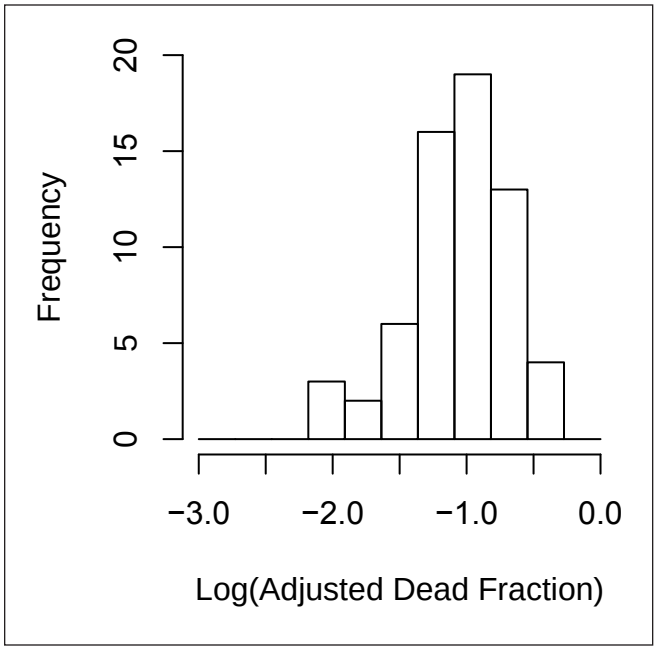


Figure 2.—Histogram of the observed dead fraction of sugar maple basal area for those plots with dead trees.

The interpretation of the intercepts in logistic regression is done using log-odds. Each unit increase in basal area increases the odds of dead basal area by a factor of 1.02. Each 10x increase in Mg:Mn reduces the odds of dead basal area to 55 percent of that for the original landscape. A till landscape reduces the odds of dead basal area to 50 percent of that for other glacial landscapes. A nonglacial landscape reduces the odds of dead basal area to 10 percent of that for a glacial (non-till) landscape.

Stage 2

In the second stage of the hurdle model, we modeled the amount of dead sugar maple basal area found on those plots that have dead sugar maple. We focused on the 58 points where dead sugar maple was observed (Fig. 2), representing 26 percent of the population of plots with sugar maple. The parameters from the most plausible model (below) are included in Table 3.

Table 3.—Parameters for the most plausible model of sugar maple death using linear regression with only those plots including dead trees

Variable Coefficient	Estimate	Std. Error	t value	Pr(>|t|)
Intercept[a]	-0.675	0.587	-1.150	0.257
lat	0.018	0.014	1.334	0.190
secec	0.077	0.031	2.473	0.018
lca.al	0.027	0.013	2.066	0.046
lmg.mn	-0.018	0.011	-1.636	0.110
lesp	0.080	0.022	3.674	0.001
lemp	-0.078	0.033	-2.362	0.023
forest (MBB)	-0.110	0.077	-1.428	0.162
forest (OH)	0.213	0.085	2.501	0.017
forest (Other)	-0.140	0.104	-1.340	0.188
age	0.002	0.001	1.660	0.105
size (Medium)	0.055	0.042	1.318	0.196
size (Small)	0.157	0.115	1.366	0.180
site.class (4)	0.025	0.103	0.244	0.808
site.class (5)	0.187	0.107	1.743	0.089
site.class (6)	0.111	0.111	1.004	0.322
dist	0.065	0.056	1.164	0.252
geo:nonglacial	0.045	0.098	0.455	0.652
geo:till	0.089	0.039	2.245	0.031
ba	-0.001	0.001	-2.543	0.016

[a]The model intercept includes forest (AB), size (Large), site (3), and geo (glacial, not till). Multiple R-squared: 0.6118, Adjusted R-squared: 0.4177, F-statistic: 3.152 on 19 and 38 DF, p-value: 0.001269.

The exploratory model developed in Stage 2 presents results affirming and challenging previous evaluations of sugar maple decline. Rising Mg levels (lmg.mn and lemp) are associated with declines in death, but contrary to expectations, increases in other forms of mineral soil nutrition available to trees (lecec, lca.al, and lesp) are associated with increasing death of sugar maple (Horsley et al. 2000, Long et al. 2009).

DISCUSSION AND CONCLUSIONS

Statistical inference in a hurdle model approach is complicated by the use of two stages of model building. In stage 1, we analyzed the full dataset using logistic regression, and log (odds) can be difficult to interpret. The model developed in the second stage is constructed more traditionally—by linear regression—so interpretation of the resulting coefficients is relatively straightforward. Additionally, while these two sets of models are similar, they are not identical.

Our emphasis here is to outline a process whereby more comprehensive datasets (namely those including both live and dead trees) can be used to evaluate the likelihood of sugar maple death across the species' range, so additional interpretations are being set aside for more thorough consideration in a subsequent manuscript. Given our use of AIC, multi-model inference will be a useful tool for assessing predictors within and potentially between the two stages (Burnham and Anderson 2002). Our key point is that hurdle models offer an opportunity to model comprehensive, zero-inflated datasets, like those collected by FIA, where the zero-inflation results from the presence of true zeros in the dataset (Martin et al. 2005).

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UTILITY OF TREE CROWN CONDITION INDICATORS TO PREDICT TREE SURVIVAL USING REMEASURED FOREST INVENTORY AND ANALYSIS DATA

Randall S. Morin, Jim Steinman, and KaDonna C. Randolph[1]

Abstract.—The condition of tree crowns is an important indicator of tree and forest health. Crown conditions have been evaluated during surveys of Forest Inventory and Analysis (FIA) Phase 3 (P3) plots since 1999. In this study, remeasured data from 39,357 trees in the northern United States were used to assess the probability of survival among various tree species using the suite of crown condition variables. Logistic regression procedures were employed to assess the importance of individual crown condition variables alone and in combination for predicting tree survival. Results of the regression analyses indicated that crown dieback was the most important crown condition variable for predicting tree survival for all species combined and for the 10 individual species in the study. Additionally, one-way analysis of variance (ANOVA) results identified differences among the ability of different tree species to survive varying levels of crown dieback. The results provide statistical evidence for selecting crown dieback as one of the crown condition variables to be collected on a subset of Phase 2 plots (P2+) starting in 2012.

INTRODUCTION

An important indicator of the health of a tree is the condition of its crown. The U.S. Forest Service Forest Inventory and Analysis (FIA) Program uses visual assessments of tree crown condition to monitor trends in forest health. Trees with vigorous, healthy crowns tend to have higher growth rates. By contrast, trees with damaged or degraded crowns have a reduced capacity for photosynthesis and slower growth rates. Many stressors can cause crown degradation including insects, disease, weather events, senescence, and competition or other stand conditions (Kenk 1993). Additionally, trees with unhealthy crowns are more susceptible to mortality (Kulman 1971, Lawrence et al. 2002).

Assessments of tree crown conditions have been conducted as part of the U.S. Forest Service Forest Health Monitoring (FHM) Program since 1990 and as a part of FIA since 1999 (Riiters and Tkacz 2004). Preliminary analyses of crown condition data through the FHM program demonstrated the data's utility in classifying tree health and likelihood of survivorship, with crown dieback as the best indicator of crown condition (Steinman 2000). The crown health indicators for live overstory trees (d.b.h. $\geq$ 5.0 in) that have been consistently collected since 2001 are uncompacted live crown ratio (UNCR), crown light exposure (CL), crown density (CDEN), crown dieback (CDBK), and foliage transparency (TRANS) (Schomaker et al. 2007). Results from crown condition data have been presented as frequency statistics for individual crown indicators (e.g., Randolph et al. 2010), summaries of tree health by species in FIA

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5-year reports (e.g., Widmann et al. 2012), and more specific analyses investigating changes in forest health (e.g., Morin et al. 2004, Will-Wolf and Jovan 2009).

To increase the efficiency of field data collection, FIA is evaluating the analytical utility of numerous variables such as collected as indicators of forest health. Here, we assess the importance of crown indicators individually and in combination for predicting tree survival; the study objective is to provide statistical evidence for choosing crown condition indicators for continued inclusion in FIA data collection. This study focuses only on the utility of the crown condition variables for predicting tree survival and does not explore other applications.

METHODS

A three-phase forest inventory and monitoring effort is implemented by the FIA program within the U.S. Forest Service (Bechtold and Patterson 2005). Phase 1 (P1) is the development of a post-stratification scheme using remotely-sensed data. The second phase (P2) entails measuring sample plots on the ground for the usual suite of forest mensuration variables such as tree species, d.b.h., height, forest type, stand age, etc. Overstory trees (d.b.h. $\geq$ 5.0 in.) are measured on four 24-ft radius subplots; saplings (1.0 $\leq$ d.b.h. $<$ 5.0 in.) are recorded on four microplots of 6.8-ft radius each. Phase three (P3) occurs on a 1/16th subset of the P2 plots, where additional data are collected on forest health indicators, including the crown condition variables.

In this study, remeasured data from 39,357 trees in the northern United States (2001-2005 to 2006-2010) were used to assess the probability of survival among various tree species using the suite of crown condition variables. Tree species with at least 1,000 remeasured trees were included in the individual species models. Survival of an individual tree is a discrete event where each remeasured tree can only have the value of 1 (live) or 2 (dead); removed trees were not included.

The probability of survival was modeled using the logistic equation:

$$P(1) = 1 / (1 + e(b'x))$$

where $b'x$ is a linear combination of parameters b and independent variables x, and e is the base of the natural logarithm. The PROC LOGISTIC procedure (SAS Institute 2009) was used to estimate the parameters of the logistic regression using maximum likelihood methods. Additionally, one-way analysis of variance (ANOVA) tests were used to test the effect of CDBK on tree survival. Tests were conducted for all trees combined and for five the most abundant species individually: red maple, sugar maple, northern white-cedar, balsam fir, and quaking aspen. The Student-Newman-Kuels test was employed to determine significant differences in survivorship among CDBK classes.

RESULTS

All parameters listed in Table 1 are significant (α=0.05) and many are highly significant (p-value <0.0001 indicated by an *). For all species combined, we found all crown variables to be highly significant in predicting survival; for each species individually, we found CDBK to be highly significant. The area under the receiver operating characteristic (ROC) curve is provided for the classification models as an indicator of classification accuracy (Table 2). To judge the relative importance of the variables, standard errors are listed in Table 1 and Chi-square values are given in Table 2.

Parameter estimates conform to expectations in nearly all cases. The coefficient of CDBK is negative in all cases (Table 1), indicating decreasing survival with increasing CDBK. Similarly, the coefficient of TRANS is negative in the most significant cases, indicating decreasing survival with increasing TRANS. The coefficients of the other variables are all positive, except for CL in the models for balsam fir and eastern hemlock (Table 1), which indicates increasing survival with increases in those variables.

Table 1.—Estimated parameters for survival models. All parameters are significant at the 95 percent level of confidence (α = 0.05)

Species	Sample Size (n)	Variable				
		CDBK	UNCR	CDEN	CL	TRANS
All species	39,357	-0.0371 (0.00185)*	0.0165 (0.00113)*	0.0290 (0.00168)*	0.0821 (0.0180)*	-0.0118 (0.00183)*
Red maple	4,459	-0.0464 (0.00672)*	0.0340 (0.00486)*	0.0356 (0.00582)*	0.5933 (0.0978)*	0.0221 (0.00985)
Sugar maple	3,003	-0.0423 (0.00945)*	0.0219 (0.00651)	0.0525 (0.00900)*	0.4488 (0.1291)	0.0308 (0.0153)
Northern white-cedar	1,962	-0.0436 (0.00594)*			0.3484 (0.1054)	
Balsam fir	1,603	-0.1127 (0.0166)*	0.0260 (0.00361)*	0.0264 (0.00560)*	-0.1965(0.0483)*	
Quaking aspen	1,536	-0.0622 (0.0109)*	0.0233 (0.00585)*	0.0320 (0.00556)*		
White oak	1,336	-0.0775 (0.0124)*			0.4609 (0.1686)	
Paper birch	1,290	-0.0265 (0.00754)		0.0268 (0.00613)*	0.2979 (0.0725)*	
Northern red oak	1,092	-0.0655 (0.0150)*			0.5081 (0.1727)	-0.0474 (0.00779)*
Eastern white pine	1,027	0.0661 (0.0149)*	0.0275 (0.00748)		0.4159 (0.1391)	
Eastern hemlock	1,009	-0.0908 (0.0178)*				

CDBK is crown dieback, UNCR is uncompacted live crown ratio, CDEN is crown density, CL is crown light exposure, and TRANS is foliage transparency.
Standard errors are given in parentheses.
* indicates significance (p <0.0001).

Table 2.—Receiver operating characteristic (ROC) curve area and Chi-square values for the parameter estimates in Table 1

Species	ROC Curve Area	Chi-Square Statistic Variable				
		CDBK	UNCR	CDEN	CL	TRANS
All species	0.7176	403	215	298	21	42
Red maple	0.8059	48	49	37	37	5
Sugar maple	0.8015	20	11	34	12	4
Northern white-cedar	0.7200	54			11	
Balsam fir	0.7557	46	52	22	17	
Quaking aspen	0.7075	32	16	33		
White oak	0.7532	39			7	
Paper birch	0.7015	12		19	17	
Northern red oak	0.7805	19			9	37
Eastern white pine	0.7699	20	14		9	
Eastern hemlock	0.7340	26				

CDBK is crown dieback, UNCR is uncompacted live crown ratio, CDEN is crown density, CL is crown light exposure, and TRANS is foliage transparency.

The Chi-square statistics in Table 2 reveal that the most important variable for all species combined and most species individually is CDBK. The second most important variable for all species combined is CDEN, and it is also the most important for sugar maple, quaking aspen, and paper birch. Among individual species the rankings of importance of the variables is inconsistent except that CDBK is the most important in most models.

One-way ANOVA analyses indicate that the proportion of trees that survived until remeasurement decreased as CDBK increased (Figs. 1 and 2). For all species combined, the proportion of surviving trees for each CDBK class is significantly different from all others. For most individual species, the proportion of survivors in the greater than 50 percent CDBK class is significantly different from all other classes, but for balsam fir and quaking aspen, proportion of surviving trees in the 26 to 50 CDBK class is similar to the greater than 50 percent CDBK class. Based on the proportion of surviving trees in the 26 to 50 and greater than 50 CDBK classes, sugar maple and northern white-cedar appear to be able to tolerate high levels of CDK better than red maple, balsam fir, and quaking aspen (Fig. 2).

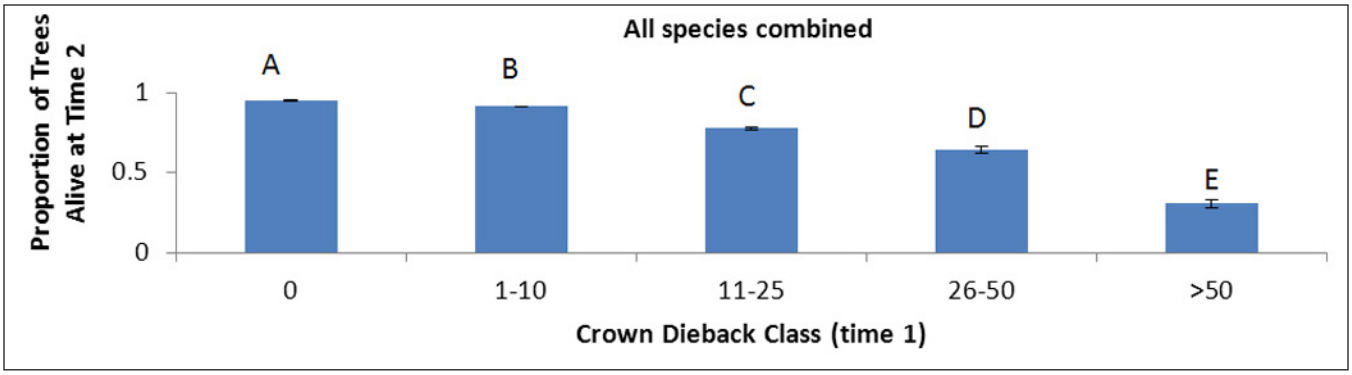


Figure 1.—Proportion of trees that were alive at remeasurement in crown dieback classes from time 1 measurement. Bars labeled with the same letter (A-E) are not significantly different (ANOVA, Student-Newman-Keuls test, a = 0.05).

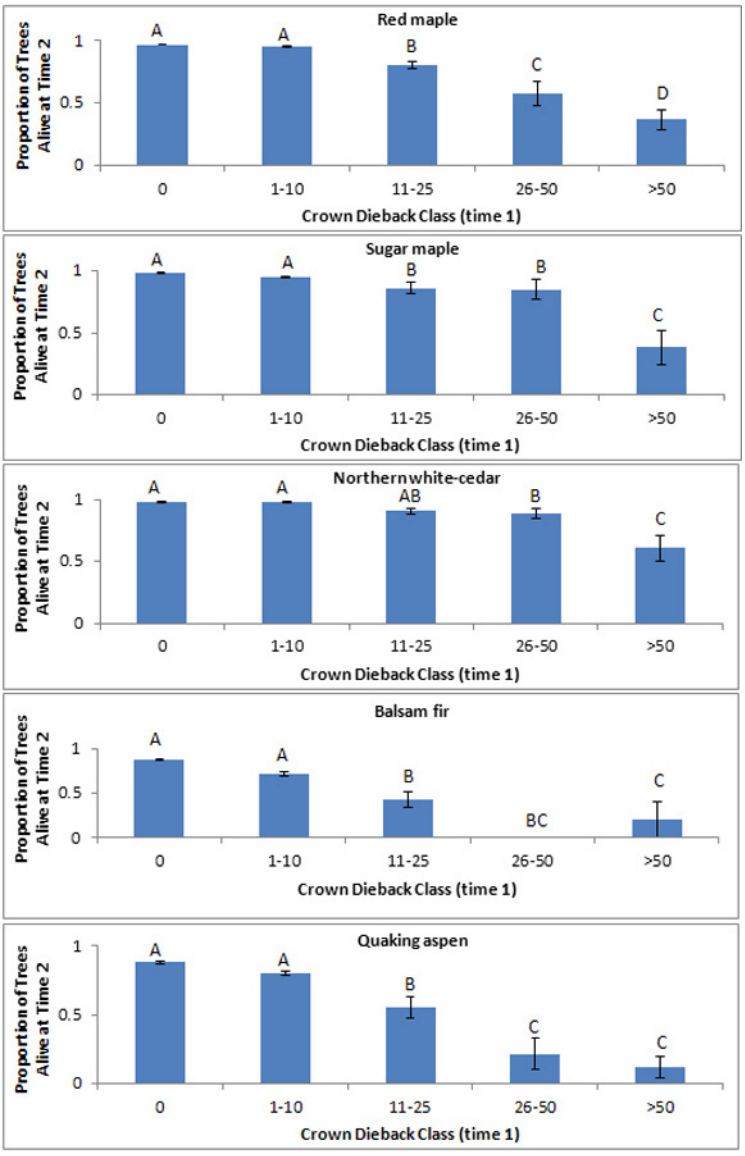


Figure 2.—Proportion of trees that were alive at remeasurement in crown dieback classes from time 1 measurement, by species. Bars labeled with the same letter (A-E) are not significantly different (ANOVA, Student-Newman-Keuls test, a = 0.05).

DISCUSSION

Results of the logistic regression analysis for all species combined indicate that the crown condition variables are all significant predictors of survival, but CDBK was the most important variable. It should be noted, however, that even though UNCR was not a significant predictor of survivability for all species, by way of establishing the base of the live crown UNCR forms the basis for assessing all of the other crown condition variables and therefore must always be assessed. Additionally, results of the logistic regression analyses for individual species indicate that CDBK is the only crown condition variable that is a significant predictor of survival for all 10 species in this study. Based on differences in the proportion of survivors among individual species, CDBK is also a useful metric for assessing the ability of different species to tolerate and survive varying levels of crown health.

The results of this study provide statistical evidence for selecting CDBK as one of the crown condition variables to be collected on a subset of Phase 2 plots (termed P2+) beginning in 2012. The P2+ sample will be larger than the P3 sample. Therefore, moving the CDBK indicator from P3 to P2+ will increase statistical power for this line of research. Additional research that is suggested by the results of this study include looking at successive measures of CDBK on surviving trees to determine whether crown health recovery has occurred and predicting future mortality based on CDBK values. There is also great potential in using crown dieback as a means to parse FIA reporting attributes (e.g., volume) of live trees into healthy and unhealthy categories.

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The content of this paper reflects the views of the author(s), who are responsible for the facts and accuracy of the information presented herein.

LARGE LANDSCAPE ASSESSMENTS

TEMPORAL TRENDS OF FOREST INTERIOR CONDITIONS IN THE UNITED STATES

Kurt Riitters and James Wickham[1]

Abstract.—Nature's benefits derived from forest interior environments cannot be sustained if the natural capital of forest interior area is not sustained. We analyzed the spatial patterns of forest loss and gain for the conterminous United States from 2001 to 2006 to determine whether forest interior environments were maintained at five spatial scales. A 1.1 percent net loss of total forest area translated to net losses of 3.2 percent to 10.5 percent of forest interior area over spatial scales of 4.41 ha to 5,310 ha. At the 65.6-ha scale, the reduction of forest interior area was 50,000 km^2—almost double the net loss of total forest area. The geographically pervasive discrepancy between total forest loss and forest interior loss indicates a widespread shift of the extant forest to more fragmented conditions, even in regions exhibiting small net changes in extant forest area. Forest dynamics could be monitored spatially to better understand the potential impacts of fragmentation on the sustainability of forest interior.

INTRODUCTION

Most forests are naturally extensive, and as they become fragmented a variety of physical and biological mechanisms begins to limit their capability to support the ecological attributes and functions that depend on interior environments (Laurance 2008, Murcia 1995, Ries et al. 2004). Continental to global forest monitoring tends to focus on trends in the absolute area of forest, but forest interior is a contextual attribute that depends on the spatial arrangement of forest area at multiple spatial scales (Riitters et al. 1997). Trend assessments should account for the initial spatial patterns and the patterns of forest loss and gain to more accurately reflect trends in forest interior area (Kurz 2010, Wickham et al. 2008). Riitters and Wickham (2012) analyzed the spatial patterns of forest loss and gain for the conterminous United States from 2001 to 2006 to determine whether forest interior environments were maintained at five spatial scales. This paper highlights the results and calls for spatial monitoring of forest dynamics using land cover maps to better understand the potential impacts of fragmentation on forest conditions.

METHODS

Forest interior was measured on the 2001 and 2006 National Land Cover Database (NLCD) land cover maps (Fry et al. 2011), which identify 16 land cover classes at a spatial resolution of 0.09 ha/pixel. The 16 NLCD land cover classes were combined into two generalized classes called forest (the NLCD deciduous, evergreen, mixed forest, and woody wetlands classes), and nonforest (all other NLCD classes). At each date, the spatial context of each forest pixel was measured by its forest area density (FAD), defined as the proportion of all pixels in a surrounding fixed-area neighborhood that were forest. A given forest pixel

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was called forest interior if FAD ≥ 0.9. The analysis was repeated at five spatial scales with neighborhood sizes[†] of 4.41, 15.2, 65.6, 590, and 5,310 ha (Riitters et al. 2002). Thus, maps of FAD at a spatial resolution of 0.09 ha/pixel were produced for each date and neighborhood size. The corresponding maps of forest interior comprised the subset of all extant forest pixels which met the criterion defining forest interior.

To relate forest area gains and losses to the dynamics of forest interior area from 2001 to 2006, the NLCD forest maps from 2001 and 2006 were overlaid, on a pixel-by-pixel basis, upon the maps of FAD. Pixels that were forest in 2001 but not in 2006 represented forest area loss, and pixels that were forest in 2006 but not in 2001 represented forest gain. Pixels of forest loss were evaluated in relation to FAD in 2001 to determine whether forest area losses were also removing forest interior. Pixels of forest gain were evaluated in relation to FAD in 2006 to evaluate whether forest area gains were adding forest interior. The differences between gross gains and gross losses for FAD ≥ 0.9 represent the net changes of forest interior area.

RESULTS

The total forest area[††] in 2001 was 2,352,000 km^2. Forest area losses and gains were 54,000 km^2 and 27,000 km^2, respectively, resulting in a net loss of 27,000 km^2 (1.1 percent of total forest area). In comparison, the net loss of forest interior area was at least 29,000 km^2 with a maximum loss of 50,000 km^2 for the 65.6-ha neighborhood size (Table 1). The rate of loss of forest interior area increased with neighborhood size and was approximately 3 to 9 times larger than the rate of loss of total forest area.

The disproportionate loss rates are explained by the patterns of original forest area, forest loss area, and forest gain area in relation to FAD in 2001 and 2006 (Fig. 1). Overall forest losses tended to follow the distribution of all forest area in relation to FAD in 2001, but the area lost at high FAD values exceeded the area gained by 2006 at high FAD values. As a result, a smaller percentage of the extant forest area qualified as forest interior in 2006. Regional analyses of 36 ecological provinces (Bailey 1995) showed that these observations were typical of a wide range of initial forest conditions (Riitters and Wickham 2012).

In terms of total forest area, most of the naturally forested ecological sections (Cleland et al. 2007) exhibited a net loss while net gains were concentrated in sections where forest is not the dominant land cover (Fig. 2a). In comparison, for the 65.6-ha neighborhood size there was a net loss of forest interior area in 175 of 190 ecological sections, and 74 sections exhibited losses greater than 5 percent (Fig. 2b). In naturally forest-dominated regions, forest interior area losses greater than 5 percent were typical in the Pacific Northwest and Southeast but were less common elsewhere. The Intermountain and Great Plains

[†] Rounded to three significant digits; exact sizes were 4.41, 15.21, 65.61, 590.49, and 5,314.41 ha.

[††] Area estimates differ from official statistics because of differences in the definitions of forest.

Table 1.—Change in forest interior area in the conterminous United States from 2001 to 2006 for five neighborhood sizes

Neighborhood Size[a] (ha)	Forest Interior Area			
	2001 (1,000 km^2)	2006 (1,000 km^2)	Change (1,000 km^2)	Change (%)
4.41	1,419	1,374	-45	-3.2
15.2	1,151	1,102	-49	-4.3
65.6	867	817	-50	-5.8
590	523	482	-41	-7.8
5,310	277	248	-29	-10.5

[a] Rounded to three significant digits.

regions had relatively low total forest area and the forest interior area changes there had relatively little influence on national statistics. The nearly national extent of differences between total forest loss and forest interior loss (Fig. 2) suggests a widespread shift in the spatial pattern of the extant forest to a more fragmented condition, including regions exhibiting relatively small net changes in extant forest area.

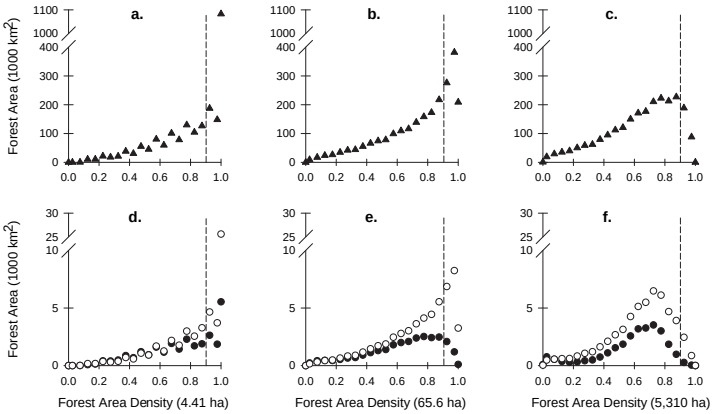


Figure 1.—The area distributions of initial forest, forest gains, and forest losses in relation to forest area density in 2001 or 2006 for three representative neighborhood sizes. Top row: initial forest area in relation to initial forest area density in 2001 (triangles) for neighborhood sizes of (a) 4.41 ha, (b) 65.6 ha, and (c) 5,310 ha. Bottom row: gross forest area lost in relation to initial forest area density in 2001 (open circles) and gross forest area gained in relation to final forest area density in 2006 (closed circles), for neighborhood sizes of (d) 4.41 ha, (e) 65.6 ha, and (f) 5,310 ha. The net change for each value of forest area density is the difference between gross loss and gross gain. Forest interior area for each data series includes the three symbols to the right of the dotted vertical reference lines.

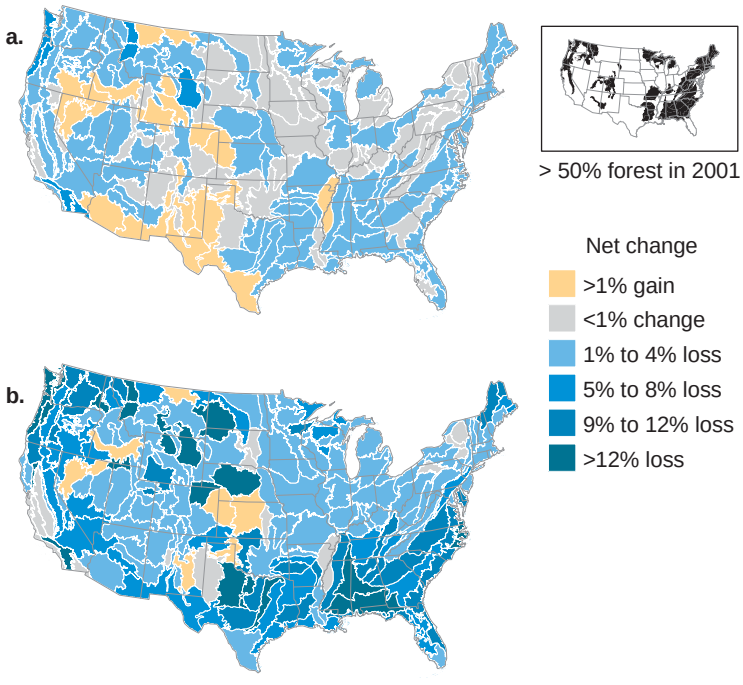


Figure 2.—Net change in forest area from 2001 to 2006. (a) All forest. (b) Forest interior in a 65.6-ha neighborhood. Ecological sections are shaded and State boundaries are shown for comparison. In the inset map, forest-dominated ecological sections are those that contained more than 50 percent forest in 2001.

DISCUSSION

The unavoidable dependence of perceived pattern on measurement scale requires analysis of forest interior at multiple spatial scales. Knowledge of forest interior at a single scale is required to understand the ecological attributes and functions which interact with the forest environment at that scale. A multiple-scale analysis can inform a wider range of ecological questions and identifies the range of spatial scales over which forest interior can be said to exist. Furthermore, from an inventory perspective forest interior may exhibit net gains, net losses, or equilibrium depending on the scale at which it is measured. Thus, a multiple-scale analysis is more useful than a single-scale analysis when the goal is to assess forest interior as a generic constraint affecting many ecological attributes and functions.

The recent spatial patterns of forest gains and losses have not maintained forest interior area in the conterminous United States. Forest losses tended to follow the distribution of all forest area in relation to FAD in 2001, indicating that preservation of forest interior was not usually an important consideration when forest was removed. Conversely, forest gains tended to occur where the gains did not create new forest interior, indicating that creation of forest interior was not usually an important consideration when forest was added. The dispersed and non-compensating patterns of forest losses and gains resulted in rates of net change of forest interior area that were at least 3 times larger than the rate of net change of total forest area. While the identity of forest interior is naturally scale-dependent, the multi-scale analysis showed that the non-compensating pattern of forest loss and gain was exhibited over a wide range of spatial scales from 4.41 ha to 5,310 ha. If the recent patterns of change continue, the extant forest interior area will become smaller in the future. As a result, maintaining the benefits derived from forest interior environments will become more difficult and fewer options will be available to natural resource managers.

Some degree of forest fragmentation is a natural condition, and the loss of interior forest per se does not imply an anthropogenic cause. Our analysis did not distinguish between natural and anthropogenic loss and gain, nor did it compare conditions in 2001 with the patterns of potential natural vegetation absent human influences. Knowledge of potential natural vegetation is helpful for understanding specific impacts of fragmentation, but it is not essential when evaluating trends of forest interior area within the human dominated era. More information is needed to evaluate quantitatively the relative importance of the causes of fragmentation in different parts of the United States. As a first approximation, the principal drivers of forest area change appear to be human activities in the East and intense, yet relatively local (relative to the scale of the study area), biotic and abiotic disturbances in the West (Riitters and Wickham 2012).

National land cover maps provide the synoptic perspective needed to identify indicators of forest interior consistently over large regions through time. These are coarse-scale indicators of dependent ecological changes, yet the specific impacts of forest interior loss will naturally depend upon local circumstances such as the vegetation type experiencing the forest loss, the proximate causes of loss, and anthropogenic land uses in the vicinity. Some of those details can be incorporated by spatially linking the synoptic maps of forest interior and other contextual pattern information (e.g., land cover adjacency metrics) to in situ inventory systems such as Forest Inventory and Analysis that provide better thematic resolution of forests and land uses (Riitters et al. 2011). Sustainable natural resource stewardship must account for fluxes in the natural capital that provides the desired benefits, and this research has demonstrated how forest patterns could be monitored to better understand the impact of human activities on the sustainability of forest interior.

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MONITORING TRENDS AND BURN SEVERITY (MTBS): MONITORING WILDFIRE ACTIVITY FOR THE PAST QUARTER CENTURY USING LANDSAT DATA

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Abstract.—The Monitoring Trends in Burn Severity (MTBS) project is mapping the extent, size, and severity of all large fires greater than 1,000 acres in the west and 500 acres in the east over the conterminous United States (CONUS), Alaska, and Hawaii. In 2012 the project reached a milestone, completing the mapping for all fires between 1984 and 2010. The MTBS project produces geospatial and tabular data using a consistent protocol for fire trend analysis at a range of spatial, temporal, and thematic scales. This paper reviews the objectives of the MTBS project, describes the data sets and information provided, and presents results of the analysis of the 1984-2010 MTBS data set for the United States.

INTRODUCTION

The Monitoring Trends in Burn Severity (MTBS) project has mapped all large wildland fires in the conterminous United States, Alaska, and Hawaii from 1984 through 2010 using Landsat imagery. This 5-year project was completed in April 2012 by analysts at the U.S. Forest Service, Remote Sensing Applications Center and the U.S. Geological Survey, Earth Resources Observation and Science Center. This paper presents the first analysis of the complete 1984-2010 data set and presents broad-scale trends observed in the MTBS data record. Over this period, 14,945 fires were mapped in the conterminous United States (CONUS), Alaska, and Hawaii. In addition, this paper demonstrates how MTBS data can be used to compare different regions of the country in terms of fire frequency, burned area, and burn severity.

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METHODS

For the purposes of this short paper, Geographic Area Coordination Center (GACC) boundaries are used to define the geographic regions. These GACC regions are defined by an interagency fire management organization made up of Federal and state wildland fire directors and have been chosen because the authorizing body for the MTBS project was the executive-level Wildland Fire Leadership Council. Undoubtedly there are more ecologically relevant alternatives to this tessellation of the United States.

Burn Severity Mapping

Burn severity in the MTBS project refers to "degree to which a site has been altered or disrupted by fire; loosely, a product of fire intensity and residence time" (National Wildfire Coordinating Group 2005). Burn severity is mapped by the MTBS project using Landsat Thematic Mapper and Enhanced Thematic Mapper Plus data and the differenced Normalized Burn Ratio (dNBR) (Eidenshink et al. 2007). Analysts use dNBR images to delineate fire perimeters and to determine the dNBR thresholds for distinguishing between severity classes based on both scientific protocol and experience (Schwind 2008). For each fire, burned area is classified into one of four burn severity classes: unburned to low, low, moderate, or high (Fig. 1).

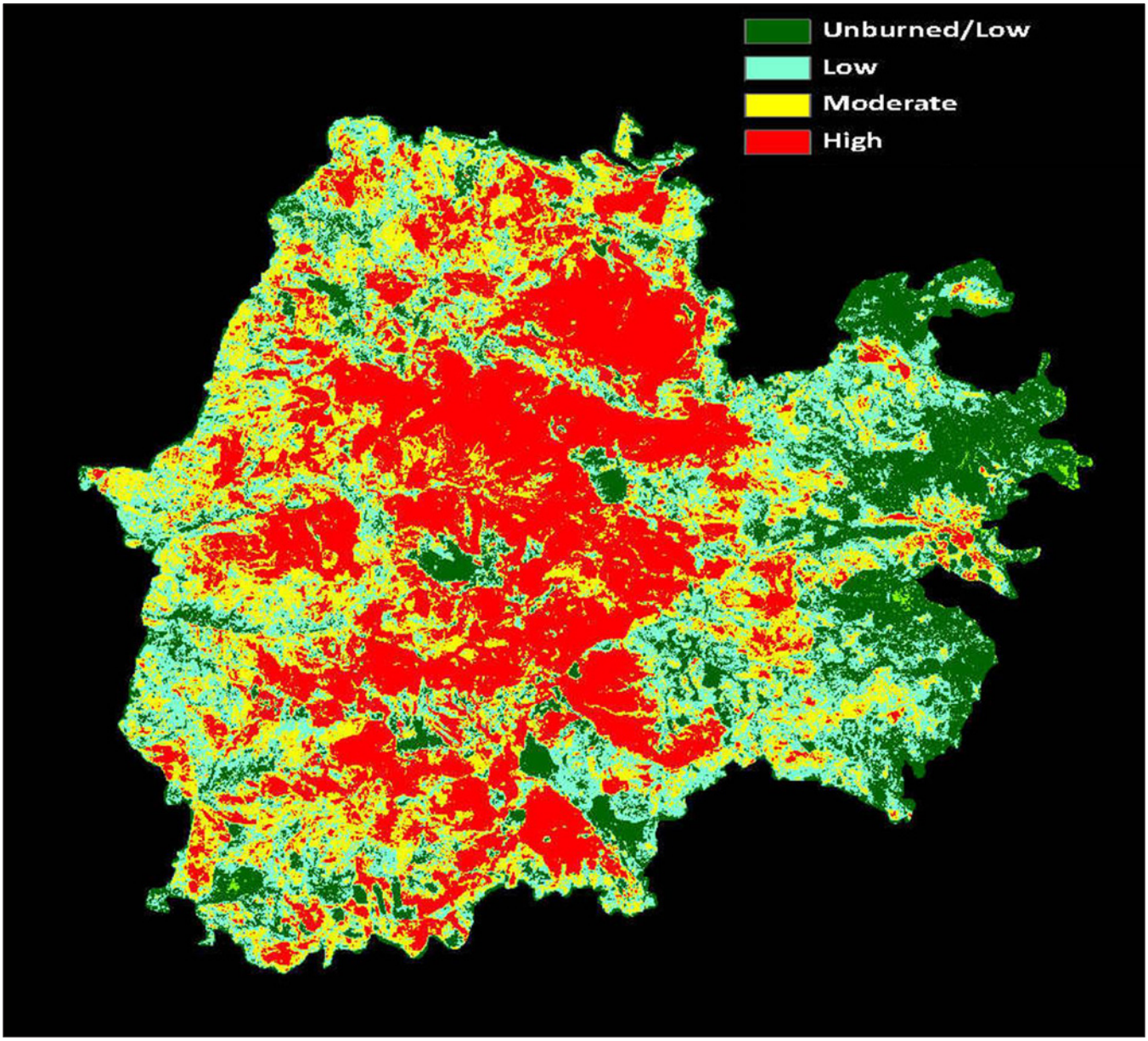


Figure 1.—Example of a burn severity map developed by the MTBS project.

Data and Analysis Methods

MTBS Fires Analyzed

The objective of the MTBS project is to provide a consistent and continuous source of 30-m resolution burn severity data for all fires greater than 1,000 acres in the western CONUS and 500 acres in the eastern CONUS, but many fires smaller than these size limits were mapped (MTBS 2012). For consistency in our analysis, this paper adheres to the original size limits. The number of fires was thus reduced to 13,400 and burned area to about 110 million acres over the 27-year data record.

The MTBS data record also contains both documented wildland fires and prescribed fires, as noted in the MTBS fire occurrence database. Because this paper's focus is on the potential influences of biophysical, geographic, and climatic factors on natural fire behavior, only wildland fires were analyzed. Excluding prescribed fires further reduced the number of fires to 10,874 and burned area to about 104.6 million acres.

Analysis Methods

The burned area and burn severity information for all large wildland fires was compiled in a database along with other attributes, such as fire name, type, and ignition date. Tabular and geographical summaries were generated from this database. This database is publicly accessible through a Web portal at www.mtbs.gov/data/search.html. Statistical summaries available through the Web portal include burn severity by state, GACC, vegetation cover type, and administrative ownership.

The MTBS database was used to aggregate large wildland fires on a yearly basis to derive trends of fire frequency, size, and burn severity for each of the 11 regions (R Core Team 2012). In this paper we compare trends in large fire frequency and size for the Eastern Great Basin GACC and the Southern California GACC. We selected the Northwest GACC and Southwest GACC for comparison of trends in burn severity.

NATIONAL AND REGIONAL WILDFIRE TRENDS

Between 1984 and 2010 approximately 22 percent of the area burned in CONUS was in the unburned to low burn severity class, 42 percent in the low class, 23 percent in the moderate class, and 12 percent in the high class. The following four figures show national and regional wildland fire trends in fire frequency, size, and burn severity.

Fire Frequency and Size

The MTBS project mapped 10,137 large wildland fires with a total burned area of about 79.5 million acres in CONUS between 1984 and 2010. Generally, both fire frequency and size exhibited trends between 1984 and 2010 towards a larger number of fires and greater burned area despite large annual fluctuations (Fig. 2). The Nation experienced the largest fire year in 2006 in terms of both frequency and burned area, reaching a frequency of 843 fires and burned area of

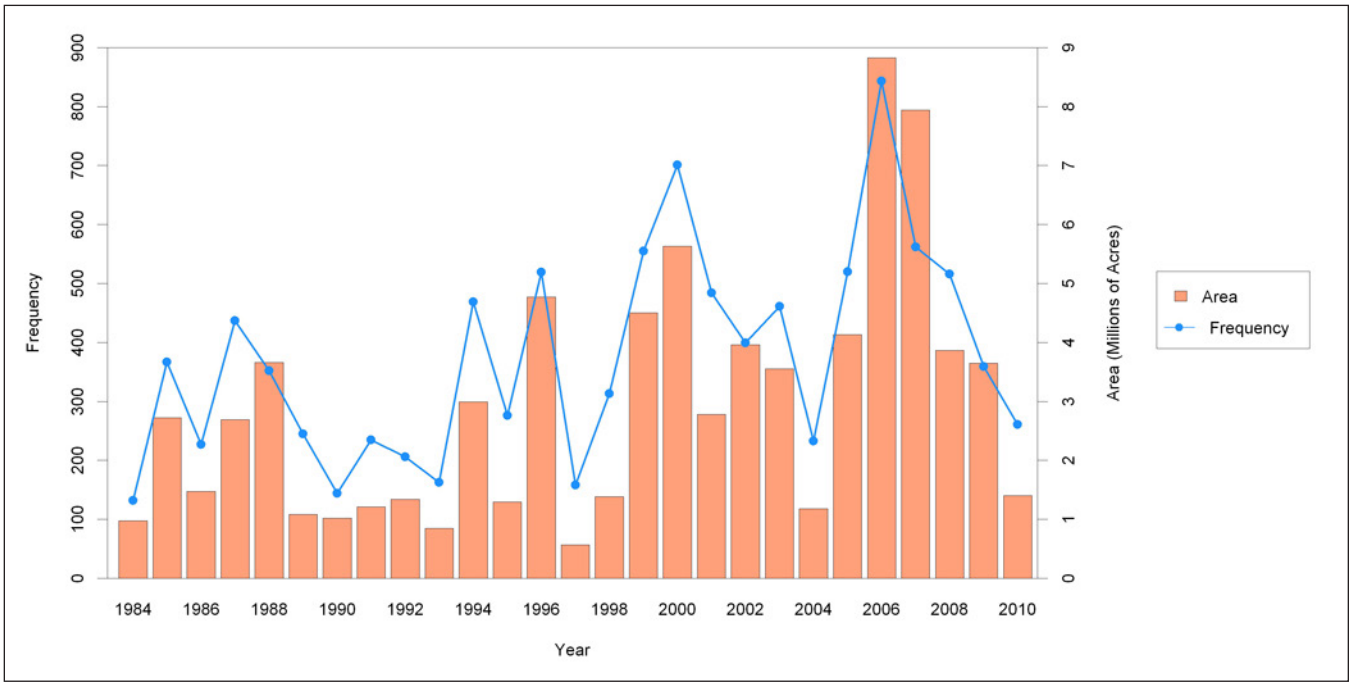


Figure 2.—Large fire frequency and size for CONUS, 1984-2010.

8.8 million acres. Outside of 2006, the years with the largest number of fires were, in descending order, 2000 (701), 2007 (562), and 1999 (555). The years with greatest burned area in descending order were 2007 (8 million acres), 2000 (5.6 million acres), and 1996 (4.8 million acres). The trend of burned area has a positive correlation ($R^2 = 0.835$) with fire frequency. The largest mean fire size, 14,000 acres, occurred in 2007. The smallest, 3,600 acres, was in 1997. The 27-year mean fire size was about 2,500 acres and frequency was approximately 375 fires per year.

We compared trends in large fire frequency and size between the Eastern Great Basin GACC (EGB) and the Southern California GACC (SC) (Fig. 3). Although these regions have few biophysical similarities, using these two GACCs demonstrates how MTBS data can capture the variability in fire activity and acres burned between regions. While beyond the scope of this paper, comparison and evaluation of results can be made in the context of land cover and administrative ownership; immediate and long-term effects of weather, climate, and ecological conditions; and land management strategies.



Figure 3.—Large fire frequency and size in the EGB and SC, 1984-2010.

The EGB showed a small increasing trend in fire frequency in the EGB, while the SC did not show an obvious trend towards greater number of fires. The burned area in both GACCs slightly increased from 1984 to 2010. The EGB had a larger burned area and greater number of fires in most of the years than SC. The EGB also had a wider range in terms of both burned area and frequency, which parallels the cyclical nature of the fire seasons in that part of the country.

In the EGB, the largest burned area was about 2.56 million acres in 2007 and the smallest burned area was about 0.027 million acres in 1993. The highest fire frequency, 121 fires, occurred in 2006. The lowest number of fires was nine in 1993. In the SC, the largest burned area was in 2003 (0.8 million acres), and the smallest was about 0.014 million acres in 1991. The year 1996 had the largest fire frequency with 61 fires and 1991 had the smallest with 5. The mean fire size increased in recent years and reached the highest in 2007 in both GACCs (the same year of the largest mean fire size in CONUS): about 25,000 acres in the EGB, and 24,000 acres in the SC. The overall mean fire size over 27 years is slightly higher in the EGB (about 10,000 acres) than in the SC (about 8,500 acres), both being much higher than that of CONUS (2,500 acres). Approximately 53 fires occur annually in the EGB and about 31 in the SC. The fire frequency is more correlated with burned area in the EGB (R^2 = 0.696) than in the SC (R^2 = 0.325), indicating a more stable yearly mean fire size in the EGB and episodic occurrences of megafire activity in SC. The trends of burned area and frequency in both GACCs do not fully correspond (R^2 = 0.183 for burned area; R^2 = 0.095 for frequency). Notable outliers were found in 1991 and 2000 for frequency, and in 2003 for burned area.

Regional Differences in Burn Severity

Burn severity trends were analyzed and compared for the Northwest GACC (NW) (Fig. 4) and the Southwest (SW) GACC (Fig. 5). The mean percentage of severely burned area (moderate or high burn severity) in the NW was 32 percent, slightly above the CONUS average (28 percent) and significantly higher than that of the SW, which was about 24 percent. The NW also showed a wider range and fluctuation in the percentage

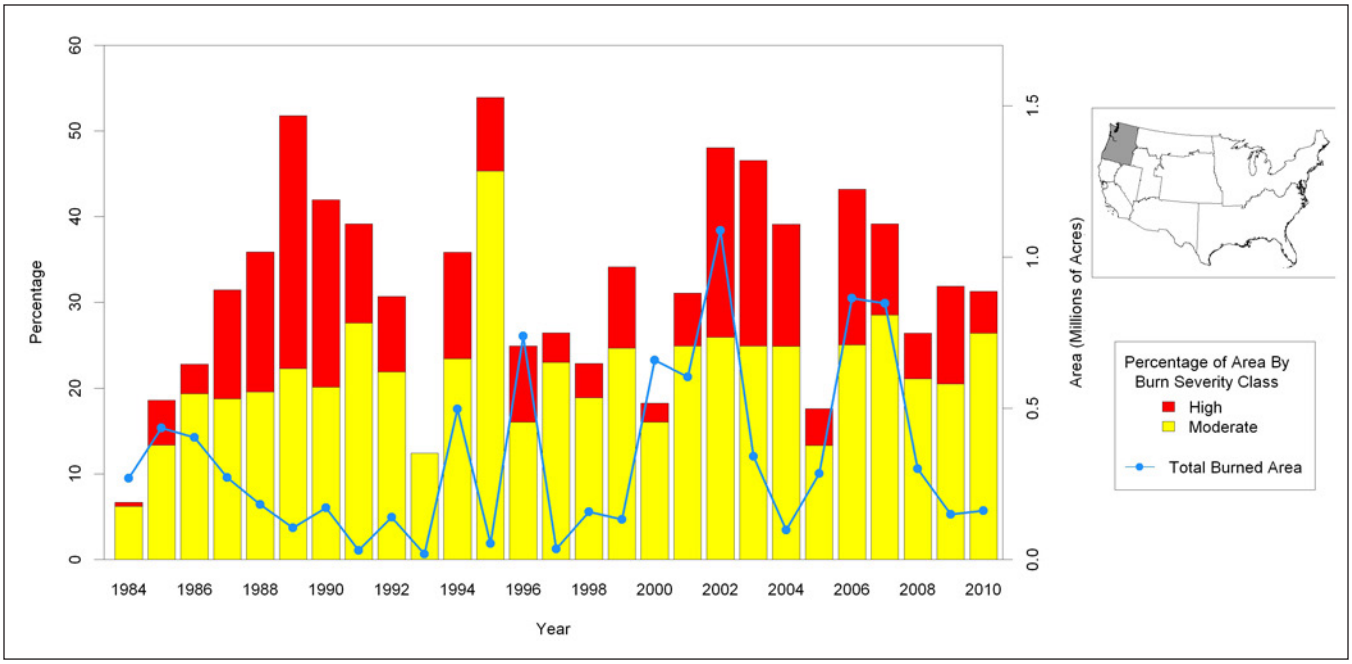


Figure 4.—Percentage of severely burned area (area with moderate or high burn severity) (scale on left axis) and total burned area (scale on right axis) in the Northwest GACC, 1984-2010.

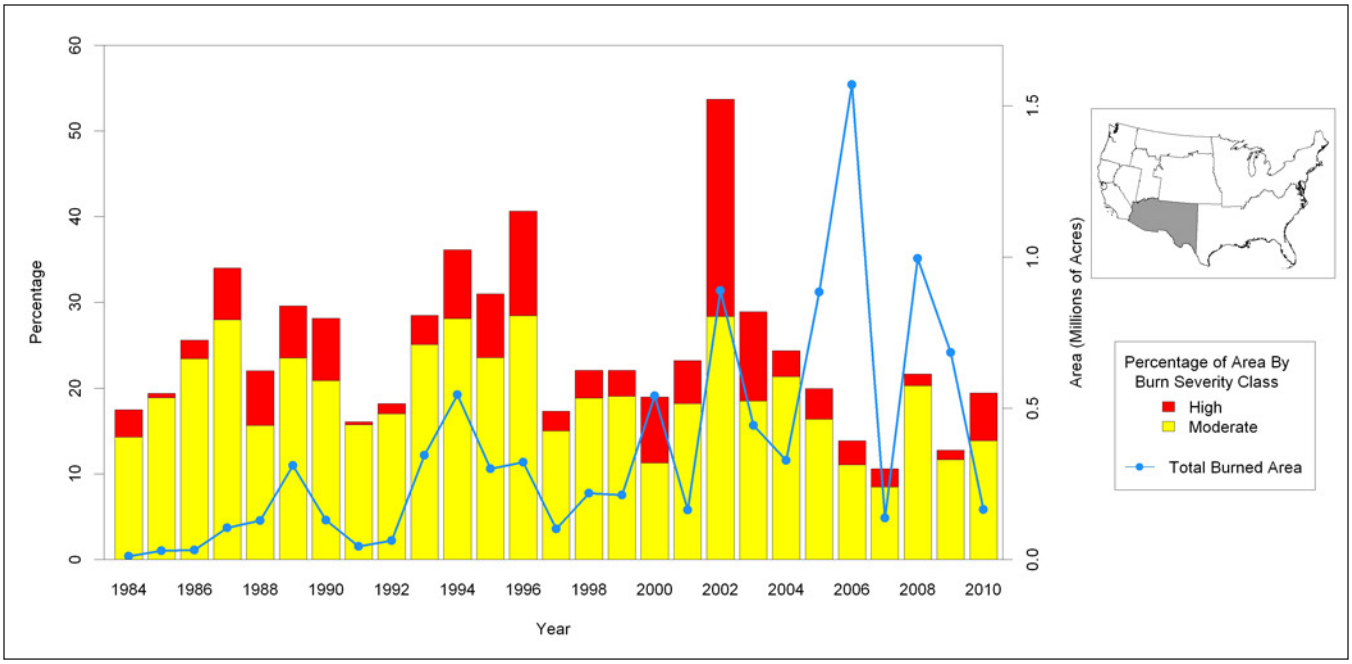


Figure 5.—Percentage of severely burned area (area with moderate or high burn severity) (scale on left axis) and total burned area (scale on right axis) in the Southwest GACC, 1984-2010.

of severely burned area. In the SW, the total burned area showed an increasing trend throughout the data record while in the NW, the total burned area decreased in the 1980s and early 1990s, and then greatly increased thereafter. In both GACCs, total burned area fluctuated more sharply from year to year in more recent years.

Because of the higher proportion of forest and biomass in the NW, that region burned more severely than the SW. The SW showed a trend toward lower burn severity; 2002 was an anomaly. Trends in burn severity and burned area did not correspond between the NW and SW, which is likely due to different weather and climate patterns, vegetation composition, and fire management. The R^2 between the burned area and the sum of the percentage of area in the moderate and high burn severity classes was 0.202 for the NW and 0.085 for the SW. In both GACCs, the years with higher burn severity were not necessarily the years with larger burned areas. For example, in the NW, the most severely burned year was 1995, when the percentage of severely burned area was 54 percent, but the area burned in that year was among the smallest, only about 0.052 million acres.

DISCUSSION

For scientists interested in understanding regional and national trends in wildland fire, the MTBS dataset has no peer. As with any data set, however, a clear understanding of how the MTBS data were created and what fires are included is important before analyzing trends. Without this knowledge, the trends observed could be an artifact of the data selected for analysis or the data generation process.

When appropriately filtered, the data show clear fluctuations and trends in fire frequency, size, and burn severity, both nationwide and between regions. Our analysis showed a trend toward increasing fire size (though very cyclical), but not such a clear trend toward increasing fire severity. Comparison of fire frequency, size, and severity for different geographic areas highlights what we hypothesize to be biophysical and climatic differences between the regions in this time period. Further analysis is required to substantiate these causal relationships.

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APPROACHES FOR LANDSCAPE-SCALE FOREST CARBON ASSESSMENT

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Abstract.—Increasingly, public and private forest landowners need to estimate their carbon stocks and analyze the impacts of alternate management plans. Here we describe approaches designed to work at landscape scales: one involves estimating carbon stocks from existing Forest Inventory and Analysis (FIA) data; another involves downscaling results from a continental-scale biogeochemistry model known as InTEC; and the third uses Lidar remote sensing to provide high resolution biomass maps. Combining FIA data with a biogeochemistry model gives the most useful information for analyzing causes of historical trends, while the biomass maps support implementation of management decisions. Application of these approaches is illustrated by pilot studies in the eastern United States. Analysis of FIA data for northern Wisconsin revealed that private landowners held more than half of the forest carbon but that the rate of carbon sequestration had slowed dramatically over two decades. Causes of the decline were hypothesized to include increased harvesting, aging forests, and increasing disturbances. The InTEC model for the same region revealed trends over a much longer historical period as well as providing information about changes in soil C that are lacking in the FIA data analysis. The effects of long-term forest age dynamics and higher inter-annual climate variability became evident, and the model results suggest a significant increase of soil C stocks. Using this information base, we identified several ways to increase landscape-scale average forest carbon stocks: allow some forests to reach full maturity and highest carbon stocks; manage other forests to maximize carbon uptake and transfer of harvested carbon into wood products; and avoid conversion of existing forests to nonforest land uses. Strategic implementation of these kinds of management decisions can be facilitated with high resolution biomass maps.

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U.S. FOREST SERVICE INTERNATIONAL PROGRAM ACTIVITIES RELATED TO FOREST MONITORING

ANALYSIS OF THE DEFORESTATION PROBLEM IN TROPICAL LATIN AMERICA

Jorge Malleux[1]

Abstract.—The driving forces of land use changes have been analyzed and discussed for a long time with different solutions proposed and implemented. Unfortunately the reduction of natural forest cover continues in the same direction, generating an increasing alarm all around the world among scientist and politicians, related to the climate change awareness and strategies for its reduction and mitigation. This paper discusses the causes of deforestation, causes and effects in tropical Latin America.

INTRODUCTION

This paper discusses the causes of deforestation in tropical Latin America.

Deforestation is an issue that has long been a concern of the international community, especially in the tropics. It is increasingly important to provide updated and reliable information based on accountable and transparent procedures. There is still much work to be done to develop standardization of terms, definitions, and procedures for the evaluation of changes in forested areas at the national and local levels.

The forest cover of any area is referred to as the physical presence at a particular time of continuous or fragmented vegetation, defined as forest, which is a type of woody vegetation with a minimum height of 5 m at maturity, with a minimum coverage of 10 percent of the canopy on the soil surface. Within this classification are dense forest (>40 percent coverage), open (between 10 and 40 percent coverage), or fragmented forest in isolated stands but which collectively cover extensions reaching a minimum of 0.5 ha.

In ecological terms, the most important concept is the forest's ability to meet minimum production of goods and services, i.e., the protection of soil, conservation of water sources, regulation of the water system, wildlife habitat, recreation, conservation of biological biodiversity (understood as the total variety of genetic strains), species and ecosystems that exist in the nature and are able to survive in a sustained way.

This document is only a part of this broad and complex problem of the relationship of deforestation to specific socioeconomic parameters. Once both aspects of definition and concepts of classification of forests are standardized or formalized for a particular purpose, the immediate problem is how to measure or evaluate the parameters that serve to integrate a reliable database that is structured for a particular purpose or agenda, such as the FRA, Kyoto, Convention of Biodiversity, Reducing Emissions from Deforestation and forest Degradation (REDD), and the sustainable forest management procedures, generating information of the first order, so the accuracy and reliability of the information may have fairly broad range of consistency and reliability.

METHODS

Based on information provided by 14 reporting countries for the FAO-FRA program (between 1980 and 2010), 71 references were pre-selected. Parameters for evaluating the information consistency (IC) were given a value from 0 to 5 and a specific weight or

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importance. Based on the calculation of coverage and/or changes of the forest cover, the following parameters were considered:

a: Quality of the source of information: P1 = 0.15
b. Detail information: P2.20
Consistency and back: P3, 40
d. Age: P4 0.25
IC. Weighted reliability index =
(a * b * p1 + p2 + + c * d * p3 + p4)

The sum of multiplying the score of each parameter by its specific weight gives a final score which can be up to 5. These final scores are grouped into three categories:

A: 0 to 3.0: low, removed or held in reserve in case there is no other better reference
B: 3.1 to 4.0: means, we choose the most recent or consistent
C: > 4: high is used directly

To do a quick analysis on the relationship of these parameters to annual deforestation rates, some major macroeconomic parameters at the country level for 14 countries of tropical Latin America were identified. However, to bring the analysis to smaller or manageable contexts, seven Brazilian states from the Amazon region were selected, with a total of 129 districts and about 60 socioeconomic parameters, out of which only 26 were considered significant. These 26 parameters were analyzed using linear and logarithmic correlation with the annual deforestation rates (2000-2005), yielding R^2 values, indicating the degree of correlation between deforestation rates recorded for each country and the seven Amazonian Brazilian states.

RESULTS

Of the 14 countries evaluated in terms of the reliability of the information provided (IC), 10 values were above 3.1. and 4 countries had rates above 4. This is an indication that there is still a lot of work to do to collect more reliable and consistent information regarding forest deforestation. The results of this analysis are expressed in terms of R^2 values.

As shown in Table 1, the factor that is the most influential in deforestation is the population density, particularly the rural population, which should be understood as the necessity of living space and food, which is stronger than the need to conserve the environment, especially in societies where there are no valid alternatives through job opportunities, income to fund the family basket, and so on. A second influential factor, but in a favorable manner to the preservation of forests, is the annual growth of gross domestic product, which means improved job opportunities for people, better prices for agricultural products, and increased consumption, particularly for rural populations.

At the Subnational Level

From the seven states of the Brazilian Amazon, numerous socioeconomic parameters were considered, including: total population from urban, rural, agricultural land, pastures, forests, secondary forests, production and productivity agricultural state investment in development projects, agricultural machinery, etc. These were analyzed for their relationship or correlation with the average rate of deforestation for the period 2000-2005; results are shown in Tables 2 and 3.

Table 1.—Factors related to forest conservation

Parameters	R^2 for Linear Correlation	Influence Over Forest Conservation
Rural Population Density	0.626	Negative
Gross Domestic Product (GDP)	0.2486	Positive
Percent of Rural Population	0.2103	Negative
Annual Growing Population Rate	0.1514	Negative

Table 2.—R^2 Values, parameters are positive for the conservation of the forest

		ACRE	AMAZONAS	M.GROSSO	PARA	RONDONIA	TOCANTINS	TOTAL
HA/FARMER (AGR & GL)	**V**	-0.322	-0.374	-0.297	-0.125	-0.583	-0.281	-0.142
HA/FARMER (AGR)	**U**	0.271	-0.383	0.029	-0.390	-0.506	-0.388	-0.040
PRODUCTION $/HA (AGR & GL)	**BJ**	0.163	-0.304	0.187	-0.436	0.271	-0.181	0.218
PRODUCTION $/HA (AGR)	**BK**	-0.333	0.238	0.032	0.059	-0.294	-0.640	0.110
PRODUCTION $/FARMER	**BL**	-0.237	0.108	0.164	-0.482	-0.204	-0.500	0.065
PRODUCTION AGR+GL $/FARMER	**BY**	-0.257	-0.074	-0.038	-0.273	-0.543	-0.231	-0.092
PRODUCTION AGR. $/FARMER	**BZ**	0.241	-0.024	-0.004	-0.273	-0.538	-0.243	0.062
PRODUCTION $/HA GL	**CA**	-0.250	-0.245	-0.179	-0.274	-0.542	-0.218	-0.137
ANNUAL INCOME $/FARMER	**BX**	-0.194	-0.447	-0.008	-0.261	-0.531	-0.237	0.060
MUNICIPAL INVESTMENT $/FARMER	**CB**	-0.110	0	0.023	0	0	-0.367	0
MUNICIPAL INVESTMENT $/RURAL HABITANT	**CC**	0.040	0	0.135	0	0	-0.268	0
POPULATION DENSITY HAB./KM^2	**F**	0.375	-0.370	0.231	-0.192	-0.249	-0.551	-0.130
ANNUAL YIELD $/AGR	**BR**	0.229	0.019	-0.113	0.125	-0.472	0.165	-0.027
ANNUAL YIELD $/AGRL	**BS**	0.220	0.061	0.181	-0.491	0.276	-0.175	0.138

Table 3.—R^2 values, parameters turn out to be negative for the conservation of the forest

		ACRE	AMAZONAS	M.GROSSO	PARA	RONDONIA	TOCANTINS	TOTAL
AGR&G LINVESTMENT $/HA	BN	0.475	0.080	0.131	0.058	-0.012	0.040	-0.010
AGR INVESTMENT $/HA	BO	-0.143	0.057	-0.112	0.500	-0.390	0.391	-0.027
GL INVESTMENT $/HA	BP	0.526	0.593	0.128	-0.086	0.096	0.043	0.266
AGRI & GL ANNUAL YELD $/HA	BQ	0.623	-0.103	0.202	-0.256	0.114	0.100	0.060
NUMBER OF TRACTORS/HA AGRI & GL	BT	0.043	0.187	0.322	-0.070	-0.199	0.108	0.086
NUMBER OF TRACTORS/HA AGR	BU	-0.259	0.184	-0.104	0.358	-0.408	0.170	-0.039
NUMBER OF TRACTORS/GL	BV	-0.115	-0.055	0.267	-0.158	-0.156	0.085	0.062
% OF FALLOW FOREST/ AGR	W	-0.397	-0.091	0.096	0.609	-0.247	0.618	0.086
% OF FALLOW FOREST/AGRIC & GL	X	-0.135	-0.022	0.149	-0.255	-0.140	0.264	0.068
POPULATION ANNUAL GROWTH	G	-0.067	0.251	0.336	0.155	0.295	-0.131	0.157
% OF RURAL POPULATION	J	-0.322	0.117	0.183	0.370	0.564	0.274	0.163
LIFE STOCK INVESTMENT $/HA	BM	0.226	0.423	0.106	-0.344	0.153	-0.070	0.018

Figures 1 and 2 show that some socioeconomic indexes are highly significant for forest conservation, particularly those related to the per capita National Gross Product (NGP) and the productivity of income-generating activities, to benefit the local population.

On the other hand, population density, type of investments, and population growth are working against forest conservation and actually stimulating deforestation.

DISCUSSION

There is no single cause for deforestation. In any case this does not occur in isolation but there are several factors that together establish a context quite complex, including:

- Extreme poverty and lack of job opportunities and family income sufficient for economically disadvantaged people
- Lack of policies and legislation and strategies or policy mistakes of the occupation of forest areas in the humid tropics
- Insufficient capacity in decisionmaking of the forest authority in the occupation and use of the forest land
- Lack of planning on land use, use of inappropriate technologies, and deficiencies in the use of land and forest.

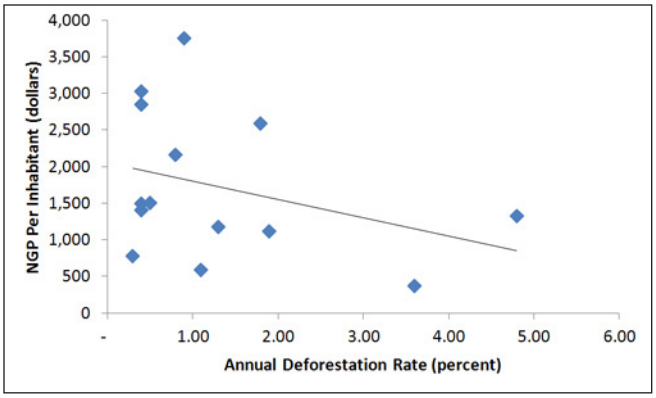


Figure 1.—National gross product per inhabitant by annual deforestation rate.

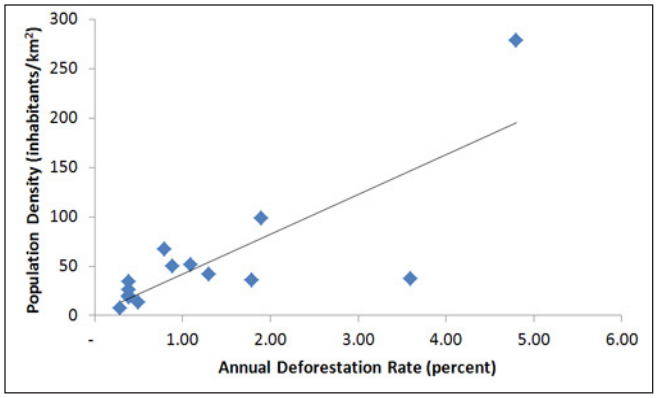


Figure 2.—Population density by annual deforestation rate.

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The content of this paper reflects the views of the author(s), who are responsible for the facts and accuracy of the information presented herein.

FOREST INVENTORY AND ANALYSIS CANOPY COVER ACTIVITIES

A GIS-BASED TOOL FOR ESTIMATING TREE CANOPY COVER ON FIXED-RADIUS PLOTS USING HIGH-RESOLUTION AERIAL IMAGERY

Sara A. Goeking, Greg C. Liknes, Erik Lindblom, John Chase, Dennis M. Jacobs, and Robert Benton[1]

Abstract.—Recent changes to the Forest Inventory and Analysis (FIA) Program's definition of forest land precipitated the development of a geographic information system (GIS)-based tool for efficiently estimating tree canopy cover for all FIA plots. The FIA definition of forest land has shifted from a density-related criterion based on stocking to a 10 percent tree canopy cover threshold. This definitional change required a consistent method of estimating tree canopy cover, which is now a core FIA variable, using a combination of field-based and image-based assessments. In order to accomplish the image-interpretation task for thousands of plots annually, the FIA program, working in collaboration with the Remote Sensing Applications Center, developed a GIS-based canopy cover tool. Design considerations for the tool include the following: desired precision of the tree canopy cover estimate, seamless use across regions, compatibility with the existing Forest Service streaming image technology, and ease-of-use for image interpreters. Data from this image interpretation effort will not only serve the needs of FIA, but will also be used to update the National Land Cover Dataset tree canopy cover data layer.

INTRODUCTION

With the release of Forest Inventory and Analysis (FIA) Field Guide 5.0, the FIA program began collecting canopy cover information (specifically, percent canopy cover) on all plots. To complement the new field-based canopy cover protocols, the national prefield task team designed an image-based canopy cover protocol for plots that are withheld from field visits via the prefield process (i.e., plots that are obviously nonforest). The prefield canopy cover assessment protocol is applied at tens of thousands of plots annually and involves dozens of image interpreters. Therefore, it was necessary to develop a user-friendly, geographic information system (GIS)-based tool that facilitates efficient image-based interpretation and documentation of percent canopy cover. During inventory year 2012, the canopy cover tool was used to assign a percent canopy cover at all FIA plots in support of an update of the National Land Cover Dataset (NLCD) canopy cover data. This paper presents the development history, design considerations, and practical advantages of the canopy cover tool.

METHODS

Collaboration

FIA's national prefield task team, which includes members from the four FIA regions, identified the need for a GIS-based canopy cover tool and prepared a functional needs assessment. Subsequent tool development was supported by the Techniques Research Band in collaboration with the Forest

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Service's Remote Sensing Applications Center (RSAC). The RSAC and the FIA program have had a longstanding partnership applying remote sensing technology to the national forest inventory of the United States. In addition, RSAC has expertise and experience developing software tools to assist with image interpretation, such as Digital Mylar (Clark et al. 2004). The project team, which consisted of a programmer and a project manager from RSAC and the national prefield team from FIA, collaboratively developed a specification document based on FIA's needs assessment. A number of additional FIA personnel served as software testers. The project followed a rapid application development paradigm with iterative versions of the software prepared by RSAC and promptly tested by FIA staff. One of the agreements in this partnership was the delivery of the tool's source code to the FIA program, which will provide flexibility to adapt the tool to other resource settings or dot grid designs.

Design Considerations

Multiple image-based methodologies were considered and tested (see Goeking and Liknes 2009), and a dot grid approach was selected due to favorable repeatability performance and minimal training requirements. The question of dot grid sample size was investigated using statistical methods, and it was determined that 100 dots would provide a suitable compromise between precision and interpretation time. Dots were to be fit within a circle of 43.9-m radius, which contains all four subplots in the FIA plot design. Additionally, the dot grid was to be rotated clockwise 15 degrees in order to reduce alignment with cultural features. The final dot arrangement uses an integer spacing (8 m) between dots, resulting in 109 dots in the 43.9-m circle (Fig. 1).

Software Development

Because all FIA image interpreter personnel have experience using ArcGIS® products (e.g., ArcMap™)

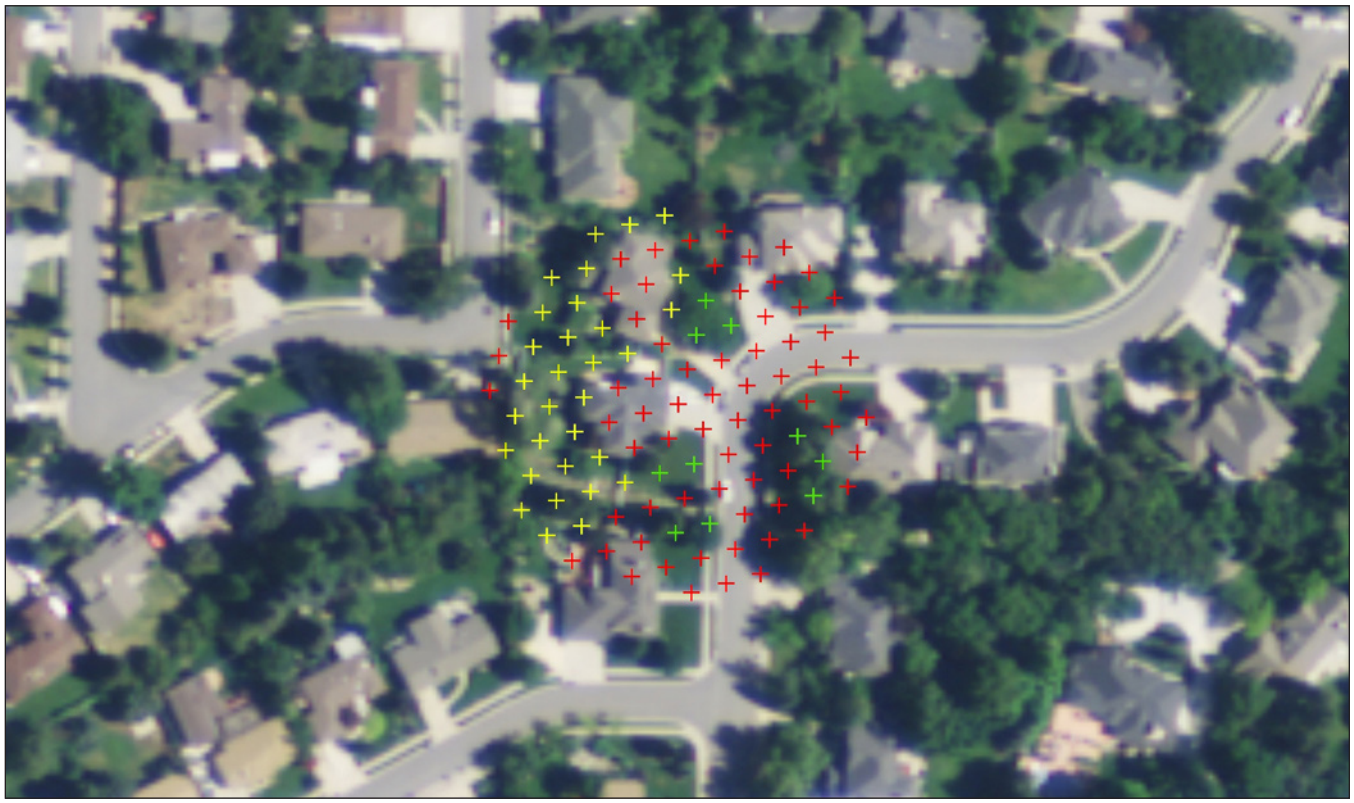
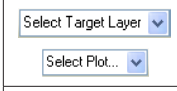
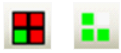


Figure 1.— Screen capture of dot grid overlain on NAIP imagery using the FIA canopy cover tool. Red crosshairs indicate non-tree dots, green indicate tree dots, and yellow indicate dots that have not yet been classified. This example illustrates a situation where the plot does not meet the FIA definition of forest land yet includes a substantial amount of tree canopy cover.

and the software can seamlessly utilize imagery from RSAC's ImageServer (Vines 2007), the canopy tool was developed as an ArcMap™ add-in using C# and ArcObjects® in ArcGIS® 10. The add-in can be hosted at a network location, and users therefore automatically use the latest version of the software each time they restart the ArcMap™ application. This reduces the technical support effort required to ensure all users have the same version of software and enables the use of the software tool at the Forest Service's Enterprise Data Center.

Working from the basic functionality outlined in a specification document, a prototype of the tool was developed. Image interpreters from all four FIA regions tested several iterations of the tool, working toward consensus while still meeting the workflow requirements in each region. Particular attention was paid to optimizing efficiency of the interpretation process. A summary of the tool's components appears in Table 1.

Table 1.—Summary of functions within the canopy cover tool. Note that the options function permits flexibility in defining parameters that may vary across FIA regions or resource applications.

Icon	Utility	Functionality
	Select layer/ Select plot	Dropdown menus that specify the plot layer and individual plot to which other operations will be applied.
	Generate dots	Creates the 109-dot grid for the currently selected plot.
	All no tree	Single click operation that assigns all no tree attributes to the current plot's dot grid.
	Select based on location	Out-of-the-box ArcMap tools used to select dots; default tools included are select by polygon (left) and select by lasso/freehand (right).
	Attribute dots	Assign either tree (left) or not tree (middle) to currently selected dots. Another option allows users to distinguish between tally trees (left) and non-tally trees (right).
	Select based on attributes: Invert select/ select null	Custom selection tools; either selects all dots not currently selected and makes all currently selected dots not selected (left) or selects all dots that have not yet been assigned a tree/not tree value (right).
	Undo	Removes the last assigned tree/not tree attribute. Successive clicks of this button step through older attribute assignments and remove them.
	Confidence	Dropdown box that allows user to indicate how confident they are in the percent canopy for the current plot. Options are high (default) and low; a low confidence value prompts the user for a low confidence reason (e.g., clouds).
	Done	User can indicate they have completed work on a plot. Saves attribute information for the currently selected plot and zooms to the next plot in the plot dropdown list.
	Percent canopy	Calculates and reports the percent canopy cover based on dots that have been attributed. Also reports the number of dots that have not yet been attributed.
	Options	Launches a dialog that allows the user to specify the following parameters: *Plot key:* Specifies an attribute field in the plot layer used to uniquely identify plots (e.g., CN, or a concatenation of state, county, plot). The values of this key populate the "Select plot" dropdown list. *Data frame reprojection:* Specifies behavior of data frame in the event imagery or plots are in different projections. *Dot layer projection:* Specifies the output projection of dot grids. *Zoom level:* Defines the display scale when application moves to a new plot; default is 1:1000. *Attribute levels:* Option to turn off distinction between tally and non-tally trees. *Symbology:* Option to load custom symbology. *Canopy cover button:* Option to disable the informational Percent Canopy Cover button. *Big undo:* Option to delete all dot files in the directory of the currently active layer and to reset the associated plot file to its original state by deleting the canopy cover attributes. *Dot output folder:* User-specified location for storage of dot layers. *Current data frame:* Specifies to which data frame tool operations apply.

Practical Advantages and Applicability

There are several practical advantages of both the tool's user-friendly design and the simplicity of the dot grid protocol. First, the ability to host the tool at a network location is critical for minimizing software support and troubleshooting. Second, the tool requires only minimal GIS experience and technical training, which is a significant advantage over object-oriented image segmentation methods. Third, no field data are required. While some assessments of tree canopy cover rely on mapped-plot data including tree size and location (see Toney et al. 2009), this approach requires only high-resolution imagery along with either a point shapefile or comma-separated value file of plot locations. As with any photo-interpreted evaluation of tree cover, however, photo interpretation skills and familiarity with regional vegetation are required for accurate and repeatable percent canopy cover values.

A fourth advantage is the ability to assess repeatability and sampling error. The tool's visible output includes a new shapefile, which contains each of the 109 dots in each plot's dot grid, as well as the tree/no tree attribute for each dot. Therefore, multiple interpreters can evaluate quality control plots using consistent dot locations and imagery. Further, the existence of dot grids allows straightforward calculation of sampling error. In contrast, while census-based approaches (e.g., image segmentation, which produces polygons) have no sampling error, they do have misclassification and boundary errors that are difficult to quantify. Finally, datasets representing dot grids are relatively small in size, parallel in structure given that each plot always contains the same number of dots and attributes, and generally easier to manage than polygon outputs produced by image segmentation.

The straightforward design of the canopy cover tool lends itself to applications in other projects and resource settings. The tool's principal requirement is a point shapefile or comma-separated values (CSV) file, wherein each point or record represents one plot and contains a unique identifier in the attribute table. Based on user-assigned dot grid values, canopy cover is calculated for each sample plot and stored in this attribute table. RSAC has made available an adaptable version of the tool called Image Sampler, which is part of the Digital Mylar toolkit (USDA FS 2012). This version of the tool allows the user to specify whether the dots should be randomly or systematically arranged within an area of interest, and also allows for a user-defined classification scheme.

DISCUSSION

A new GIS-based tool facilitates the determination of percent canopy cover, which is a critical component in FIA's new definition of forest land, using a dot grid and high-resolution imagery. A partnership between RSAC and FIA successfully led to delivery of a functional tool within a few months' time.

The canopy cover tool was used to assign percent canopy cover to tens of thousands of FIA plots for the 2012 inventory year. The resulting data will not only populate the canopy cover variable for non-visit plots in the national FIA database, but will also be used in the update of the NLCD percent canopy cover layer, which is currently under development as a collaboration among several national agencies. In future inventory years, percent canopy cover will continue to be assigned at all non-visited FIA plots using this method. The determination of percent canopy cover at all FIA plots will allow FIA to align with international cover-based definitions of forest land and also monitor trends in tree cover on nonforest lands.

ACKNOWLEDGMENTS

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BUILDING CAPACITY FOR PROVIDING CANOPY COVER AND CANOPY HEIGHT AT FIA PLOT LOCATIONS USING HIGH RESOLUTION IMAGERY AND LEAF-OFF LIDAR

Rachel Riemann, Jarlath O'Neil-Dunne, and Greg C. Liknes[1]

Abstract.—Tree canopy cover and canopy height information are essential for estimating volume, biomass, and carbon; defining forest cover; and characterizing wildlife habitat. The amount of tree canopy cover also influences water quality and quantity in both rural and urban settings. Tree canopy cover and canopy height are currently collected at FIA plots either in the field or by dot-grid interpretation of digital aerial imagery. These techniques can be time consuming and costly. The University of Vermont's Spatial Analysis Laboratory has developed an automated approach using Object-Based Image Analysis (OBIA) techniques for extracting canopy cover, canopy height, and land cover from readily available high resolution aerial imagery and leaf-off LiDAR. We used datasets generated by the OBIA approach for 10 different counties spread across 4 states, representing a range of conditions. Canopy cover, canopy height, and land cover information were computed for each FIA plot, at scales of 144-foot-radius (plot circle) and 3,280-foot-(1-km)-radius, and compared to FIA estimates at the plot level. Results are discussed in terms of the comparative assessment of the three canopy cover data sources (including what is missing when nonforest plot data are not available), and the prognosis for using the OBIA techniques to extract this type of information at the county and state levels. Acquiring tree canopy cover data using the OBIA approach would allow FIA to apply a consistent method for acquiring canopy cover to both visit and non-visit plots, and even potentially increase the reliability of the canopy cover data available. This approach also provided valuable data on canopy height for FIA plots not visited in the field and additional data on landscape context for all FIA plots, improving capacity to characterize and analyze forest characteristics with respect to local levels of urbanization.

INTRODUCTION

The importance of information on tree cover, irrespective of land use, has been recognized by the U.S. Forest Service's Forest Inventory and Analysis (FIA) Program for some time. In 2010 FIA decided to add it as a standard variable, to be collected in the field for all visited plots, and via photointerpretation at the prefield stage for all non-visit plots, with some overlap for quality assurance (QA) to assess the relationship between the two. Once the protocol is fully implemented, these data will provide FIA with tree canopy cover data on all plots, providing a much more complete and consistent estimate of tree canopy cover information than is currently available. Data collected via these two methods are directly relevant to the 1/6-acre plot cluster and thus the other inventory variables collected on the plot. There are some limitations with this data, however. Data from visited (mostly forest) and non-visited (mostly nonforest) plots are collected by different methods and at different scales, potentially

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resulting in systematic differences in measurement quality between the two populations. These effects will be unknown until enough QA overlap data are available for analysis. Furthermore, collecting tree canopy cover data in this manner is labor intensive. If semi-automated or fully automated approaches to determining canopy cover are available that provide data at similar scales and with similar estimates and standard errors, it could make the protocol more efficient in the long term.

Another source of tree canopy cover information has been developed by O'Neil-Dunne et al. (2009) using a combination of high resolution aerial imagery and LiDAR (Light Detection And Ranging) data. It has been used to generate citywide and countywide estimates of existing tree canopy cover for resource managers (e.g., O'Neil-Dunne and Pelletier 2011). This approach leverages the vast amounts of high resolution remotely sensed data available through the National Agricultural Imagery Program (NAIP) along with LiDAR data acquired by federal, state, and local governmental organizations. Object-Based Image Analysis (OBIA) techniques are used to extract seven-class land-cover datasets with an overall accuracy exceeding 90 percent. The combination of spectral (imagery) and height (LiDAR) data in conjunction with OBIA techniques enables features to be extracted using the same elements of image interpretation used by photointerpreters (see Olson 1960).

Our four primary goals in this study were to (1) compare plot-level estimates of tree canopy cover obtained from the OBIA technique with those obtained by FIA via ground inventory in the field and via photointerpretation in prefield procedures, (2) compare plot-level estimates of stand height with those obtained by FIA in the field, (3) examine the canopy cover and canopy height characteristics of forest vs. nonforest plots, and (4) illustrate the type of landscape context information that is available for each plot from the OBIA approach.

METHODS

Of the 10 counties for which OBIA data are already available, only 6 were included in this paper: Allegheny and Lancaster Counties in Pennsylvania, and Anne Arundel, Montgomery, Prince Georges, and Howard Counties in Maryland. The six counties range from 16 percent forested in Lancaster, PA, to 40 percent forested in Prince Georges, MD. Species composition is primarily hardwoods.

Our study was based on FIA field plots visited from 2006 to 2011. Tree height was available on all forested plots. Because canopy cover variables were just introduced last year, only a subset of these plots had canopy cover data. At the time of this study, about 20 percent of forested plots had field canopy data, collected in 2011. A different subset (~20 percent of all plots) had photointerpreted (PI) canopy cover collected using imagery from 2007 to 2010. Of the 369 plots in the 6 counties for which data were available at the time of this paper, we had PI percent canopy cover data for 75 plots (all counties) and field-collected canopy cover data for 19 plots (MD counties only). FIA canopy height and field canopy cover were calculated as the mean of all live trees on the forested conditions on the 1/6-acre plot. FIA photointerpreted canopy cover was estimated using a 100-point dot grid over a 1.5-acre (144-foot-radius) area surrounding each plot.

The imagery used for all the counties in the study consisted of NAIP 4-band 1-m data from 2009 to 2011. The LiDAR was sourced from a broad range of federal, state, and local agencies. The various LiDAR datasets were similar in that they had a nominal post spacing of 0.6 m to 1.4 m, had ground points classified (LAS class = 2), and were acquired during leaf-off conditions. Digital Elevation Models (DEM) and Normalized Digital Elevation Models (nDSM) were generated from the LiDAR data. The LiDAR surface models, imagery, and ancillary GIS datasets (e.g., road centerlines) were integrated into the OBIA system,

which was built using the eCognition® software platform. Within eCognition®, a rule-based expert system was used to extract seven classes of land cover at a nominal resolution of 1 m: (1) tree canopy, (2) grass/shrubs, (3) bare soil, (4) water, (5) buildings, (6) roads/railroads, and (7) other paved surfaces. The rule-based expert system was built using the Cognition Network Language (CNL), which is the underlying programming language for eCognition®. In this approach, image processing, segmentation, classification, and morphology algorithms are iteratively applied, thereby successively building contextual information, which can then be used to improve the classification. To effectively process the billions of data points making up the imagery and LiDAR and support iterative processing approach, the OBIA system was built on 64-bit computing architecture and the processing load was distributed to multiple cores.

Following the development of the land cover dataset, the FIA plot data were integrated into the OBIA system. A separate rule-based expert system iteratively processed each FIA plot, extracting canopy coverage, topographic, and land cover information.

OBIA estimates of canopy height and canopy cover were calculated at two different neighborhood sizes for each FIA plot: a 144-foot-radius area around plot center (1.5 acres), representing the plot circle encompassing all four subplots, and a 3,280-foot-radius area around plot center (776 acres). OBIA estimates were calculated as the mean canopy height and canopy cover of all tree canopies greater than 8 feet in height. FIA and OBIA estimates were compared using linear regression (r-squared).

RESULTS

OBIA canopy cover estimates are strongly correlated to the FIA photointerpreted tree canopy estimates ($r^2 = 0.91$), but relative to the FIA data they tend to overestimate canopy values. OBIA and field-collected tree canopy estimates exhibited a poor correlation ($r^2 = 0.07$) (Fig 1).

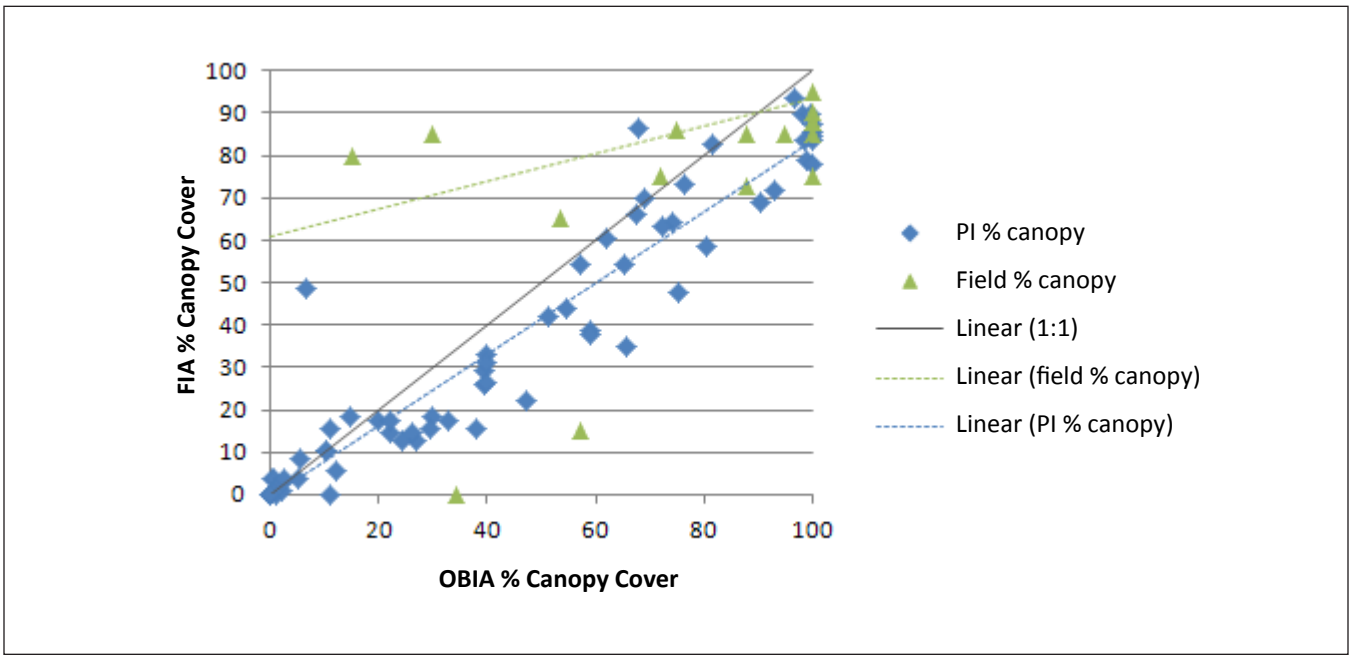


Figure 1.—Comparison of OBIA-based canopy cover information with FIA canopy cover information. OBIA information is derived from an automated classification procedure using NAIP high resolution aerial imagery and LiDAR data. FIA canopy cover information is either observed in situ or estimated from a NAIP image using a dot grid.

Agreement between FIA canopy height and LiDAR-derived OBIA height for forested plots is poor, with an r-squared of 0.23 (Fig. 2). Additional investigation needs to be done to determine if this is due to a locational mismatch between FIA plot locations and the OBIA data or if the difference in collection dates between LiDAR and FIA field visits accounts for the differences (or some combination of both). It is likely that the leaf-off nature of the LiDAR data is at least partly to blame, particularly in deciduous forests where the morphological profile of the trees (tall, thin, with few branches) results in relatively few LiDAR returns with the 0.6- to 1.4-m post spacing. FIA currently has no information on tree heights on nonforest plots. Based on the OBIA data, nonforest plots have trees ranging from 10 to 60 feet in height (Fig. 2), information not available from the FIA photointerpreted data for nonforest plots.

The OBIA data provide information on tree canopy cover and stand (mean tree) heights for all plots. From this information we can summarize characteristics for both forest and nonforest plots for these six counties. For example, in Lancaster County, the average canopy cover for the entire county is 23 percent, with an average height of 17 feet. Breaking this down, we find that the averages are 68 percent canopy cover and 37 feet high for forested plots, and 12 percent canopy cover and 12 feet high for nonforest plots. For a county that is 85 percent nonforest, this represents considerable tree canopy cover for which very little FIA data exist. Table 1 presents this information for six counties.

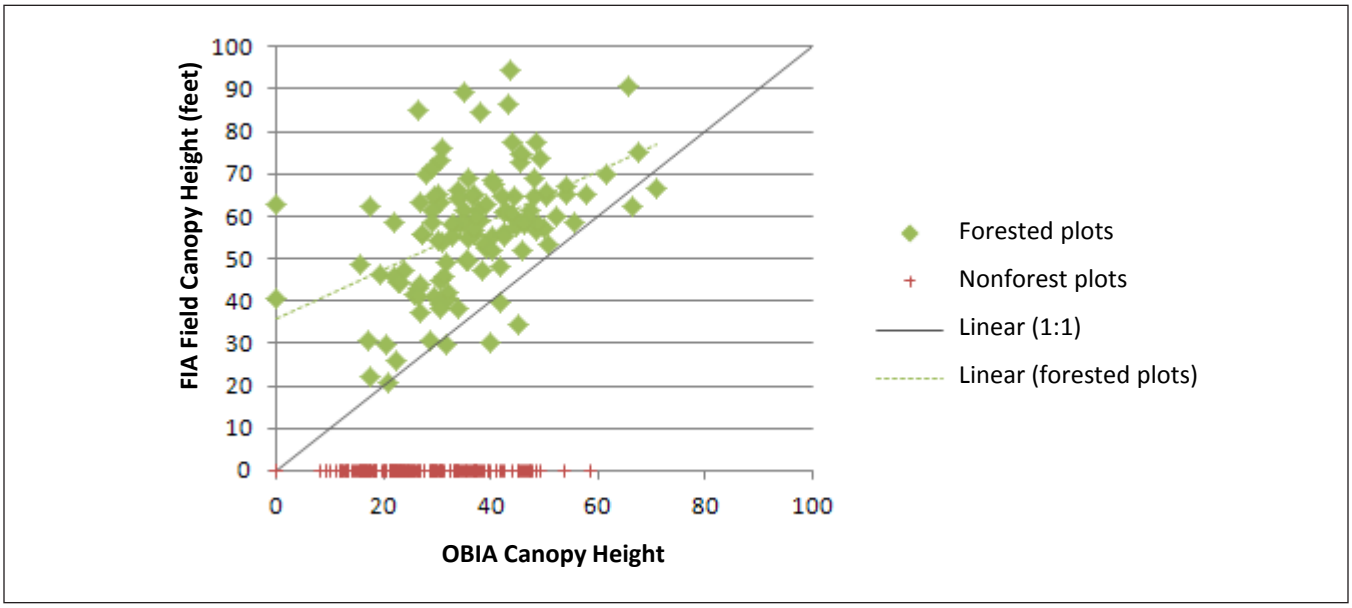


Figure 2.—Comparison of OBIA-based canopy height information with FIA canopy height information. OBIA-based heights are derived from a LiDAR point cloud while FIA height information is obtained using field methodology.

Table 1.—Summary of tree canopy cover and canopy height statistics for forest vs. nonforest plots from the OBIA data

	Percent Canopy Cover						Canopy Height					
	All Plots		Forested Plots		Nonforest Plots		All Plots		Forested Plots		Nonforest Plots	
County	Mean	SE (n)	Mean	SE (n)	Mean	SE (n)	Mean	SE (n)	Mean	SE (n)	Mean	SE (n)
Anne Arundel	49	5.3 (41)	76	7.1 (13)	36	5.5 (28)	33	2.6 (41)	45	3.1 (13)	28	2.9 (28)
Montgomery	46	4.8 (53)	75	4.7 (22)	26	4.9 (31)	25	3.3	31	5.5	20	1.4
Prince Georges	51	5.3 (53)	83	19.0 (19)	33	5.6 (34)	33	2.6	46	10.6	25	4.3
Allegheny	49	3.5 (84)	68	5.0 (37)	34	3.7 (47)	28	1.2	33	1.8	24	1.4
Lancaster	23	3.1 (107)	68	6.7 (20)	12	2.3 (85)	17	1.6	37	2.8	12	1.5
Howard	54	6.6 (28)	79	8.0 (11)	38	7.2 (17)	33	2.1	40	1.9	28	2.7

The OBIA datasets also provide information on the land cover context or neighborhood in which the plot occurs. This context can be important to understanding the status of an individual plot. For example, plots in the study area with relatively low canopy cover within the 1.5-acre circle were found to have substantially more canopy cover within the larger 776-acre circle (Fig. 3). And plots with 100 percent canopy cover within the 1.5-acre circle were found to contain other land uses within the larger 776-acre context area.

DISCUSSION AND CONCLUSIONS

The OBIA datasets offer several opportunities. First, the OBIA datasets provide an alternative assessment of the photointerpreted and field-collected tree canopy cover values. Second, it is an opportunity to provide consistent tree canopy cover information for both visited and non-visited plots at a scale relevant to the FIA plot data without additionally impacting the FIA prefield process. As can be seen in Table 1, the magnitude of tree canopy cover in nonforest areas supports the need to gather this information, whether via prefield interpretation or the OBIA approach. Third, the OBIA datasets offer an opportunity to gather canopy height information on all plots, not just those visited in the field. Finally, and equally importantly, these datasets can provide landscape context information important for understanding local urbanization pressures for each FIA plot at a scale and accuracy not possible from NLCD data sources and with an efficiency not possible from photointerpretation. The OBIA data provide information about the larger neighborhood and therefore can show us how well the FIA plot is representative of its surrounding area.

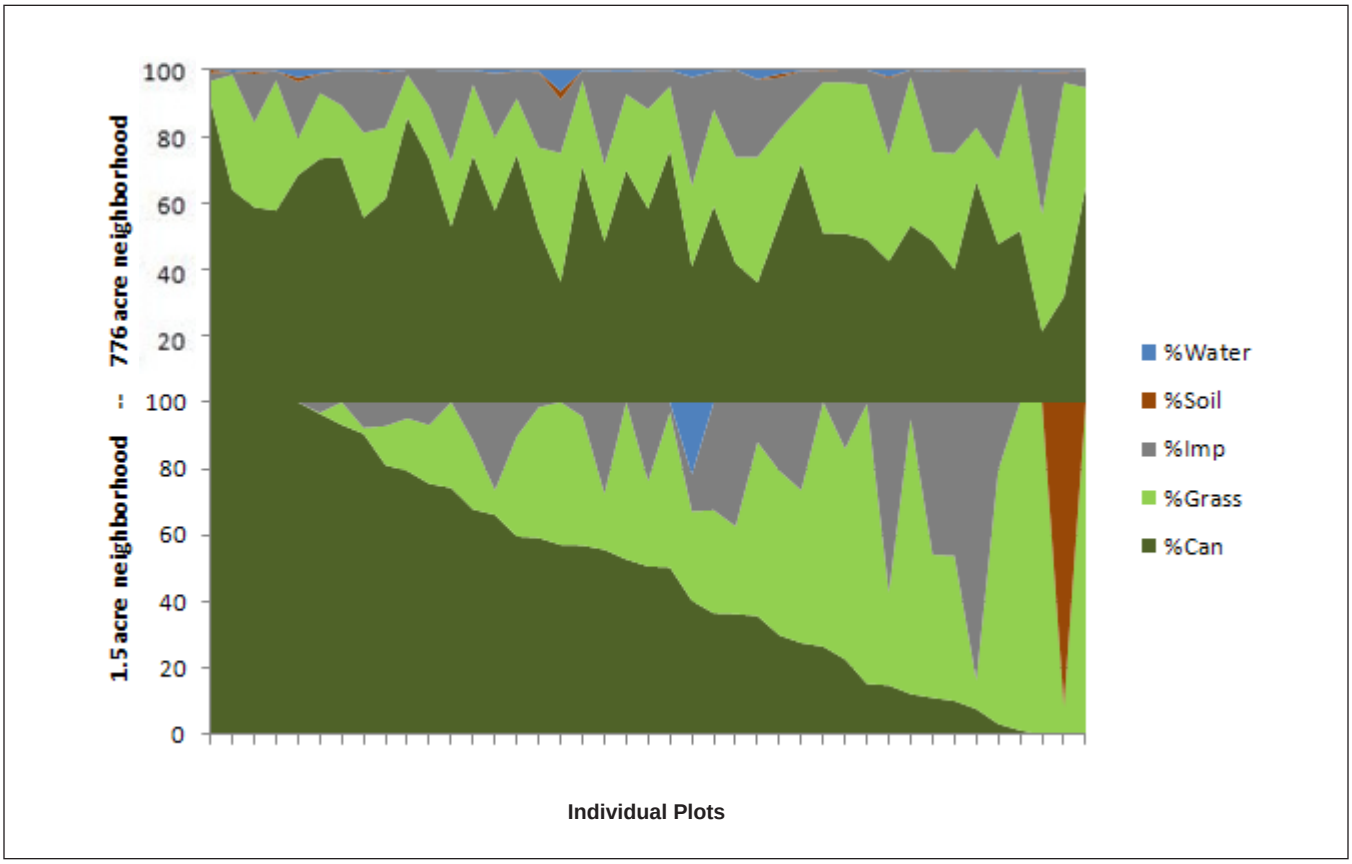


Figure 3.—Summary of the land cover context around individual plots in Anne Arundel County at two scales. Plots are sorted by the proportion of canopy cover present within the 144-foot- radius area.

OBIA approaches to land cover and FIA metric extraction have been shown to be efficient when applied to large datasets, providing those datasets have somewhat consistent properties. Although OBIA systems require a great deal of expertise to design and deploy, they are cost effective over large areas due to economies of scale. Furthermore, in addition to computing plot metrics, the OBIA approach provides a means by which to conduct a complete census, which is increasingly important as development pressures stemming from urbanization and natural resource exploitation fragment the forested landscape. The greatest barrier to the OBIA approach is the availability of data. Although NAIP data are acquired for each state aside from Alaska at least every 3 years, there is no nationally coordinated LiDAR program. For states that do have comprehensive coverage, the LiDAR data are typically available for only a single point in time and are frequently leaf-off to create terrain DEMs. The approach used in this study allowed us to take advantage of leaf-off LiDAR for estimating tree canopy cover and height to generate data comparable to current FIA estimates.

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The content of this paper reflects the views of the author(s), who are responsible for the facts and accuracy of the information presented herein.

CANOPY COVER ESTIMATES FOR INDIVIDUAL TREE ATTRIBUTES

James A. Westfall and Randall S. Morin[1]

Abstract.—In most forest inventory data, it is not feasible to estimate the canopy coverage of trees having certain characteristics due to the lack of information on crown size. In this study, data from the Forest Inventory and Analysis (FIA) program was used to assign crown sizes to individual trees using published crown width models. This process effectively links trees to area such that canopy cover area estimates can be made using domains that include tree-level attributes (e.g., canopy cover of red maple having total height ≥80 feet). Advantages of implementing this approach are 1) estimation can proceed as with any other estimate of area derived from FIA data, and 2) canopy cover estimates provide different information than classical indicators such as number of trees. A disadvantage is the need to dissolve overlapping crowns after the tree-level domain is selected. Two examples are provided to illustrate applications of the method.

INTRODUCTION

Tree canopy cover is the proportion of an area covered by the vertical projection of tree crowns (Jennings et al. 1999). Canopy cover plays a critical role in defining current and future forest characteristics via impacts on understory species composition and structure (Canham et al. 1990). Canopy cover is often a primary indicator of wildfire risk and behavior of both modeled and actual wildfires (Agee and Skinner 2005). Additionally, amounts and types of canopy cover and structure influence habitat suitability for many forest-dwelling vertebrate species (Massé and Côté 2009). A key factor in studies of the aforementioned relationships between canopy cover and forest-related phenomena is that relevant analyses often focus on specific aspects of canopy cover, e.g., cover of trees having certain characteristics such as species, diameter at breast-height (d.b.h.), and total height (Abrahamson and Gohn 2004). Thus, expansion of research results to landscape-scale assessments can be difficult.

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Area coverage estimates for tree-level attributes are usually not feasible from forest inventory data due to the lack of information on how much area is represented by an individual tree. Alternatively, the area occupied by each inventory tree can be approximated from the plot data using techniques such as Thiessen polygons or crown width models (Bechtold 2003). Applying crown width models to forest inventory data with mapped tree locations allows for spatial representation of canopy cover while also allowing for gaps between trees. Because the crown width approach is specific to individual trees, there is an explicit relationship that links area coverage to tree-level attributes. In this paper, we present methodology to estimate the area coverage of virtually any tree-level attribute(s) available in forest inventory data.

METHODS

A three-phase forest inventory and monitoring effort is implemented by the Forest Inventory and Analysis (FIA) program within the U.S. Forest Service (Bechtold and Patterson 2005). Phase 1 (P1) is the development of a post-stratification scheme using remotely-sensed data. The second phase (P2) entails

measuring sample plots on the ground for the usual suite of forest mensuration variables such as tree species, d.b.h., height, forest type, stand age, etc. Overstory trees (d.b.h. ≥5.0 in.) are measured on four 24-ft radius subplots; saplings (1.0 ≤ d.b.h. ≤ 4.9 in.) are recorded on four microplots of 6.8-ft radius each. Phase 3 (P3) occurs on a subset of the P2 plots, where additional data on forest health indicators are collected (e.g., down woody material). To evaluate the efficacy of the methods presented below, one full cycle of data from Pennsylvania was used (data collected between 2006 and 2010).

To estimate the amount of canopy cover for each tree measured in the inventory, the crown width models described by Bechtold (2003) were used. When species were encountered that were not listed in Bechtold (2003), coefficients for species of similar form were used. For this analysis, the model using d.b.h. and crown ratio as input variables was used.

[1] $$\hat{CW} = \hat{\beta}_0 + \hat{\beta}_1 D + \hat{\beta}_2 D^2 + \hat{\beta}_3 CR$$

where: $\hat{CW}$ = estimated crown width (feet)
D = d.b.h. (inches)
CR = crown ratio
$\hat{\beta}_{0\text{-}3}$ = species-specific coefficients

Spatial representation of plot canopy cover was accomplished by centering circles of estimated crown width at the tree location recorded during the plot visit. To assess cover of overstory trees (d.b.h. 5.0+ inches), overlapping crowns from neighboring trees were combined such that crown overlap was accounted for, i.e., the cover as it would appear as viewed from above. A geographic information system (GIS) was employed to dissolve the boundaries between individual tree crowns in order to create polygons of non-overlapping crown cover for each FIA plot condition (Fig. 1). A key point in the analytical method is that crowns extending beyond the sample plot boundary are included in the total canopy cover for the plot. It is surmised that, on average, this will account for crown areas of nonsampled trees extending into the plot that are not explicitly accounted for.

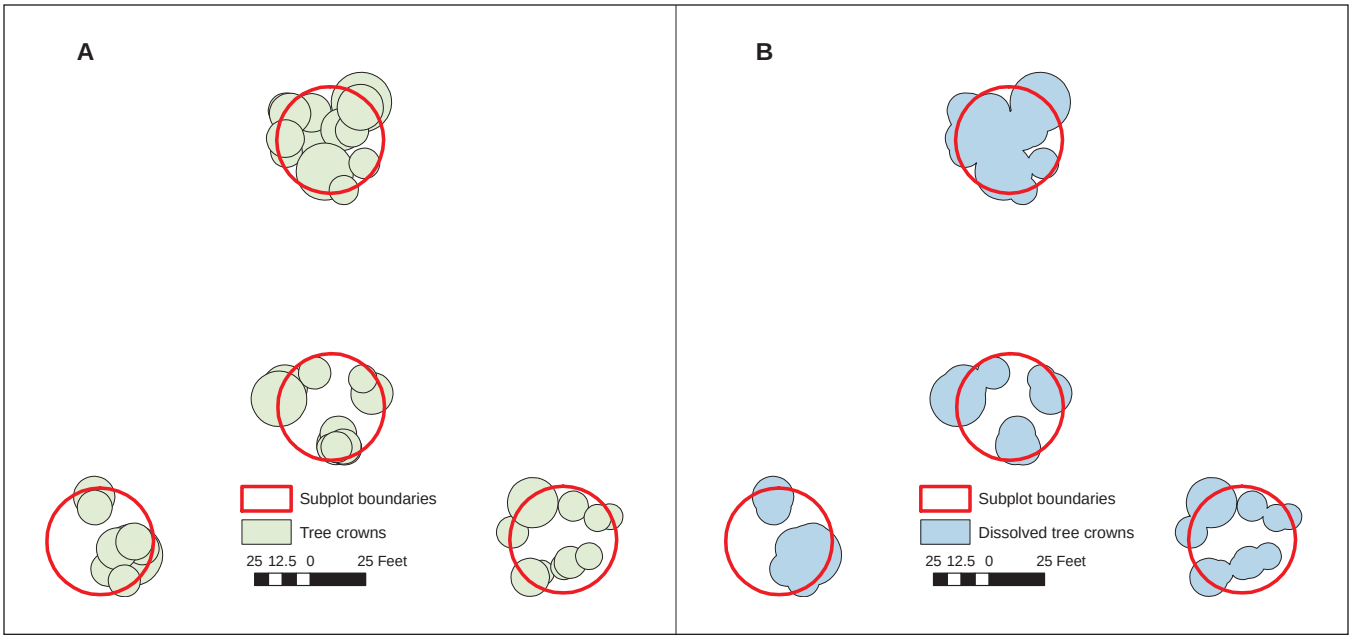


Figure 1.—Maps of (A) individual tree crowns on an FIA plot, and (B) dissolved polygons of crown cover on an FIA plot.

While the models presented by Bechtold (2003) were fitted to subplot trees (d.b.h. ≥5.0 in.), these same models were used to quantify sapling (d.b.h. 1.0 to 4.9 inches) crown cover on the microplot area. At this point, there are estimates of overstory and sapling tree cover on forested portions of subplots and microplots, respectively. These cannot simply be summed to obtain the total cover as 1) overstory trees may partially/wholly obscure sapling cover, and 2) the overstory and sapling cover estimates are on a different area basis. To reconcile total cover at the subplot level, the amount of overstory cover for trees whose stems occur within the microplot was calculated. Also, the amount of sapling cover remaining visible once overstory trees were accounted for was quantified. This was accomplished by using GIS to remove the sapling cover that had microplot tree crown cover growing above (Fig. 2). The ratio of remaining sapling cover to overstory microplot cover was used to estimate the amount of sapling cover that would be visible if saplings were measured over the entire subplot area—producing an estimate of cover for all trees and saplings combined. Due to the use of crown area occurring outside plot boundaries and the method of estimating the contribution of saplings, the area of crown cover exceeded the forested area of the subplot in some cases. When this phenomenon occurred, the cover estimate was constrained to the forested area. As the plot is the primary sampling unit, plot-level cover estimates were obtained by summing over subplots.

Under standard FIA protocols, the total height of saplings is measured only on P3 plots. To facilitate analyses related to vertical structure, tree heights for saplings on non-P3 plots were predicted from linear models developed using observed sapling height data obtained on P3 plots. Due to the relatively small amount of model fitting data available, coefficients were estimated for hardwood and softwood species categories (Table 1).

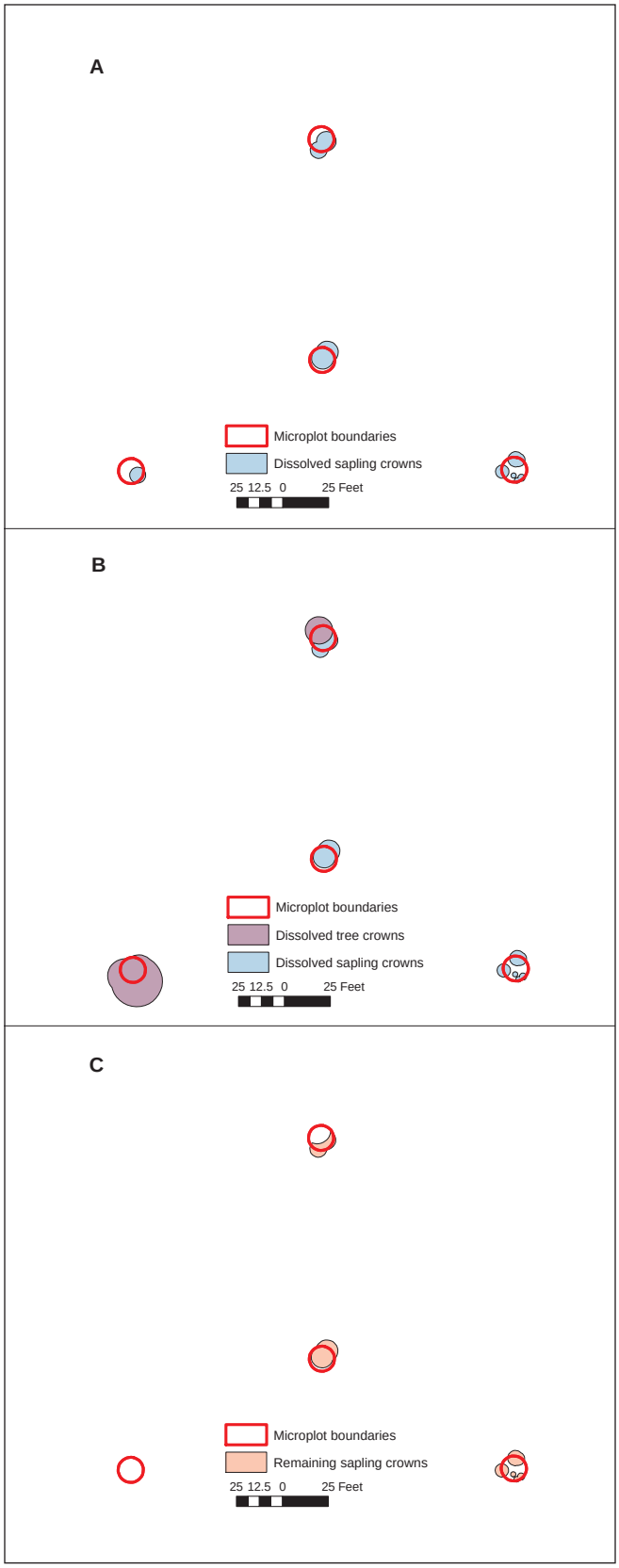


Figure 2.—Maps of (A) dissolved polygons of sapling crown cover on an FIA plot, (B) microplot tree cover above sapling cover, and (C) sapling cover remaining after tree cover is accounted for.

Table 1.—Linear regression analysis results for equation [2] by major species group. RMSE is the square-root of mean squared error.

Species Group	n	$\hat{\theta}_0$ (Std. Error)	$\hat{\theta}_1$ (Std. Error)	R^2	RMSE
Hardwood	1481	9.3057 (0.3424)	5.4529 (0.1332)	0.53	5.7
Softwood	33	2.0837 (1.5163)	5.3902 (0.5501)	0.76	3.4

[2] $$\hat{H}_S = \hat{\theta}_0 + \hat{\theta}_1 D$$

where: $\hat{H}_S$ = estimated sapling height (feet)

D = d.b.h. (inches)

$\hat{\theta}_{0\text{-}1}$ = coefficients estimated from the data

Computation of area of forest land, area of crown cover within forest land, and the proportion of forest land area having canopy cover was accomplished using the standard FIA methods documented in Scott et al. (2005).

Two example analyses are presented to illustrate the utility of the method for assessing contemporary forestry issues like forest health and wildlife habitat. First, beech bark disease kills or injures American beech (*Fagus grandifolia* Ehrh.). The estimated tree cover susceptible to the disease was estimated for trees of 8.0 inches d.b.h. and larger, as these are the most susceptible to mortality (Houston and O'Brien 1983). The second example assesses habitat availability for the cerulean warbler (*Dendroica cerulean*). Jones and Robertson (2001) found that successful nesting of cerulean warblers most often occurred where crown cover occurred at 19.7 to 39.4 feet with additional high cover above 59.1 feet. In the absence of crown shape models, estimates of canopy area were calculated for trees having height of 19.7 to 39.4 feet when there also existed at least one tree having height of 59.1 feet or greater on the same subplot.

RESULTS

A preliminary analysis was conducted to estimate the proportion of forest area in Pennsylvania having tree cover. The area of forest land was estimated to be 16,482,968.6 acres with a standard error (SE) of 156,471.9 acres. The estimated area of tree cover was 14,821,653.7 acres (SE = 150,823.1) (Table 2). The resultant proportion $\hat{R}$ was 0.899 (SE = 0.007). The roughly 10 percent of forest land area without tree cover is due to gaps between tree canopies (9.0 percent), with a modest contribution (1.0 percent) from forested areas having no tree or sapling cover (e.g., areas only having seedlings).

Table 2.—Estimates with standard errors (SE) for area (acres) and proportion of all forested canopy cover ($\hat{R}$)

Attribute	Area	(SE)	$\hat{R}$	(SE)
Total canopy cover	14,821,653.7	(150,823.1)	0.899	(0.007)
Beech bark disease	422,893.6	(25,637.3)	0.029	(0.002)
Cerulean warbler habitat	4,149,383.5	(91,977.7)	0.280	(0.005)

The canopy cover of American beech having d.b.h. 8.0 inches and larger was estimated to be 422,893.6 acres (SE = 25,637.3). While this area estimate is informative, it is also useful to assess this area in context of total canopy cover. The corresponding proportion of existing canopy cover this area represents is 422,893.6/14,821,653.7 = 0.0285 (SE = 0.0017). Thus, approximately 3 percent of the canopy cover in Pennsylvania is potentially at risk due to beech bark disease.

Using the criteria outlined above for cerulean warbler habitat, the estimated area of canopy cover was 4,149,383.5 acres (SE = 91,977.7). Put in the context of total canopy cover, the proportion of area containing desirable conditions for cerulean warbler is 4,149,383.5 /14,821,653.7 = 0.2800 (SE = 0.0054). This outcome suggests that more than one-fourth of forest land area having canopy cover in Pennsylvania may be suitable for cerulean warbler.

DISCUSSION

Estimates of canopy cover provide a different viewpoint than classical indicators such as forest land area or numbers of trees. An example is the difference between area of forest land and area of forest land with canopy cover. At first glance, one may assume that all forest has canopy cover. However, this study has shown there to be an approximate 10 percent difference in these two characteristics. Starker contrasts are seen when comparing different metrics for identical domains of tree variables. FIA estimates for number of American beech trees having d.b.h. ≥8.0 inches as a proportion of all trees is 0.0056. The proportion of canopy cover is roughly five times larger than the proportion of trees (0.0285).

Forest managers should consider adding canopy cover area to their portfolio of analytical metrics. Canopy estimates provide new information that has largely been unavailable in the past and may suggest alternative management strategies. The individual tree crown size predictions can be added to most existing forest inventory data and estimation can proceed in a manner similar to other estimates such as area by forest type, stand size, etc. A disadvantage is this method is not easily implementable in standard analytical tools such as FIA's FIDO or EVALIDator software. This is due to the need to perform the dissolution of overlapping crowns, which must be accomplished after specification of the domain of interest. This exercise takes approximately 5 to 15 minutes, depending on the number of trees in the domain. However, the additional effort may be worthwhile in cases where canopy cover is of particular importance.

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RELATING FIA DATA TO HABITAT CLASSIFICATIONS VIA TREE-BASED MODELS OF CANOPY COVER

Mark D. Nelson, Brian G. Tavernia, Chris Toney, and Brian F. Walters[1]

Abstract.—Wildlife species-habitat matrices are used to relate lists of species with abundance of their habitats. The Forest Inventory and Analysis Program provides data on forest composition and structure, but these attributes may not correspond directly with definitions of wildlife habitats. We used FIA tree data and tree crown diameter models to estimate canopy cover, from which we assigned FIA conditions to NatureServe forest and woodland habitat domains and National Land Cover Dataset (NLCD) forest classes within the 20-state northern FIA region. Hardwood and softwood types were most abundant for FIA, least abundant for NLCD, and intermediate for NatureServe classes. NatureServe hardwood types were evenly distributed between forest and woodland, but softwood types were more abundant in NatureServe woodland than forest. Mixed types were substantially more abundant for NLCD, intermediate for NatureServe (equally distributed between forest and woodland), and least abundant for FIA. Area of woody wetlands, which were defined only for NLCD, exceeded area of NLCD softwoods. These habitat assignments are useful for estimating current and potential future abundance of habitats for forest-associated terrestrial vertebrate wildlife species in the region.

INTRODUCTION

Strategic estimates of wildlife habitat abundance can be obtained from forest composition and structure data provided by the Forest Inventory and Analysis (FIA) Program (Woudenberg et al. 2010). FIA data spanning several decades are easily queried to estimate status and trends of coarse-scale habitat characteristics, like area of young hardwood forest or old softwood forest. However, FIA attributes are not directly relatable to wildlife species-habitat matrices, such as those developed by NatureServe (2011). Furthermore, spatially explicit landscape metrics are required for assessing habitat quality for many wildlife species but are not available directly from FIA plot data. Landscape metrics typically are obtained from ancillary geospatial datasets such as the National Land Cover Database of 2006 (NLCD) (Fry et al. 2011), but NLCD forest classes are defined differently from FIA forest types. There is an opportunity for increasing the utility of FIA data by relating it to species-habitat relationships and to ancillary datasets used for assessing habitats.

Tree canopy cover thresholds are used to characterize NatureServe forest and woodland habitat domains and NLCD forest land cover classes, but historical and current FIA data do not include estimates of tree canopy cover. Therefore, we adapted a procedure described by Toney et al. (2009) to estimate tree canopy cover from FIA tree data, which we used to assign NatureServe and NLCD classes to conditions in the FIA Database (FIADB; Woudenberg et al. 2010). The NatureServe system defines canopy cover thresholds that separate forest from woodland, with subcategories of hardwood, conifer, and mixed

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classes, resulting in six habitat types (Table 1). Similarly, NLCD forest land cover is separated into deciduous, evergreen, and mixed forest classes based on canopy cover thresholds. Canopy cover thresholds for NatureServe and NLCD differ from one another. NLCD's woody wetland class was included in this study as an additional forest class, but is not based upon a canopy cover threshold (Table 2).

Table 1.—NatureServe habitat domains (adapted from NatureServe 2011)

Code	Habitat Domain	Description
0	No data	
	Forest	Woody vegetation at least 6 m tall (usually much taller) with a fairly continuous and complete (two-thirds or greater) canopy closure.
1	Forest-Hardwood	Angiosperms comprise over two-thirds of the canopy.
2	Forest-Conifer	Gymnosperms comprise over two-thirds of the canopy.
3	Forest-Mixed	Composed of both hardwood and conifer trees, neither dominating as much as two-thirds of the canopy.
	Woodland	Crowns often not interlocking; tree canopy discontinuous (often clumped), averaging between 40 and 66 percent overall cover [Modified to include tree canopy between 10 and 40 percent (Savanna), per recommendations from NatureServe.]
4	Woodland-Hardwood	Angiosperms comprise over two-thirds of the canopy.
5	Woodland-Conifer	Gymnosperms comprise over two-thirds of the canopy.
6	Woodland-Mixed	Stand composed of both hardwood and conifer trees, neither dominating as much as two-thirds of the canopy.
--	Savanna	Mosaic of trees or shrubs and grassland; between 10 and 40 percent cover by trees and shrubs.

Table 2.—National Land Cover Dataset (2006) forest cover classes (adapted from NatureServe 2011)

Code	Land Cover Class	Description
0	No data	
41	Deciduous Forest	Areas dominated by trees generally greater than 5 m tall, and greater than 20 percent of total vegetation cover. More than 75 percent of the tree species shed foliage simultaneously in response to seasonal change.
42	Evergreen Forest	Areas dominated by trees generally greater than 5 m tall, and greater than 20 percent of total vegetation cover. More than 75 percent of the tree species maintain their leaves all year. Canopy is never without green foliage.
43	Mixed Forest	Areas dominated by trees generally greater than 5 m tall, and greater than 20 percent of total vegetation cover. Neither deciduous nor evergreen species are greater than 75 percent of total tree cover.
90	Woody Wetlands	Areas where forest or shrub land vegetation accounts for greater than 20 percent of vegetative cover and the soil or substrate is periodically saturated with or covered with water.

DATA AND METHODS

A canopy cover modeling approach (Toney et al. 2009) was used to estimate canopy cover for trees (≥ 5 inches d.b.h., on subplots), if present, or saplings (1 to 4.9 inches d.b.h., on microplots) on forested FIA conditions within 20 states of the Upper Midwest and Northeast, during the inventory period 2004-2008. These states include Connecticut, Delaware, Illinois, Indiana, Iowa, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Vermont, Wisconsin, and West Virginia. FIA forest land is defined as having "…at least 10 percent cover (or equivalent stocking) by live trees of any size, including land that formerly had such tree cover and that will be naturally or artificially regenerated" (Woudenberg et al. 2010).

Canopy cover estimation was based on tree species-specific predicted crown dimensions, and tree stem location coordinates recorded by field crews within FIA subplots and microplots. Tree and sapling crown width predictions are based on Bechtold (2003) and Bragg (2001). An optional spatial statistic (Ripley's K) included as a predictor in Toney et al. (2009) was not used for canopy cover modeling in the present study. Because FIA plots may contain multiple conditions, tree and sapling canopy cover estimates were weighted based on condition proportion and appended to the CONDITION table in a Microsoft Access database.

All forested conditions with more than 0 percent estimated canopy cover were assigned a NatureServe forest or woodland habitat type and an NLCD forest land cover class using tree or sapling canopy cover thresholds defined in Tables 1 and 2, respectively, with minor modifications. NatureServe wildlife habitat categories are distinct from those developed by NatureServe and others for the U.S. National Vegetation Classification (FGDC 2008). That classification defines a "Forest to Open Woodland" class that includes all forest stands with tree canopy cover >10 percent, including stands where the sapling layer is the dominant layer (e.g., regenerating stands) (Faber-Langendoen et al. 2012). Conditions with canopy cover below the minimum thresholds in Tables 1 and 2 were assigned to NatureServe woodland or NLCD forest class, respectively. Canopy cover between 10 and 40 percent is defined as "Savanna" in NatureServe's habitat domains (Table 1), but was grouped with woodland in this study because sparse canopy cover in this region is predominately associated with young/regenerating woodland or forest (NatureServe, personal communication).

A small number of forested FIA conditions contained no trees or saplings. Thus, no canopy cover estimates were available for these conditions, and canopy cover could not be used to assign habitat or land cover classes to those conditions. During a plot visit, a field crew can look beyond subplot boundaries to determine some condition attributes via visual interpretation, including those conditions containing no trees at the time of field data collection. For conditions with no trees or saplings (i.e., estimated canopy cover = 0), habitat and land cover classes were recoded to valid classes using other FIA condition attributes, including ALSTKCD–"a code indicating the stocking of the condition by live trees, including seedlings"; FORTYPCD–"the forest type used for reported purposes, primarily derived using a computer algorithm, except when less than 25 percent of the plot samples a particular forest condition"; and PHYSCLCD–"the general effect of landform, topographical position, and soil on moisture available to trees" (Woudenberg et al. 2010).

NatureServe:
If ALSTKCD = 5 (nonstocked), then assign condition to "0".
Else, if ALSTKCD = 4 (poorly stocked, 10-34 percent), assign to "Woodland".
if FORTYPCD is between 500 and 998, assign to code "Woodland Hardwood". (4)
if FORTYPCD <400, assign to code "Woodland Conifer". (5)
if FORTYPCD is between 400 and 499, assign to code "Woodland Mixed". (6)

Else, if ALSTKCD is between 1 and 3 (overstocked, fully stocked, medium stocked; 35-100+ percent), assign to "Forest".
if FORTYPCD is between 500 and 998, assign to code "Forest Hardwood". (1)
if FORTYPCD <400, assign to code "Forest Conifer". (2)
if FORTYPCD is between 400 and 499, assign to code "Forest Mixed". (3)

NLCD2006:
If PHYSCLCD is between 30 and 39 (hydric site), assign to code "90" (Woody Wetlands).
Else, if ALSTKCD = 5 (nonstocked), then assign condition to "0".
Else, if FORTYPCD is between 500 and 998, assign to code "41" (Deciduous Forest).
if FORTYPCD <400, assign to code "42" (Evergreen Forest).
if FORTYPCD is between 400 and 499, assign to code "43" (Mixed Forest).

An attribute was added to the Access database CONDITION table to record which method was used to determine the NatureServe and NLCD condition assignment: 1 = tree canopy cover, 2 = sapling canopy cover, 0 = other FIA condition attributes. FIA's PC-EVALIDator tool was revised to include NatureServe and NLCD categories as row and column variables. PC-EVALIDator was used to estimate forest land area for NatureServe forest and woodland classes, NLCD forest and woody wetland land cover classes, and FIA forest type group aggregations-softwoods (100-390), mixed (400), and hardwoods (500-990) (Fig. 1). Different class names have similar, but not identical, meaning among FIA, NatureServe, and NLCD (i.e., softwood/conifer/evergreen, hardwood/hardwood/deciduous, respectively); we used FIA's terminology for labeling comparisons.

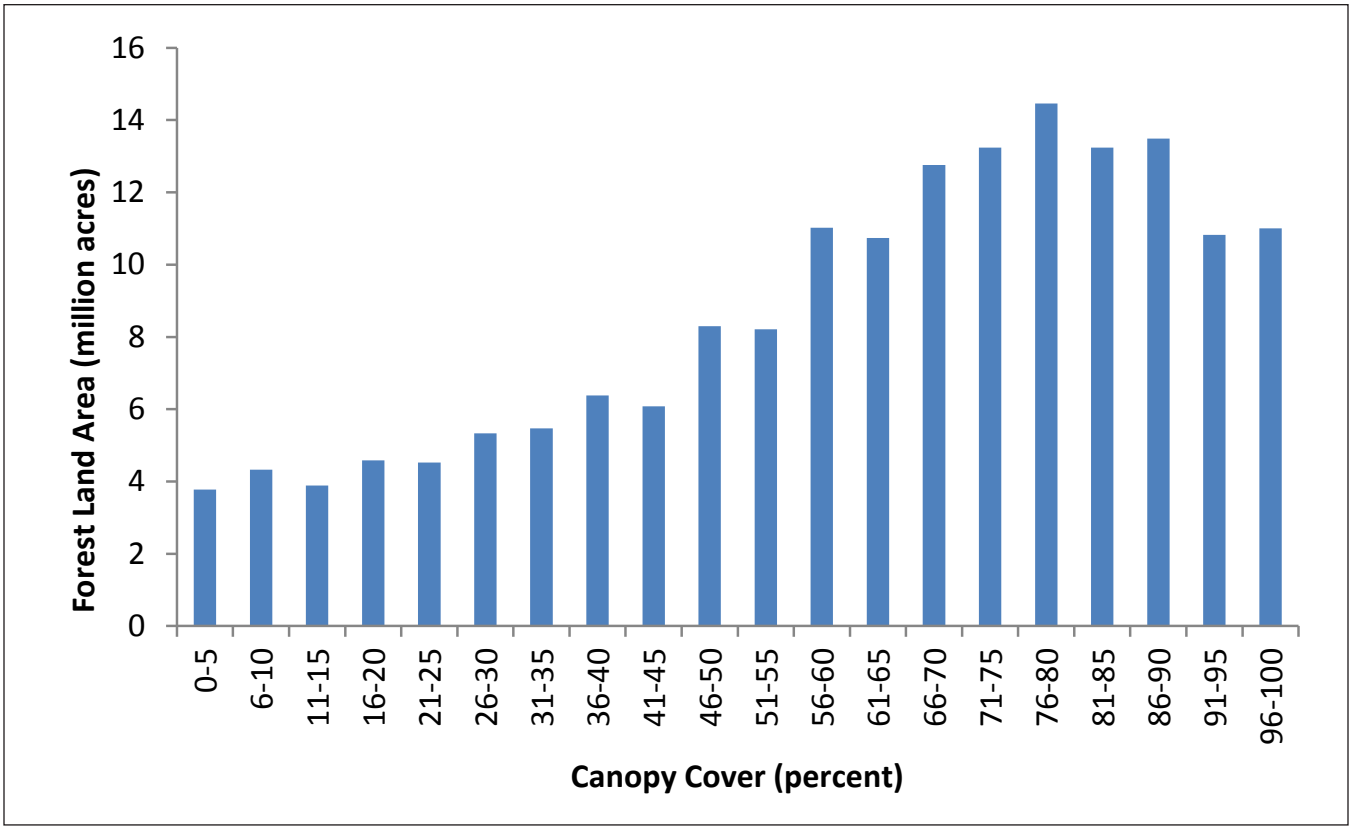


Figure 1.—Canopy cover distribution on FIA forested conditions, 2004-2008, Midwest and Northeast.

RESULTS

Figure 1 portrays the distribution of predicted canopy cover across the region. Because all FIA forested conditions were assigned labels, total area was essentially equivalent across all three classification systems (Fig. 2). Canopy cover of 0 to 10 percent was estimated for 4.7 percent of all forest land, most of which was defined as nonstocked. Hardwood and softwood types were most abundant for FIA, least abundant for NLCD, and intermediate for NatureServe. NatureServe hardwood types were evenly distributed between forest and woodland, but softwood types were more abundant in NatureServe woodland than forest. Mixed types were substantially more abundant for NLCD, intermediate for NatureServe (equally distributed between forest and woodland), and least abundant for FIA. Woody wetlands were defined only for NLCD; total area of NLCD woody wetlands exceeded NLCD softwoods (Fig. 2). No statistical validations were performed for this study.

DISCUSSION AND CONCLUSION

The method presented here provides an operational approach to predicting per condition tree canopy cover from FIA tree data. The resulting classifications were used to assign FIA conditions to NatureServe forest and woodland habitat domains and NLCD forest land cover classes, for which population estimates were produced. Although FIA's forest land definition requires a minimum of 10 percent canopy cover, a small area of FIA forest land was characterized by canopy cover below this threshold. Such conditions likely occur shortly after full canopy removal (e.g., harvest, wildfire), but before regenerating seedlings

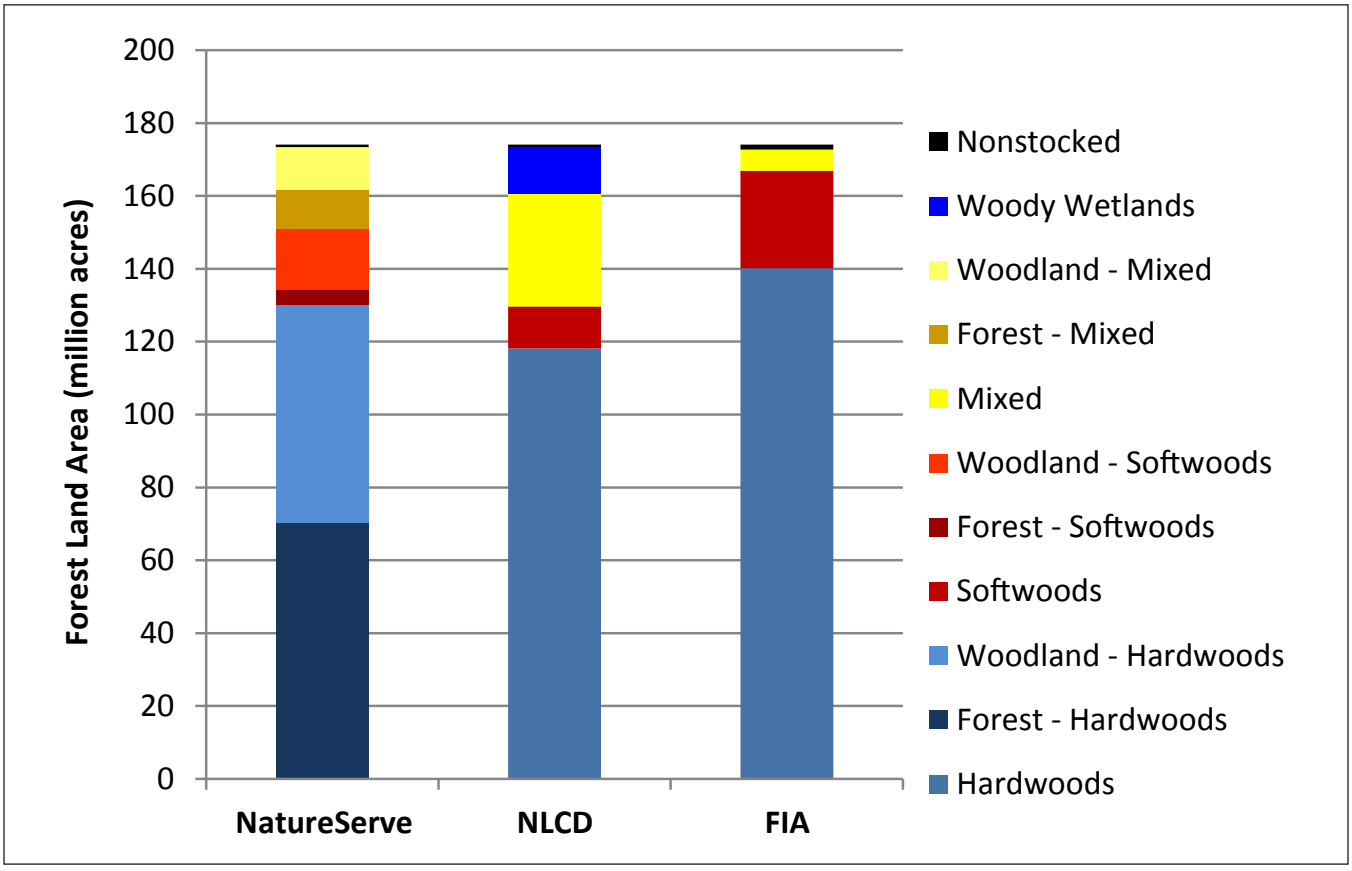


Figure 2.—Forest land area estimates for NatureServe forest and woodland habitat types, NLCD forest and woody wetland land cover types, and FIA aggregations of forest-type groups, 2004-2008, Midwest and Northeast.

have established significant canopy. Tree canopy cover predictions allowed FIA data to be used with wildlife species-habitat matrices and ancillary habitat datasets that are based on canopy cover thresholds. Choice of habitat classification systems can affect resulting estimates of habitat abundance. Resulting assignments of FIA data to NatureServe habitats were used to estimate habitat abundance.

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DENSIOMETERS AND CANOPY DENSITY MEASUREMENTS

Kenneth W. Stolte, Stanley J. Zarnoch, and Robert L. Eaton[1]

Abstract.—The productivity and vitality of forest ecosystems are dependent on the condition of tree canopies. Canopy cover and density are components in estimations of tree growth efficiency, fish and wildlife habitat, urban tree cover, composition of understory vegetation, soil erosion susceptibility, pollutant deposition, and other ecological factors. We found that a simple modification of a convex densiometer with standardized protocols eliminated two of three multiplicative measurement error factors and improved repeatability among observers. We tested this modification using Forest Inventory and Analysis (FIA) plot protocols under three scenarios in three geographical areas of North Carolina. One scenario consisted of 23 North Carolina State University undergraduate forestry students' measurements on three subplots in a pine seed orchard (piedmont geographic area). Another was the evaluation of pre- and post-harvest of 60 plots of loblolly pine in Croatan National Forest (coastal plain geographic area). The third was the adequate number of points on an FIA subplot to measure canopy density on two FIA subplots in each of eight long-term vegetation monitoring plots in pine and mixed-hardwood forests at Coweeta Experimental Forest (mountainous geographic area). We found that the variance components due to persons, points on subplots, and azimuth position of points was 5.3, 34.3, and 60.3 percent, respectively, indicating observer differences were a very small percentage of the overall measurement variance. We observed decrease in average canopy density from 90 percent to 64 percent in 60 plots at Croatan NF following an average thinning intensity of 42 percent of the number of trees in all plots. This shows the modified densiometer reflects known changes in canopy density. Four of seven sample points tested on FIA subplots were found to be adequate for measurement of canopy density at Coweeta Experimental Forest in western North Carolina. Measurements on only four of the seven points reduces the amount of time needed for data collection. These modifications of a convex densiometer meet criteria for a good indicator: high signal/noise ratio; applicable to large areas of different forest types; directly related to crown condition; and logistically feasible (e.g., weight, cost, time on plot).

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THE PAST, PRESENT, AND FUTURE OF NONNATIVE PLANT MONITORING BY THE FOREST INVENTORY AND ANALYSIS PROGRAM

THE NATIONAL PICTURE OF NONNATIVE PLANTS IN THE UNITED STATES ACCORDING TO FIA DATA

Sonja N. Oswalt and Christopher M. Oswalt[1]

Abstract.—Data collected by the U.S. Forest Service Forest Inventory and Analysis Program was assembled from each region of the United States. Occurrence, measured as the percentage of forested subplots within a county with observed nonnative invasive plant (NNIP) species, was calculated across the continental United States and Hawaii. Each region, and in some cases each state, maintains a specific watch list to constrain monitoring to only the most important NNIP species within a given area. Therefore, occurrence is based on regionally important species and is inconsistent across the United States. NNIP can be found invading forests across all of the United States. Eastern U.S. forests, however, currently exhibit high levels of NNIP occurrence. Major U.S. travel corridors and areas of considerable forest fragmentation that are often coupled with the large human population in the eastern United States can be important drivers of NNIP distributions. Travel corridors are known to play a profound role in the spread and growth of invasive plants. That fact is evident in maps of NNIP species where many major U.S. interstates are apparent. For example, the I-85 corridor from Virginia to Alabama is an area of intense invasive plant abundance. When forests are divided into smaller and smaller parcels (fragmented), the biological diversity of native animals and plants is diminished, water cycles are altered, and often nonnative invasive plants are introduced. This could help explain the high degree of plant invasions in the heavily agriculture dominated landscapes of the middle southern and middle western United States.

INTRODUCTION

Invasive plants in the United States are an expensive problem both economically and environmentally. In their last update on the economic impact of invasive species (plants and other organisms) in the United States, Pimentel et al. (2005) suggest that the cost of prevention and eradication of nonnative invasive plant (NNIP) species in crop, pasture, and forest settings is approximately $27 billion every year. In fact, the cost of combating just the invasive tree *Melaleuca quinquefolia* in the state of Florida was estimated at between $3 and $6 billion dollars in 2005 (Pimentel et al. 2005).

The environmental impacts of nonnative invasive plants are hard to quantify. Many impacts are difficult or impossible to measure in the field or to directly attribute to NNIP because of the relative lack of controlled experiments related to NNIP and the complexity of co-occurring NNIP. For example, most invasion biologists accept that NNIP cause disruptions in the ecological systems they inhabit, whether by directly altering soil chemistry (e.g., Chinese tallowtree [*Triadica sebifera*]) (Bruce et al. 1995, Cameron and Spencer 1989), through competition with native species (e.g., Japanese honeysuckle [*Lonicera japonica*]), or by hindering regeneration in forested settings (e.g., Nepalese browntop [*Microstegium vimineum*]) (Oswalt et al. 2007). However, while widely acknowledged, the environmental costs of those impacts have not been quantified in a consistently applied manner that can

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be scaled up for the nation. Additionally, we are just now beginning to recognize the need for valuation of ecosystem services, biodiversity, and aesthetics, and therefore would be hard-pressed to place a dollar value on the environmental impacts even if we were able to directly measure and sum them nationally. Many of the environmental impacts of NNIP may be secondary and virtually impossible to quantify. For example, the secondary impacts of herbicides used to control NNIP or the secondary impacts of altered regeneration pathways on wildlife species that use affected forests cannot easily be measured.

One step towards a better understanding of the impacts of NNIP at the national level is the task of identifying where invasive species occur on forest land. Monitoring plants known to be potentially invasive in forested environments enables land managers and policymakers to identify "hotspots" where efforts for eradication and control might be concentrated. Monitoring the same species over time can help to identify species that are expanding in extent versus species that have reached a stasis. Monitoring may also help to identify some species that have spread to the point that extirpation could be considered a futile effort, and thus resources can be directed at efforts that might lead to more success. Finally, collecting NNIP data in conjunction with forest inventory data can shed light on the environmental factors contributing to the invasibility of particular sites, as well as allowing for some understanding of the potential relationships between the presence or absence of NNIP and the biodiversity of the site in question.

Given the importance of monitoring NNIP on U.S. forest land, regions in the Forest Inventory and Analysis Program of the U.S. Forest Service have implemented efforts to track NNIP. Previous efforts by individual regions have been unique and specific to those units, thus no consistent method for identifying and tracking NNIP has been applied nationwide (Rudis et al. 2004). Efforts are underway to establish some modicum of consistency in measurement; however, for this paper we use data collected and compiled by each regional office. Our objectives were to map NNIP nationwide and report spatial patterns observed as a result of the compilation and mapping effort. Additionally, we discuss difficulties in evaluating invasive species at a national scale.

METHODS

Data collected by the U.S. Forest Service Forest Inventory and Analysis (FIA) Program were assembled from each region of the United States. Occurrence, measured as the percent of forested subplots within a county with observed NNIP species, was calculated across the continental United States and Hawaii. Each region and, in some cases, each state maintains a specific watch list to constrain monitoring to only the most important NNIP species within a given area. Therefore, occurrence is based on regionally important species and is inconsistently measured across the United States.

The data used in the analysis spans 1999 to 2010, depending on the state and region. Data from the Pacific Northwest were collected from 1999 to 2009, though data from Alaska spans 2004 to 2009 and data from Hawaii were collected in 2010. Data from the Intermountain West spans 1999 to 2009 while northern data were collected from 2007 to 2010 and southern data were collected from 2001 to 2010.

Each region uses a distinct program for collecting invasive species data, though plans are underway to provide a nationally consistent method for future surveys. For this paper, data collection methods differed by region and, in some cases, state. Data were normalized to minimize differences between regions by calculating the number of forested subplots present in a county, the number of forested subplots with at least one invasive species present, and by generating a "percent invaded" statistic so that counties across the country could be compared in a consistent manner. County and regional comparisons are based on visual observations of mapped data. Rudis et al. (2004) describe data collection methods for the

various regions, and specific data collection details are available through the FIA website at http://www.fia.fs.fed.us/library/field-guides-methods-proc/.

RESULTS AND DISCUSSION

The percentage of forested subplots containing one or more NNIP was highest in the North Central, Northeast, and South Central subregions of the United States with invasives affecting 56, 48, and 45 percent of subplots, respectively (Fig. 1). The Intermountain region had the smallest proportion of subplots with NNIP at 5 percent. In general, forested subplots east of the Mississippi River had higher incidences of invasive plant occurrences than those in the western half of the country (Fig. 2).

Concentrations of invasive plants appear in areas dominated by agriculture including the delta region of the Lower Mississippi Valley in Arkansas, Mississippi, and Louisiana, as well as along the I-85 travel corridor from Virginia to Alabama, the bluegrass region of Kentucky, heavily populated areas in the North and Northeast, and the area around Spokane, Washington (Fig. 2). A small concentration occurs along the gulf coast in Texas and Louisiana, which reflects large populations of Chinese tallowtree.

Major U.S. travel corridors and areas of considerable forest fragmentation that are often coupled with the large human population in the eastern United States can be important drivers of NNIP distributions. Travel corridors are known to play a profound role in the

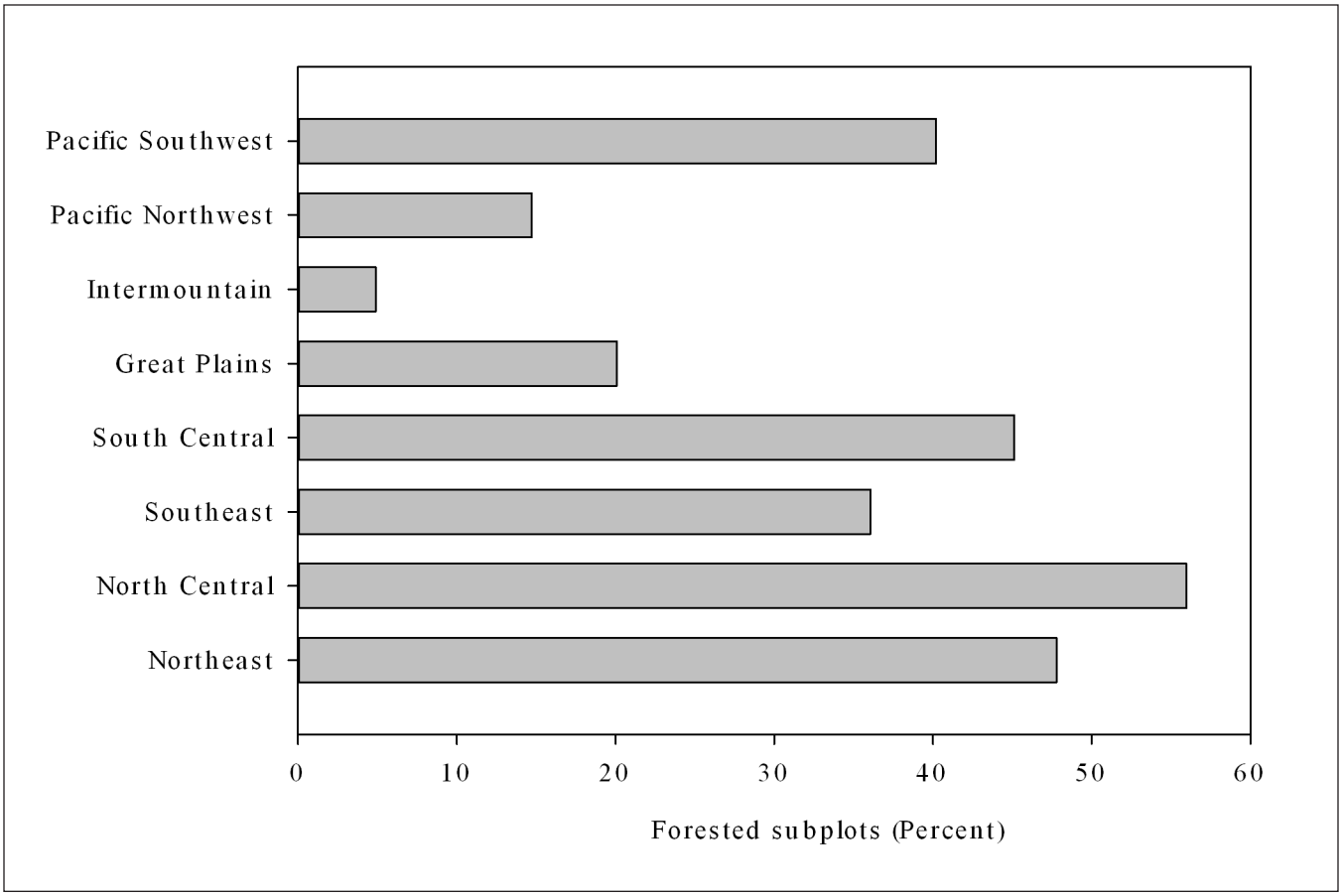


Figure 1.—Percentage of forested subplots containing at least one nonnative invasive plant, by subregion.

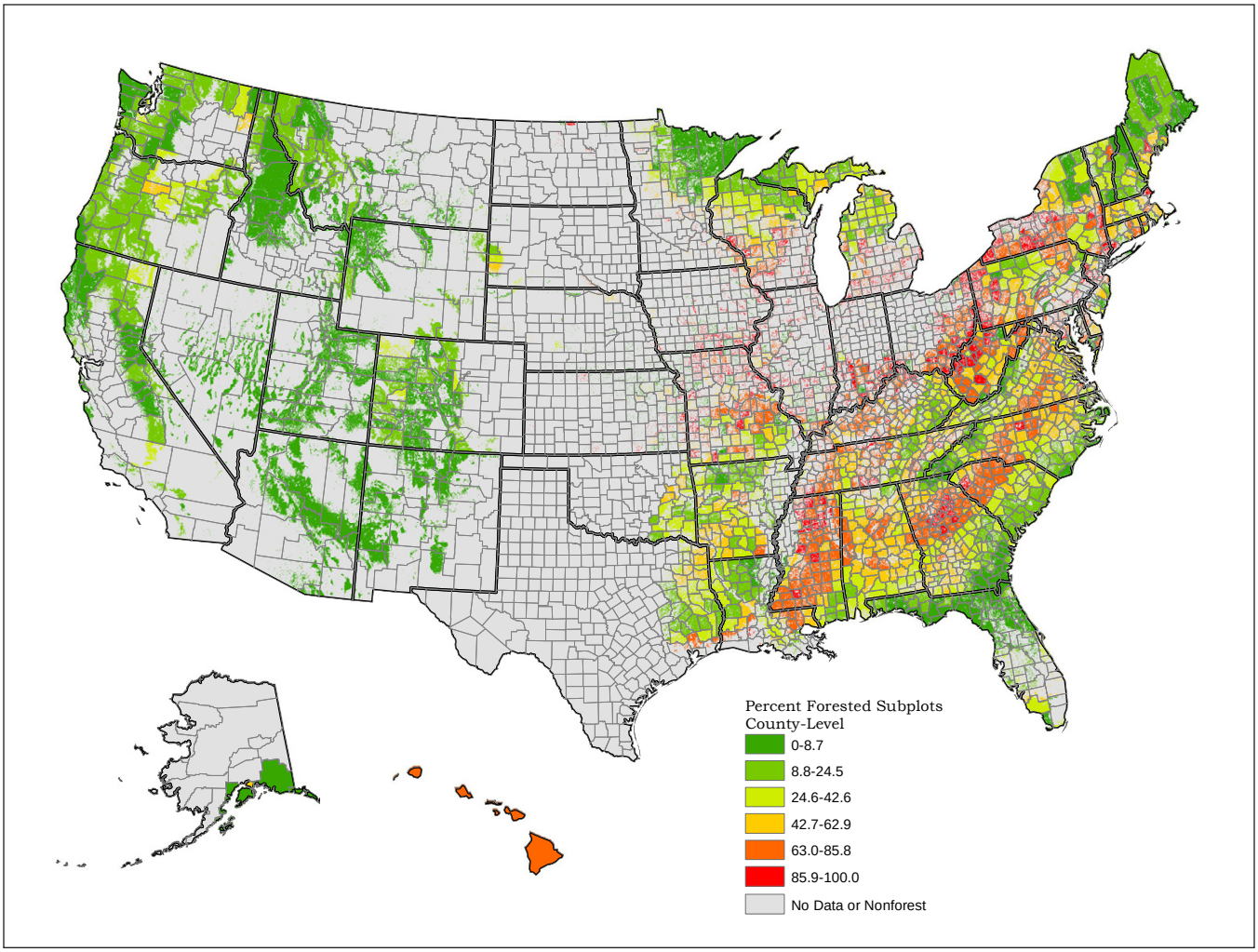


Figure 2.—National map showing percentage of forested subplots with a nonnative invasive plant (NNIP), calculated at the county level. Forest/nonforest mask applied to the contiguous 48 states.

spread and growth of invasive plants. When forests are divided into smaller and smaller parcels (fragmented), the biological diversity of native animals and plants is diminished, water cycles are altered, and often nonnative invasive plants are introduced. This could help explain the high degree of plant invasions in the landscapes of the midsouth and midwest United States that are heavily dominated by agriculture.

In the southern United States, much of the noted occurrence of NNIP on forested land is due to the ubiquitous presence of Japanese honeysuckle and nonnative privets (*Ligustrum* L.), particularly at the forest edge. When Japanese honeysuckle is removed from analysis, the NNIP situation in the south looks far less dire, and hotspots of other species are detectable (Fig 3). In the northern region, the presence of nonnative roses (*Rosa* spp.) accounts for much of the widespread invasion. In the Pacific Northwest, cheatgrass (*Bromus tectorum*) is fairly ubiquitous. Thus, one question this map and brief analysis raises is, should we continue to monitor NNIP that are so ubiquitous as to be considered naturalized and that we have no realistic expectation of exterminating from the system, and does the overwhelming presence of those species mask evidence of other invasions? From a budgetary standpoint, is it cost effective to continue to monitor such ubiquitous species, or should monitoring dollars be focused on species that are less common now, but are considered very likely to become problematic in the future? At the very least, it is worth considering removing ubiquitous species from

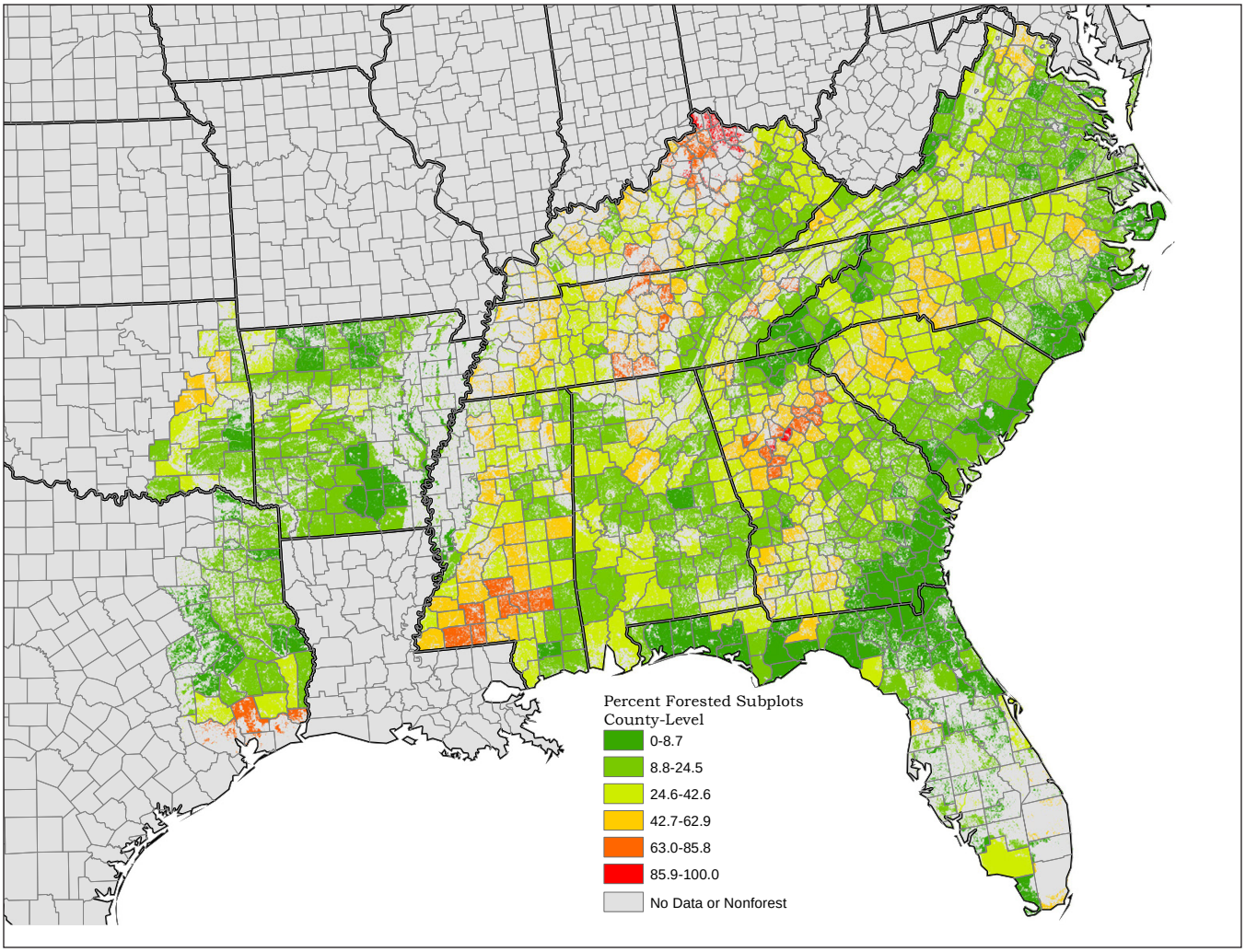


Figure 3.—Map of the southern United States showing the percentage of forested subplots with a nonnative invasive plant (NNIP), excluding Japanese honeysuckle, calculated at the county level. Forest/nonforest mask applied to the contiguous 48 states. Data from Louisiana was unavailable at the time of analysis.

analyses in order to uncover potentially more "telling" patterns.

Differing methods between regions limit the conclusions that may be drawn from a national map, and given differences in physiography and climate, perhaps the national scale isn't the best scale for evaluating nonnative invasive plants. Establishing consistency in methodology should help. However, an overview like this does give an indication of where particularly problematic areas exist and gives national leaders the opportunity to review where prevention education and eradication dollars might be best spent. Thus, as we move forward with the FIA invasive species program, it will be continually important to discuss whether the species we are monitoring are the plants most worthy of our time and money, if we are answering the questions we set out to answer with the program, and finally, how we can use this information to make forward progress in combatting the negative impacts of invasive plants in our forests.

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DISTRIBUTION AND OCCUPANCY OF INTRODUCED SPECIES: A BASELINE INVENTORY FROM PHASE 3 PLOTS ACROSS THE COUNTRY

Bethany K. Schulz and W. Keith Moser[1]

Abstract.—Invasive plant species have significant negative impacts in many ecosystems and are found in many forests around the world. Although not all introduced species become invasive, there are numerous examples of species escaping cultivation and invading natural ecosystems years or even decades after their initial introduction. Regional distributions of invasive species are influenced by climatic and physical conditions; within the landscape, fragmentation, disturbance, and surrounding land use are important factors. Inventory data can help describe the distribution (reported as constancy) and occupancy, (reported as relative richness and cover of introduced species) in forested ecosystems. Vegetation data from 1690 Phase 3 forest inventory plots collected by the U.S. Forest Service's Northern and Pacific Northwest Research Stations' FIA units are used to examine and compare the distribution and occupancy of introduced species. Introduced species were common in forests; 388 species were recorded and 61 percent of all plots had at least one introduced species. Where introduced species occurred, their mean relative richness was 10.7 percent and mean relative cover was 8 percent. However, this varied across regions, level of fragmentation, and distance from roads. Regions with high proportions of forest edge plots had higher overall constancy and occupancy of introduced species. The most commonly recorded introduced species in our analysis was multiflora rose, however, common species varied by ecological region. The most commonly recorded species are highlighted by region, with examples of how these results can inform managers who have limited budgets for invasive plant control.

INTRODUCTION

Tens of thousands of plant species have been introduced to the United States, often intentionally. Although the majority of introduced species are not problematic, many have escaped cultivation to become invasive, producing reproductive offspring at a distance from their original introduction (e.g., >328 ft. in less than 50 years for taxa spreading by seed) (Mack 2003, Richardson et al. 2000). A subset of invasive plant species can have significant negative impacts on ecosystems and are found in many forests around the world. These species are capable of transforming the ecosystems by excluding native species via competition or by exuding substances toxic to other plants, and altering water, nutrient, and fire regimes, and are hence referred to as "transformers" (Richardson et al. 2000). Direct effects on native plant populations have cascading indirect effects on other biota in the invaded communities.

Although not all invasive species become ecosystem transformers, many naturalized introduced species (capable of reproduction without further human cultivation, but not spreading beyond original site) can become invasive years or even decades after

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their initial introduction. (Mack 2003). Initially benign species can slowly expand their presence without notice or recognizable impacts. Once they are widespread, control of these species becomes difficult and expensive.

Many surveys are conducted to monitor for known transformer species. These surveys are often implemented along roadsides, trails, waterways, and areas subjected to disturbance—both human-induced and natural. Focusing on species that are new to the area and have been evaluated for invasive/transforming properties ensures that managers make the most efficient use of limited resources available for invasive species control. From year to year, the list of species may change as more is learned about the distribution and invasiveness of individual species. These surveys are invaluable, but cannot provide a systematic measure of the distribution throughout the range of forested ecosystems of the United States. A regional perspective can help land managers evaluate their local conditions and prioritize projects for effectiveness.

The distribution of invasive species in forests is influenced by the proximal ecosystem and land use patterns, disturbance intensity and distribution, and climate. Forest inventory data can help define the distribution and occupancy of such species in forested ecosystems. Introduced and invasive species are common in the forests of the northeastern United States. Schulz and Gray (in press) found two-thirds of Phase 3 plots in the U.S. Forest Service's Forest Inventory and Analysis (FIA) inventory had at least one introduced species present. Fragmentation and ecological province were important predictors of the occupancy (percent richness and cover) of introduced species. We expand upon those analyses to include data from the Pacific Northwest to further examine and compare the distribution of introduced species in relation to forest fragmentation, distance from improved roads, and ecological divisions. The most abundant species are highlighted by region.

STUDY AREA

Twenty-four states in the northeastern and midwestern regions of the United States and three states in the Pacific Northwest are included in the study area. Data collected on 1,690 Phase 3 plots were used in this analysis. Approximate plot locations in the contiguous United States are shown in Figure 1. (Alaska plots are not shown.)

METHODS

Data were collected by the Northern (NRS) and Pacific Northwest (PNW) Research Stations' FIA Programs between 2001 and 2008 as part of the Phase 3 (P3) Vegetation Diversity and Structure Indicator (VEG). VEG includes a complete census of vascular plants on the forested portion of each subplot (Schulz et al. 2009). Field crews certified for VEG data collection record each plant species and estimate percent cover over the entirety of each of four 24-ft radius subplots. Cover of each unknown species is also estimated and samples are collected for later identification. Some plants remain unidentified if they were present in very early or late stages of development or only a few individual plants were on site. Plants not ultimately identified to the species level were not included in this analysis; we assume that the proportions of native to introduced species among unknown plants are similar to that for known species.

Species origins were assigned according to the Natural Resource Conservation Service's PLANTS database (USDA NRCS 2010). Ecological divisions, as described by Cleland et al. (1997) were used to distinguish regions with broad climatic and physiographic zones. The systematic random sample design of the FIA inventory results in some plots straddling multiple vegetation conditions defined by significant differences in land use, forest type, stand size class, and forest/nonforest condition (Bechtold and Patterson 2005). Each plot was assigned one of three levels of fragmentation based on the number

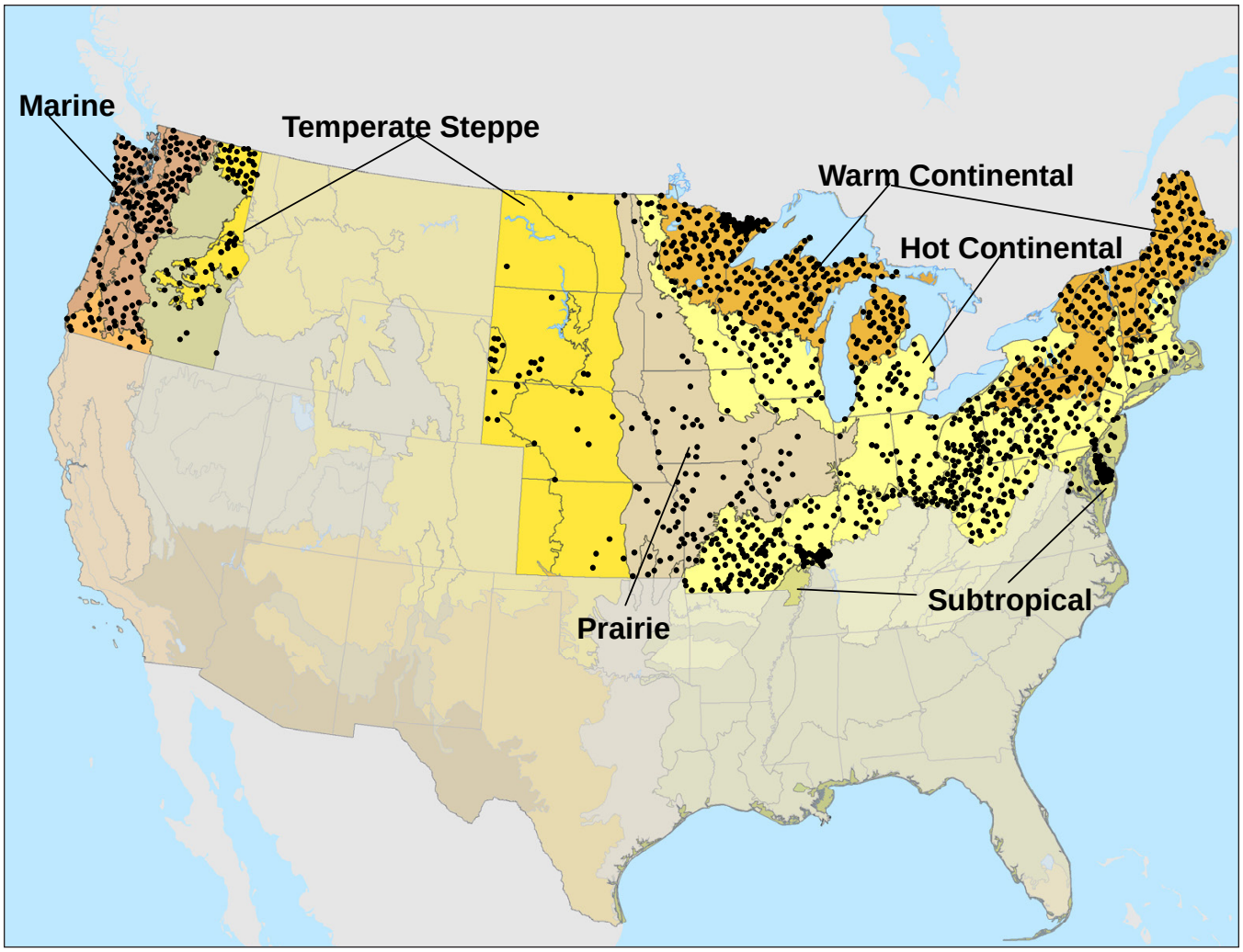


Figure 1.— Approximate location of FIA Phase 3 plots where VEG has been collected in the contiguous United States with an initial visit from 2001 through 2008. Shaded areas of map represent labeled ecological divisions.

and types of condition classes assigned. If the plot was 100 percent forest and was determined to be a single condition, it was designated as an "intact" stand. Plots that were 100 percent forest, but had more than one condition assigned, were designated as "multiple condition." Plots that were less than 100 percent forest were designated as "forest edge", although only forested portions of these plots were sampled, their proximity to nonforest land increases their potential exposure to introduced plant species flourishing on nonforested lands. This assignment creates a coarse filter for fragmentation in that some "intact" forest may, in fact, be adjacent to forest edge or be contained within small parcels of remnant forest and the forest in some plots labeled "edge" could be adjacent nonforest plant communities unaffected by invasive species. Other variables considered included distance from improved roads, latitude, and longitude.

The numbers of native and introduced species per fully forested subplot were compiled for all plots regardless of level of fragmentation. Constancy (the presence of at least one introduced species) and measures of occupancy (relative richness and relative cover of introduced species) were computed at the plot level at the site. The relative richness is simply the number of introduced species divided by the total number of all species identified to species per plot. The relative

cover of introduced species is the sum of subplot cover of all introduced species divided by the sum of subplot cover of all species. Estimates and variances for each category were computed using the ratio of means methods described in Schulz et al. (2009).

RESULTS

Sixty-one percent of the 1690 plots had at least one introduced species. Where introduced species occurred, their mean relative richness was 10.7 percent, and their mean relative cover was 8 percent. We found 386 species of nonnative plants. We included two native grasses—reed canarygrass (*Phalaris arundinacea* L.) and common reed (*Phragmites australis* (Cav.) Trin. ex Steud.)—because invasive populations are genetically distinct from relatively rare native populations (Olson and Cholewa 2009).

The distribution of introduced species on Phase 3 inventory plots varied by ecological division (Table 1). The Warm Continental Division had the lowest constancy and occupancy of introduced species and the highest proportion of intact plots. The Prairie Division, with the highest proportion of edge plots, had the highest constancy and relatively high occupancy. Constancy and occupancy varied predictably with distance from improved roads (Fig. 2). Results from Alaska differed substantially from other regions: constancy of introduced species was only 4.4 percent, and when they occurred, their mean relative richness average was 2.2 percent, and mean relative cover of less than 1 percent; 74 percent of all plots were greater than 1 mile from an improved road. Comparisons between the Pacific Northwest and the northeastern United States were limited to the lower 48 States.

Table 1.—Ecological divisions represented in the sample, with total number of plots, number of plots by level of fragmentation, overall constancy of introduced plant species, and mean occupancy when introduced species are present.

	Level of Fragmentation					Occupancy	
Division	Total	Intact	Multi	Edge	Constancy	Mean relative richness (SE)	Mean relative cover (SE)
	number of plots				percent	percent	percent
Warm Continental	538	352	64	122	48.7	7.7 (0.4)	4.0 (0.6)
Hot Continental	571	296	46	229	77.8	12.0 (0.4)	10.9 (0.7)
Subtropical	70	33	4	33	64.3	8.6 (0.9)	6.5 (1.6)
Marine[a]	173	96	21	56	60.7	11.7 (1.0)	6.3 (1.3)
Prairie	87	27	5	55	86.2	10.9 (0.9)	10.0 (1.6)
Temperate Steppe	93	55	10	28	82.8	13.8 (1.0)	9.2 (1.7)

[a] Washington and Oregon only

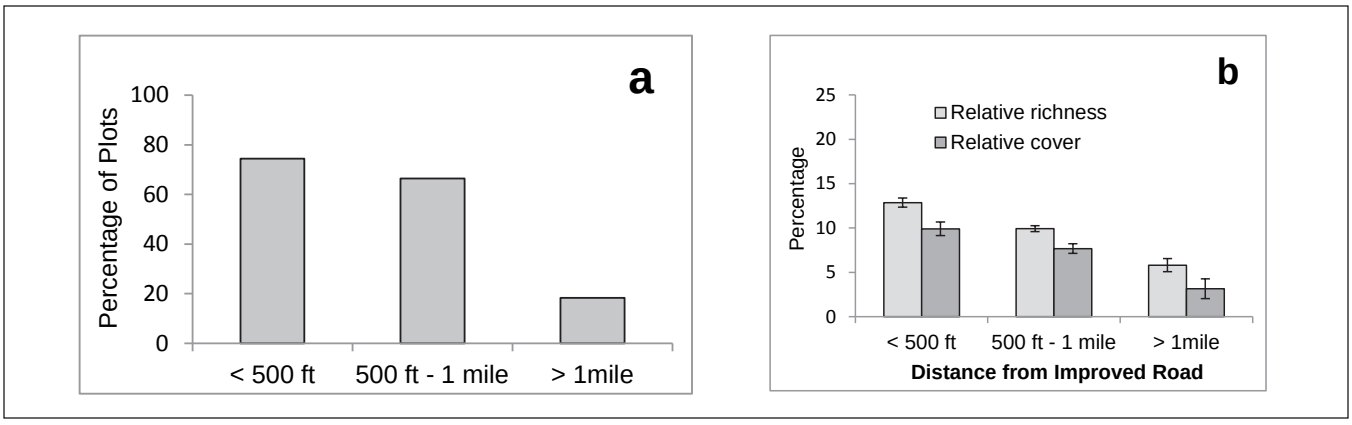


Figure 2.— Constancy (a) and occupancy (b) as a function of the distance of plots from improved roads; error bars represent plus and minus one standard error.

Despite not being found west of the Rocky Mountains, multiflora rose (see Table 2 for scientific and common names) remained the most commonly recorded species in this expanded analysis, with a constancy of over 20 percent of all 1690 plots. When the data were compiled regionally at the ecological-division level, there were some surprises among the most commonly recorded species (Table 2). Although many of the listed species are known to be problematic transformers, several, including broadleaf helleborine and wall-lettuce, are naturalized species considered benign in the past.

DISCUSSION

Full species census provides opportunities to monitor any species present on FIA plots. Our results find introduced species to be quite common in the forests of the lower 48 United States. Although some species were widely planted (e.g., multiflora rose) most of these species can be considered invasive, in that it is unlikely that they were planted in most of the stands sampled by FIA. Although many known transformer species were captured in the Phase 3 VEG sample, there were some surprises concerning the most common species by ecological region compiled. For example, orange hawkweed is found on forest edge plots of many forest types, but in intact forests, it is found most often in aspen stands; broadleaf helleborine was found most often in intact sugar maple stands in the Adirondack Mountain province. These results could inform the development of lists of species to target in local and other list-based invasive species efforts, such as the national FIA inventory, and focus research attention to invasive species considered to be benign but are more widespread than previously thought.

ACKNOWLEDGMENTS

The authors thank all who made P3 VEG data collection and stewardship happen: from program manager for their commitment, and especially to VEG field crews and information managers.

Table 2.—The three most commonly recorded introduced species by ecological division with constancies (percentage of plots in each division where the species was recorded)

Ecological Division	N plots	Scientific Name	Common Name	Division Constancy (percent)
Warm Continental	538	*Hieracium aurantiacum* L.	orange hawkweed	8.0
		Phleum pretense L.	timothy	4.8
		Epipactis helleborine (L.) Crantz	broadleaf helleborine	4.6
Hot Continental	571	*Rosa multiflora* Thunb.	multiflora rose	49.4
		Lonicera japonica Thunb.	Japanese honeysuckle	16.8
		Alliaria petiolata (M. Bieb.) Cavara & Grande	garlic mustard	13.7
Subtropical	70	*Lonicera japonica* Thunb.	Japanese honeysuckle	48.6
		Rosa multiflora Thunb.	multiflora rose	17.1
		Microstegium vimineum (Trin.) A. Camus	Japanese stiltgrass	8.6
Marine[a]	173	*Mycelis muralis* (L.) Dumort.	wall-lettuce	28.9
		Rubus laciniatus Willd.	cutleaf blackberry	16.2
		Digitalis purpurea L.	purple foxglove	15.6
Prairie	87	*Rosa multiflora* Thunb.	multiflora rose	47.1
		Morus alba Michx.	white mulberry	17.2
		Torilis arvensis (Huds.) Link	spreading hedgeparsley	16.1
Temperate Steppe	93	*Tragopogon dubius* Scop.	yellow salsify	39.8
		Bromus tectorum L.	cheatgrass	23.6
		Hypericum perforatum L.	common St. Johnswort	19.3

[a] Washington and Oregon only

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UPDATING THE SOUTHERN NONNATIVE PLANT WATCH LIST: THE FUTURE OF NNIP MONITORING IN THE SOUTH

Christopher M. Oswalt, Sonja N. Oswalt, and Lewis Zimmerman[1]

Abstract.—The Southern Research Station (SRS) Forest Inventory and Analysis (FIA) Program began monitoring nonnative invasive plant (NNIP) species in 2001 in response to a growing desire to track potential forest health threats on United States forest land. The SRS-FIA NNIP program has produced significant results and contributed considerably to the understanding of the distribution and spread of NNIP in the southern United States. However, opportunities to improve NNIP monitoring in the South do exist. Specifically, the SRS-FIA program monitors only a select number of NNIP species. Given the importance of monitoring nonnative invasive plants in southern forests coupled with the emergence of newly detected plant invaders, the emergence of previously known invasive plants as problematic species, and incomplete knowledge of accurately predicting exotic invasives, the select list of NNIP required updating. The SRS-FIA watch list was thoroughly reviewed with respect to potential removal of some species from the list of monitored plants. For example, a recent analysis found that out of over 33,000 subplots, some plant species were detected on 3 or fewer subplots. While such small detection rates do not indicate a lack of needed monitoring, with limited resources, the SRS-FIA program must review the importance of monitoring such species in the future. The watch list must also reflect current knowledge and account for newly discovered important southern forest invaders. Both scientists and land managers have identified numerous regionally and nationally important nonnative invasive plant species not currently on the SRS-FIA watch list. A group of regional and national NNIP experts (internal and external to FIA) were assembled with the task of evaluating and updating the SRS-FIA watch list. The proposed new watch list for SRS-FIA is presented.

INTRODUCTION

Given the importance of monitoring nonnative invasive plants (NNIP) in southern forests coupled with the emergence of newly detected plant invaders, the emergence of previously known invasive plants as problematic species, and incomplete knowledge of accurately predicting exotic invasives, the Southern Research Station (SRS) Forest Inventory and Analysis (FIA) Program must periodically evaluate the select list of nonnative invasive plants that are monitored by the program. The SRS-FIA watch list should be thoroughly reviewed with respect to potential removal of some species from the list of monitored plants. For example, Oswalt and Oswalt (2011) found that out of over 33,000 subplots, some plant species were detected on 3 or fewer subplots. While such small detection rates do not indicate a lack of needed monitoring, with limited funding and limited time for adequately training personnel on the identification of species, the SRS-FIA program must review the importance of monitoring such species in the future. The watch list must also reflect current knowledge and account for newly discovered important southern forest invaders. Miller et al. (2010) identified numerous regionally and nationally important nonnative invasive plant species not currently on the SRS-FIA watch list. The SRS-FIA

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watch list has been stable for approximately 10 years (2001-2011). A review of the watch list at this time was considered necessary.

METHODS

A three-step approach was defined prior to the formal evaluation by a team of national and regional experts including Christopher M. Oswalt (Lead, SRS-FIA), Sonja N. Oswalt (SRS-FIA), Zimmerman (SRS-FIA), Jim Miller (SRS, Auburn, AL), Nancy Fraley (National Park Service, Ashville, NC), Chris Brown (Texas Forest Service, College Station, TX), David Dickinson (Georgia Forestry Commission, Carrolton, GA), Jay Frost (SRS-FIA), and Rebekah Wallace (University of Georgia, Tifton, GA). First, a list of species for potential removal from the watch list was developed through a quantitative assessment of occurrence. Next, through a comprehensive assessment of potential species, the team developed a list of candidate species for addition to the watch list. A final proposed watch list was then developed by the team for submission to the U.S. Forest Service Regional Management Team with SRS-FIA programmatic oversight.

In an attempt to address the potential removal of plant species from the watch list, all available data (2001 through 2010 for most southern states) were assembled from the Southern Nonnative Invasive Plant data Extraction Tool (SNIPET) available at http://srsfia2.fs.fed.us/SNIPET/. Any species with less than 50 total observations across all data were considered candidates for removal from the watch list. Each candidate species being considered for removal or addition was discussed in detail by the team. Removals and additions to the list were evaluated using the following general criteria: (1) the plant species is considered a known invader of forested systems; (2) the plant species is considered to be a regionally significant invader (or highly likely to become regionally significant) of forests; and (3) the plant species can be invasive to any stage of forest development.

RESULTS AND DISCUSSION

Candidate species for removal included Russian olive (*Elaeagnus angustifolia*), giant reed (*Arundo donax*), English ivy (*Hedera helix*), Chinese silvergrass (*Miscanthus sinensis*), and tropical soda apple (*Solanum viarum*). Candidate species for addition to the watch list were primarily from the species listed in Miller et al. (2010).

The following decisions were made with respect to each candidate species for removal:

(1) Russian olive—primarily due to difficulty in field identification, Russian olive will be combined with autumn olive (*E. umbellata*) to form the Elaeagnus group.

(2) Giant reed—due to low occurrence (3 subplots out of over 33,000) coupled with being found primarily on nonforest conditions, giant reed will be removed from the watch list.

(3) English ivy—although observed infrequently, an increasing number of observations over time suggests the need for continued monitoring. English ivy remains on the watch list.

(4) Chinese silvergrass—although observed infrequently, an increasing number of observations over time along with potential uses of *Miscanthus* spp. as a bioenergy crop suggests the need for continued monitoring. Chinese silvergrass remains on the watch list.

(5) Tropical soda apple—due to low occurrence coupled with being found primarily on nonforest conditions, tropical soda apple will be removed from the watch list.

Two plant species, Brazilian peppertree (*Schinus terebinthifolius*) and camphortree (*Cinnamomum camphora*), were elevated from the Florida-only watch list to the regional watch list. A total of 15 species were added to the watch list from Miller et al. (2010). A new species group, *Tamarix* spp., was added due to increasing evidence of saltcedar (*Tamarix ramosissima*) invasions in the western areas of the southern region.

The new SRS-FIA watch list (Table 1) contains a total of 49 species (or species groups) that will be monitored on all southern FIA plots beginning in October 2012 with the implementation of the version 6.0 field guide.

ACKNOWLEDGMENTS

Thanks are due the many dedicated field employees who collect FIA data in each region throughout the year. Additionally, the authors are extremely grateful for all participants of the Watch List Update Team.

Table 1.—Southern Research Station Forest Inventory and Analysis 6.0 nonnative invasive plant watch list

Scientific name	Common name	Scientific name	Common name
Ailanthus altissima	Tree of heaven	*Liriope* Group	
Akebia quinata	Five-leaf akebia, chocolate vine	*L. muscari*	Big blue lilyturf
Albizia julibrissin	Mimosa	*L. spicata*	Creeping liriope, Monkey grass
Alliaria petiolata	Garlic mustard	*Ophiopogon muscari*	
Ampelopsis brevipedunculata	Amur peppervine	*Lonicera* Group	
Ardisia crenata	Coral ardisia, Hen's eyes	*L. tatarica*	Tatarian honeysuckle
Bambusa Group		*L. maackii*	Amur honeysuckle
Phyllostachys aurea	Golden bamboo	*L. morrowii*	Morrow's honeysuckle
Phyllostachys spp.	Other invasive bamboos	*L. fragrantissima*	Sweet-breath-of-spring,
Bambusa spp.	Other invasive bamboos	*L.* x *bella*	Bell's honeysuckle
Berberis thunbergii	Japanese barberry	*Lonicera japonica*	Japanese honeysuckle
Broussonetia papyrifera	Paper mulberry	*Lygodium japonicum*	Japanese climbing fern
Celastrus orbiculatus	Oriental bittersweet	*Mahonia bealei*	Leatherleaf mahonia
Cinnamomum camphora	Camphortree	*Melia azedarach*	Chinaberry
Dioscorea Group		*Microstegium vimineum*	Nepalese browntop
D. bulbifera	Air yam	*Miscanthus sinensis*	Chinese silvergrass
D. oppositifolia	Chinese yam	*Nandina domestica*	Sacred bamboo
D. alata	Water yam	*Paulownia tomentosa*	Princesstree
Elaeagnus Group:		*Polygonum cuspidatum*	Japanese knotweed
E. umbellata	Autumn olive	*Poncirus trifoliata*	Trifoliate orange
E. angustifolia	Russian olive	*Pueraria montana*	Kudzu
Elaeagnus pungens	Thorny elaeagnus	*Pyrus calleryana*	Bradford pear
Eragrostis curvula	Weeping lovegrass	*Rosa* Group	
Euonymus alatus	Winged burning bush	*Rosa multiflora*	Multiflora rose
Euonymus fortunei	Winter creeper	*R. bracteata*	Macartney rose
Firmiana simplex	Chinese parasoltree	*R. laevigata*	Cherokee rose
Frangula alnus	Glossy buckthorn	*Rosa* spp.	Other nonnative roses
Hedera Group		*Schedonorus phoenix*	Tall fecsue
H. helix	English ivy	*Schinus terebinthifolius*	Brazilian pepper
H. hibernica	Atlantic ivy	*Securigera varia*	Crownvetch
H. colchica	Colchis ivy	*Spiraea japonica*	Japanese meadowsweet
Imperata cylindrica	Cogongrass	*Tamarix* spp.	Saltcedar
Lespedeza Group		*Triadica sebifera*	Tallowtree, Popcorntree
L. bicolor	Shrubby lespedeza	*Vernicia fordii*	Tungoil tree
L. thunbergii	Thunberg's lespedeza	*Vinca* Group	
Lespedeza cuneata	Chinese lespedeza	*V. minor*	Common periwinkle
Ligustrum Group 1		*V. major*	Bigleaf periwinkle
L. sinense	Chinese privet	*Wisteria* Group	
L. vulgare	European privet	*W. sinensis*	Chinese wisteria
L. obtusifolium	Border privet	*W. floribunda*	Japanese wisteria
L. ovalifolium	California privet		
Ligustrum Group 2			
L. japonicum	Japanese privet		
L. lucidum	Glossy privet		

Indented species are identified within a group.

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INVASIVE POTENTIAL OF INVASIVE PLANTS IN THE FOREST OF THE SOUTHERN REGION, UNITED STATES

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Abstract.—Alien plants introduced for commercial or landscaping use have caused substantial problems as invaders of natural and managed ecosystems. The magnitude of the problem has dramatically increased over the past few decades with accelerated land disturbance, land use changes, and global and internal transportation. In the southern region of the United States, invasive plants are one of the threats to the long-term sustainability of our forest ecosystems along with climate change and land use change. We assessed the potential distribution of invasive plants in forests of the southern region using data from the invasive species component of the U.S.Forest Service Forest Inventory and Analysis (FIA) Program and freely available digital data including elevation, climate, and land use. Using an ensemble modeling approach, we integrated maximum entropy algorithms, logistic regression, random forest, boosted regression trees, and support vector machine. Areas of agreement between models were considered areas of high probability. This suggests the importance of adaptive management and long-term monitoring programs and the need for further development of methods for assessing probable future climate conditions. We have used this approach to evaluate the relative importance of dependent variables and the application and selection of modeling techniques.

INTRODUCTION

Invasive species pose a major threat to the sustainability of natural ecosystems through biotic homogenization and loss of biodiversity, with negative consequences for both social and economic systems (Miller et al. 2012). Invasive species are considered a major component of global environmental change (Vitousek et al. 1997). Identifying areas of potential invasion is an important part of ecosystem management, and one tool that can be applied to this is species distribution models (SDMs) (Gallien et al. 2010). SDMs can be used to predict spatial patterns of potential biological invasions and prioritize locations for early detection and control of invasion outbreaks. SDMs combine concepts from ecology and natural history with more recent developments in statistics and geospatial information systems (Franklin 2009). In this paper we focused on two questions specific to the application of SDMs: 1) Which modeling technique(s) is most appropriate for this study?; and 2) Do environmental determinates remain consistent among models? To address these questions we developed SDMs for 22 plants invasive to the forests of the southern region of the United States using five SDM methods.

METHODS

Invasive plants considered for this study included all species with more than 100 plot occurrences in the invasive plant component of the FIA database (USDA

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FS 2007) (Table 1). Twenty-two environmental variables derived from the national land cover database, digital elevation models, and Bioclim data were used (full details given in Lemke et al. 2011) (Table 2). Environmental variables were checked for intercorrelation and the statistical package R was used to develop the following five models for each species: maximum entropy algorithms, logistic regression, random forest, boosted regression trees, and support vector machine (R Core Team 2012). Data were down sampled to give a 1:4 ratio (for every occurrence location, four random absence records were selected) for logistic regression, random forest, boosted regression trees, and support vector machine models to balance the data. Models were derived using a manual backward selection method where variables that had little or no impact on the model were removed based on the results of 10 model runs (Lemke et al. 2011). The key variables in determining the occurrence of each species were identified by their percent contribution to the final model and with a jack-knife test on gain and influence on the area under the curve (AUC). This approach assisted in reducing a model that over fits. Three techniques were used to assess model reliability: the performance of test and training data, the omission rate, and AUC. Data were randomly split with 30 percent in test and 70 percent in training datasets for the regional models and were run 10 times with random selections. The omission rate was calculated using a threshold value defined by the maximized sum of sensitivity and specificity. Models with an omission rate less than 0.25 and an AUC of greater than 0.75 were considered acceptable. Ensemble models were built for each species that had more than one acceptable model using only the acceptable models. When more than 75 percent of the models agreed in occurrence, these areas were considered highly likely to be invaded, when less than 25 percent of the models agreed in occurrence, these areas were considered highly unlikely to be invaded,

Table 1.—Comparison of five species distribution modeling techniques (boosted regression trees [BRT], logistic regression [LR], maximum entropy algorithms [ME], random forest [RF], and support vector machine [SVM]) for 22 species invasive to the forest of the Southern region. An omission rate (OR) less than 0.25 and an area under the curve (AUC) of greater than 0.75 were considered acceptable models, shown in bold.

		BRT		LR		ME		RF		SVM	
Species	**n**	**AUC**	**OR**	**AUC**	**OR**	**AUC**	**OR**	**AUC**	**OR**	**AUC**	**OR**
Tree of heaven (*Ailanthus altissima*)	854	**0.88**	**0.14**	**0.81**	**0.18**	**0.88**	**0.13**	**0.89**	0.43	**0.80**	**0.17**
Silktree (*Albizia julibrissin*)	677	**0.76**	0.32	0.69	0.42	**0.76**	**0.24**	0.72	0.80	0.59	0.49
Princesstree (*Paulownia tomentosa*)	231	**0.81**	**0.22**	0.73	**0.23**	**0.80**	0.26	**0.79**	0.67	0.64	0.33
Chinaberry (*Melia azedarach*)	468	**0.87**	**0.20**	**0.79**	**0.16**	**0.86**	**0.22**	**0.86**	0.52	**0.82**	0.29
Tallowtree (*Triadica sebifera*)	930	**0.93**	**0.14**	**0.88**	**0.22**	**0.93**	**0.13**	**0.94**	0.30	**0.89**	**0.22**
Autumn olive (*Elaeagnus umbellate*)	327	**0.88**	**0.16**	**0.75**	**0.20**	**0.98**	**0.19**	**0.89**	0.44	**0.82**	**0.17**
Privets (*Ligustrum* L.)	7580	**0.81**	**0.23**	0.72	0.31	**0.77**	**0.21**	N/A		0.62	0.29
Bush honeysuckles (*Diervilla* spp.)	499	**0.89**	**0.22**	0.74	0.38	**0.89**	**0.18**	**0.90**	0.40	**0.84**	**0.18**
Nandina (*Nandina* Thumb.)	143	**0.81**	**0.21**	**0.77**	0.36	**0.80**	0.38	**0.81**	0.67	0.73	0.35
Nonnative roses (*Rosa* spp.)	3031	**0.87**	**0.18**	**0.76**	**0.21**	**0.85**	**0.16**	**0.88**	0.46	0.74	0.35
Climbing yams (*Dioscorea* L.)	120	**0.78**	0.35	0.62	0.31	**0.83**	**0.22**	**0.79**	0.52	0.61	0.31
English ivy (*Hedera helix*)	104	**0.85**	0.29	**0.79**	0.33	**0.84**	**0.21**	**0.88**	0.58	**0.81**	0.36
Japanese honeysuckle (*Lonicera japonica*)	15931	**0.82**	**0.21**	0.69	**0.23**	0.72	**0.20**	N/A		0.71	0.30
Kudzu (*Pueraria* spp.)	280	**0.79**	0.33	0.71	**0.24**	**0.82**	0.30	**0.82**	0.64	0.62	0.28
Periwinkles (*Vinca* spp.)	115	0.74	0.42	0.67	0.47	0.74	0.42	0.77	**0.77**	0.61	**0.20**
Nonnative wisterias (*Wisteria* spp.)	113	**0.78**	0.35	**0.75**	**0.25**	**0.80**	0.30	0.74	0.80	0.65	**0.23**
Tall fescue (*Schedonorus phoenix* (Scop.) Holub)	810	**0.85**	**0.22**	0.72	0.28	**0.82**	**0.25**	**0.85**	0.52	0.62	0.32
Nepalese browntop (*Microstegium vimineum*)	1740	**0.86**	**0.15**	0.73	**0.22**	**0.83**	**0.12**	**0.86**	0.51	0.56	**0.21**
Japanese climbing fern (*Lygodium japonicum*)	1299	**0.93**	**0.11**	**0.89**	**0.15**	**0.92**	**0.08**	**0.97**	0.27	**0.90**	**0.08**
Garlic mustard (*Alliaria petiolata*)	105	**0.95**	**0.17**	**0.82**	**0.11**	**0.97**	**0.19**	**0.97**	**0.19**	**0.94**	**0.13**
Shrubby lespedeza (*Lespedeza frutescens*)	964	**0.82**	0.35	0.67	0.39	**0.79**	0.30	**0.79**	0.68	0.54	**0.19**
Chinese lespedeza (*Lespedeza cuneata*)	1909	**0.77**	0.26	0.62	0.39	**0.76**	0.27	**0.78**	0.66	0.53	**0.10**
Percent of acceptable models		86%	59%	45%	55%	91%	68%	90%	5%	36%	50%

Table 2.—Number of models using each of 22 environmental variables across five species distribution modeling techniques (boosted regression trees [BRT], logistic regression [LR], maximum entropy algorithms [ME], random forest [RF], and support vector machine [SVM]) for 22 species invasive to the forests of the Southern region

	Elevation	Slope	Dist River	Min Temp	Rainfall	Rain in the Wettest Month	Rain in the Driest Month	Rain in the Warmest Quarter	Temp Range	Temp in the Wettest Quarter	Temp in the Driest Quarter	Pop Density	Dist City	Dist Main Road	Dist Road	% Farming	% Forest	Change in Forest	% Grass	% Pine	Change in Pine	Residential
Tree of heaven	3	1	0	4	2	4	2	2	0	2	3	2	1	0	0	1	1	0	1	0	1	1
Silktree	4	0	0	4	2	3	2	2	1	2	4	3	1	0	2	3	1	0	0	0	0	5
Princesstree	3	4	1	4	2	3	2	3	0	1	2	2	2	0	0	1	1	0	0	1	0	1
Chinaberry	3	0	0	5	2	3	3	3	2	3	2	0	0	0	0	5	0	1	0	0	0	0
Tallowtree	1	0	0	5	2	2	5	3	1	1	3	2	0	0	0	0	3	0	0	0	0	0
Autumn olive	4	0	0	3	3	4	1	1	0	4	2	4	0	0	0	1	2	0	1	0	0	1
Privets	3	0	1	3	1	1	1	2	1	2	1	3	0	0	0	4	0	0	0	0	0	1
Bush honeysuckles	4	0	0	4	1	4	2	2	1	2	2	3	0	0	0	3	2	0	0	0	0	1
Nandina	2	0	0	5	3	3	1	2	2	3	1	5	2	0	1	2	1	0	0	0	0	4
Nonnative roses	4	0	0	4	1	1	2	3	0	1	2	0	0	0	0	4	5	0	1	0	0	1
Climbing yams	4	1	0	4	1	1	0	3	1	3	4	4	1	1	0	0	0	1	0	2	0	0
English ivy	1	0	0	4	1	1	1	0	2	0	1	5	2	0	2	1	0	0	0	1	0	5
Japanese honeysuckle	3	0	0	3	0	0	3	1	2	2	4	1	1	0	0	3	1	0	0	0	0	1
Kudzu	3	0	1	3	2	1	2	3	1	4	4	3	1	1	2	3	1	0	0	1	0	5
Periwinkles	1	4	0	3	2	2	3	1	0	4	3	4	0	1	0	3	2	2	0	1	0	2
Nonnative wisterias	2	0	0	5	0	0	0	0	4	1	0	4	2	2	2	3	3	0	0	1	0	5
Tall fescue	4	0	0	4	2	4	2	4	0	3	2	0	0	0	0	3	2	0	1	0	0	1
Nepalese browntop	3	0	0	4	2	3	4	4	0	2	4	2	0	0	0	1	1	0	1	0	0	1
Japanese climbing fern	1	0	0	5	5	2	2	3	1	1	1	0	0	0	0	0	0	0	0	0	0	0
Garlic mustard	3	0	0	3	1	2	0	2	2	1	2	2	0	0	0	1	1	0	0	0	0	1
Shrubby lespedeza	4	1	0	4	3	4	3	4	2	2	3	0	0	1	0	2	4	0	1	2	0	0
Chinese lespedeza	3	0	0	4	3	4	1	3	1	1	3	0	0	0	0	1	2	0	4	1	0	1
BRT (%)	73	9	0	95	36	45	23	41	14	45	59	64	27	18	18	50	18	9	5	5	0	18
LR (%)	14	14	0	23	5	0	50	0	45	9	32	23	0	5	0	86	59	5	32	0	0	77
ME (%)	59	5	0	95	14	41	32	59	14	41	41	64	14	5	23	45	32	0	5	27	0	27
RF (%)	100	15	0	100	95	95	65	90	20	90	90	20	5	0	0	10	30	0	0	5	0	25
SVM (%)	50	9	14	95	45	68	27	55	18	36	23	55	14	0	0	14	14	5	5	9	5	23
Overall (%)	58	10	3	81	38	49	39	48	22	44	48	45	12	6	8	42	31	4	9	9	1	34

and when the model agreement was between 25 and 75 percent the area was considered moderately likely to be invaded.

RESULTS

The results are reported in two components: model comparisons, and the influence and relevance of the dependent variables (environmental). Most species had at least one acceptable model as assessed by both test AUC and omission rates with the exception of kudzu, periwinkles, shrubby lespedeza and Chinese lespedeza (Table 1). Only one species, garlic mustard, had five accepted models, and four species (tree of heaven, tallowtree, autumn olive, and Japanese climbing fern) had four acceptable models (logistic regression, maximum entropy algorithms, boosted regression trees, and support vector machine). Overall, boosted regression tree and maximum entropy algorithms produced the strongest models with 59 percent of

models considered acceptable (Table 1). Minimum temperature was the most useful of the dependent variables, occurring in 81 percent of the models, followed by elevation (58 percent) and rainfall in the wettest month (49 percent) (Table 2). Every species used minimum temperature in at least three of the models and elevation in at least one of the models (Table 2). Seven variables (distance to roads and rivers, proportion of grass and pine, and change in forest and pine) contributed information to less than 10 percent of the models (Table 2). Tree of heaven was the only species to use the dependent variable change in pine, and distance to river was only used in the support vector machine models for three species. On average, the logistic regression models use the fewest number of variables (five) and random forest models use the highest number (nine). Logistic regression differed from the other methods in the selection of variables, with few logistic models using minimum temperature (23 percent) and elevation (14 percent), but instead being dominated by land use (Table 2). Eleven ensemble models (combining 2 or more models) were developed.

DISCUSSION

The goal of this study was to assess the impact of variable and model selection in SDMs, by comparing the consistency of the independent environmental variables across models, and the consistency of models across species. These issues are fundamental to all SDMs but of particular interest to invasive species. Invasive species often have expanding distributions, and limited information is available on this species, resulting in less defined models. Through identifying agreement between modeling techniques and variables selection, we can have greater confidence in models.

The area of distribution of a species is determined by its ecological and evolutionary history. Many factors affect species distribution, but the most important are the limits of the species' tolerances and needs for certain abiotic conditions, the suite of other species with which it interacts, and the potential for dispersal and colonization within a given time period (Soberón and Peterson 2005). Aboitic conditions can be used to define the potential distribution (the focus of our work), with species interactions and dispersal constraints defining the realized distribution. Many studies have found large-scale environmental factors can produce strong SDMs (Franklin 2009). Overall we found similar results, with the environmental variables used in this study useful in predicting the species potential distribution with 40 percent of the models considered good (test AUC > 0.75 and test omission rate < 0.25). Physiographic variables dominated the model over land use variables, suggesting these distributions are driven by species tolerances. Minimum temperature was the dominate variable suggesting many of these species are limited by the extreme temperatures of winter or length of growing season and competition with other species in that niche. Elevation, the second most dominate variable, has some correlation with temperature and was selected over temperature for inclusion in some models, while in others it was selected in conjunction with temperature. By selecting in conjunction with temperature, it may assist in more narrowly defining climatic conditions associated with the species or forest communities that occupy the area. When used without temperature, elevation is likely a representation of climatic conditions, with elevation integrating both aspects of temperature (high elevation, cooler temperature) and rainfall. Some of the finer-scale characteristics such as slope and distance to rivers were not widely used in models, suggesting the models may apply across a regional scale but not necessary at a local scale. Many of these relationships are nonlinear, with species having preferences for the intermediate temperatures and elevations. The two models that gave the strongest results (boosted regression and maximum entropy algorithms) capture nonlinear relationships well. Logistic regression is not designed to assess bimodal relationships, and as such, many of the models do not integrate temperature, rainfall and elevation-based variables, instead focusing on land cover characteristics. Our results were similar to other studies (Elith et al. 2006), with maximum entropy algorithms coming out as one of the strongest modeling techniques.

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INVASIVE PLANT MONITORING FOR NORTHERN U.S. FORESTS

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Abstract.—Invasive plants are monitored through canopy cover estimates for a list of species developed by FIA for the northern region of the U.S. that is integrated with a national list. Nearly all of the invasive plants on the NRS-FIA list are exotic species, but a few native species are listed. Highly invasive native species such as rhizomatous fern are absent, making the list limited in scope. Some useful applications include describing all vegetation other than trees, competing vegetation, as well as indices for "invasive-ness," "native-ness," and others. The major advantage of the invasive survey is a fourfold increase in sample size. The primary disadvantage is that the list of invasive species does not include several important native species at the regional level. The invasive protocols offer a flexible system for estimating occurrence and abundance that can be segmented to address a wide array of questions.

INTRODUCTION

Understanding the composition and cover of the forest understory helps explain future forest canopy composition and structure, particularly the number of established seedlings and the character of other vegetation. An underlying objective is to describe where the more invasive species are and their impact on native forest flora. This information is important for managers and policy makers evaluating broad-scale forest health, as well as scientists working on forest dynamics models that require information on forest vegetation.

The history of invasive plant survey for Northern Research Station Forest Inventory and Analysis (NRS-FIA) includes methods that have changed over time and space, but this has been minimized through careful field manual preparation, training, and attention to the need for "trend." Invasive trees have been part of the standard FIA tree list for many decades, including important species like tree-of-heaven (*Ailanthus altissimma*), Norway maple (*Acer plataniodes*), and paulownia (*Paulownia tomentosa*). Invasive plants survey efforts began in earnest during the 1990s and have continued to develop regionally and nationally since then. For NRS-FIA, the methodology and list of invasive plants has been relatively consistent over time and space. Exotic and native species are included in the invasive plant survey.

METHODS

NRS-FIA ceased collection of Phase 3 (P3) data in 2011 for budgetary reasons. To maintain some of the P3 indicators into the future, a modified suite of indicators, referred to as Phase 2+ (P2+), was developed for the 2012 field season. The sampling intensity for P2+ is one plot per 24,000 acres, a level that falls between the 1/96,000 acres for P3 samples and 1/6,000 for standard Phase 2 (P2) samples. This sampling intensity is based on the maximum number of plots that can be measured in a 3-month

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leaf-on summer window. The P2+ design includes measurement of a vegetation profile and adult trees on the 24-ft radius subplots, as well as seedlings and saplings on 6.8-foot radius micro-plots (USDA Forest Service 2012). This paper focuses the invasive survey in the context of other measures of vegetation character.

The P2+ design includes the following components for vegetation other than adult trees:

1. Invasive plant areal canopy cover
2. Percentage canopy cover for vegetation growth habits (trees, shrubs, woody vines, forbs, fern, and graminoids) on a 24-ft radius plot in four height classes
3. Advance tree seedling regeneration (ATSR) on 6.8-ft radius plot in six height classes with a browse impact code (USDA Forest Service 2012)

Invasive plants are monitored by collecting canopy cover for a list that includes exotic and native species. NRS-FIA has adopted a list of invasive plants developed by screening variables according to methodology of Morse et al. (2004). The list was developed for the northern United States region and is integrated with a national list (Table 1). The definitions and conventions used in naming species are adapted from the USDA Natural Resources Conservation Service, Plants Database (NRCS 2012).

In 2012, one-eighth of the forested sample conditions are being visited as P2+ samples and beginning in 2013, the percentage will be expanded to include up to one-fourth of the conditions.

Table 1.—List of NRS-FIA invasive plants

Species	Common name
Microstegium vimineum	Japanese stiltgrass, Nepalese browntop
Phalaris arundinacea	reed canarygrass
Phragmites australis	common reed, phragmites
Alliaria petiolata	garlic mustard
Centaurea biebersteinii	spotted knapweed
Cirsium arvense	Canada thistle
Cirsium vulgare	bull thistle
Cynanchum louiseae	Louise's or black swallow-wort
Cynanchum rossicum	European swallow-wort
Euphorbia esula	leafy spurge
Hesperis matronalis	Dame's rocket
Lysimachia nummularia	creeping jenny
Lythrum salicaria	purple loosestrife
Polygonum cuspidatum	Japanese knotweed
Polygonum x *bohemicum*	(*P. cuspidatum* x *P. sachalinense* hybrid)
Polygonum sachalinense	giant knotweed
Berberis thunbergii	Japanese barberry
Berberis vulgaris	common barberry
Elaeagnus umbellata	autumn olive
Frangula alnus	glossy buckthorn
Ligustrum vulgare	European privet
Lonicera maackii	Amur honeysuckle
Lonicera tatarica	Tatarian bush honeysuckle
Lonicera x *bella*	Showy fly honeysuckle
Lonicera morrowii	Morrow's honeysuckle
Rhamnus cathartica	common buckthorn
Rosa multiflora	multiflora rose
Spiraea japonica	Japanese meadowsweet
Viburnum opulus	European cranberrybush
Acer platanoides	Norway maple
Ailanthus altissima	tree-of-heaven
Albizia julibrissin	silktree
Elaeagnus angustifolia	Russian olive
Melaleuca quinquenervia	punktree
Melia azedarach	Chinaberry
Paulownia tomentosa	princesstree
Robinia pseudoacacia	black locust
Tamarix ramosissima	saltcedar
Triadica sebifera	tallow tree
Ulmus pumila	Siberian elm
Celastrus orbiculatus	oriental bittersweet
Hedera helix	English ivy
Lonicera japonica	Japanese honeysuckle

RESULTS AND DISCUSSION

Perhaps the most important indicators of forest understory health are species composition and abundance. Vegetation other than trees is vital for wildlife food and cover, tree seedling development, and native plant diversity. Competing vegetation often inhibits native tree regeneration (Jackson and

Finley 2005). Understory flora can include both invasive and non-invasive plants, as well as exotic and native species, thus complicating the analysis of impacts. Combining invasive survey data with vegetation profile estimates of cover and advance tree seedling regeneration (ATSR) data provides a useful characterization of forest understory vegetation. To illustrate, the following list shows a simple, but useful, breakdown of commonly found species:

- Native/non-invasive: witch-hazel (*Hamamelis virginiana*), lowbush blueberry (*Vaccinium angustifolium*)
- Native/invasive: hay-scented fern (*Dennstaedtia punctilobula*), grape vine, (*Vitis vinifera*)
- Exotic/non-invasive: dandelion (*Taraxacum officinale*)
- Exotic/invasive: Garlic mustard (*Alliaria officialis*), Japanese stiltgrass (*Micriostegium vimineum*), oriental bittersweet (*Celastrus orbiculatus*), and tree-of-heaven

The NRS-FIA invasive species and vegetation profile tallies address a broad range of needs. However, some filtering is suggested for concise analyses, e.g., screen out the native species from the list of invasive plants. The vegetation indicator and its use are well described by Schulz and others (2009).

Nearly all of the invasive plants on the NRS-FIA list are exotic species (USDA Forest Service 2012), but some native species are included, such as black locust (*Robinia pseudoacacia*). Some highly invasive native species, such as rhizomatous fern in the Mid-Atlantic region, are absent thus limiting scope. This complicates the analysis, but does not preclude development of indices of "invasive-ness," and "native-ness" of understory vegetation. To illustrate, Figure 1 depicts the invasive survey nested within the vegetation profile and includes most of the growth habits encountered. The computations are relatively simple, but cover estimates must be adjusted to account for overlap since total cover can be greater than 100 percent:

- Vegetation other than trees = total cover *minus* cover of tally trees
- Invasive-ness = invasive plant cover/vegetation other than trees
- Native-ness = native plant cover/vegetation other than trees.

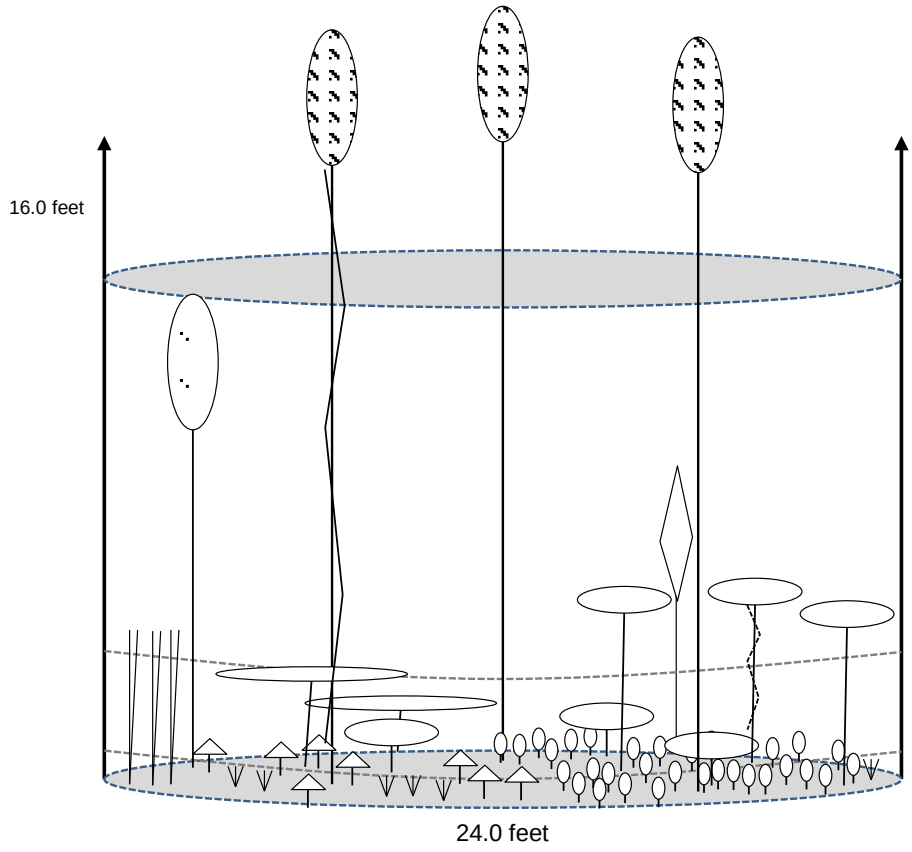
Other potential analyses include indices for special studies of ecoregions, major forest types or species, or areas of forest health concern. Assessments of wildlife habitat, biomass, forage availability, grazing potential, fuel loadings, and potential site productivity are other possible uses.

The advantages of the invasive survey include:

1. The methodology and list of invasive plants is consistent over time and space
2. The results can be used with results from other FIA regions to fill national needs; regional lists will differ
3. Estimates of invasiveness, native-ness, and other indices of interest can be derived

Since the invasive plant protocols are nested within the 24-foot radius subplot used for vegetation and tree monitoring, there are further advantages associated with the P2+ framework:

4. Fourfold increase in sample size, allowing finer-scale estimates and geo-spatial products
5. Cost reduction by limiting the time for measuring vegetation and invasive plants to 1 hour
6. Integration of all measurements of vegetation, including trees
7. Simplification of training and species identification
8. Allows development of new improved methods of estimating the competing vegetation layer, e.g., assigning more weight to woody vines that are found above 16 feet



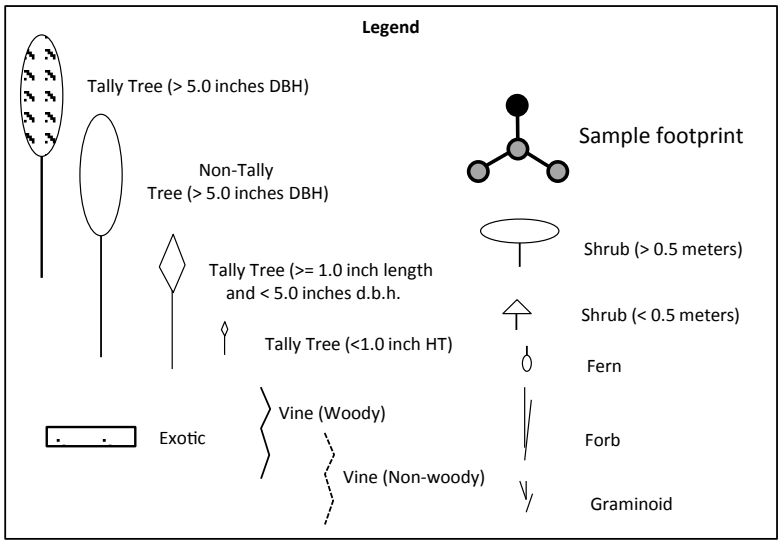


Figure 1.—Example of NRS-FIA nested vegetation samples, including the vegetation profile and exotic/invasive survey for a single FIA subplot.

Disadvantages of the invasive plant survey are generally limited to the technique that was used to define "invasive," a common issue in plant surveys:

1. The list is not complete and ignores several important regional species which limits full accounting of the impact on native flora
2. The list includes only three native species
3. The list includes species that are rare on forest land, e.g., purple loosestrife (*Lythrum salicaria*) that is a wetland obligate, and bull thistle (*Cirsium vulgare*) that occurs primarily on land other than forest

The invasive protocols offer a flexible system for estimating occurrence and abundance that can be utilized to address a wide array of questions. The system will provide for core national products and novel regional analyses.

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NONNATIVE INVASIVE PLANT INVENTORY IN THE NORTHERN RESEARCH STATION: PATTERNS AND TRENDS

W. Keith Moser and Cassie M. Kurtz[1]

Abstract.—Nonnative invasive plants (NNIPs) are an important component of suite of biological disturbances that are influencing forests in the 24 state region of the Northern Research Station (NRS) of the U.S. Forest Service. Along with locally high deer populations and nonnative earthworms, NNIPs have the potential to impact the biodiversity of the ground flora, site productivity, wildlife habitat, and the composition and structure of forests, present and future. Northern Research Station Forest Inventory and Analysis Program (FIA) has several sets of data that can be used to evaluate NNIP. A select list of 25 species were measured on 100 percent of the panels in the 11 midwestern states from 2005 through 2006. About 20 percent of all plots were inventoried for the presence of 43 species from 2007 through 2010 for all 24 states of NRS-FIA. Our presentation discusses the results and the slightly different methodologies between the 2005-6 and 2007+ inventories, and examines the implications specifically for tree regeneration and future stand development.

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MODELING REGENERATIVE CAPACITY ACROSS THE EASTERN UNITED STATES: CAN FIA INFORM CONTEMPORARY MODELS?

SAMPLING FOREST REGENERATION ACROSS NORTHERN U.S. FORESTS: FILLING A VOID IN REGENERATION MODEL INPUT

William H. McWilliams, Charles D. Canham, Randall S. Morin, Katherine Johnson, Paul Roth, and James A. Westfall[1]

Abstract.—The Forest Inventory and Analysis Program of the Northern Research Station (NRS-FIA) has implemented new Advance Tree Seedling Regeneration (ATSR) protocols that include measurements of seedlings down to 2 inches in height. The addition of ATSR protocols is part of an evaluation of NRS-FIA Phase 3 indicator variables to increase sampling intensity from 1/96,000 acres to 1/24,000 acres per sample location. The sampling scheme for understory vegetation consists of (1) estimating canopy-cover percent for six vegetation growth habits on 24-foot-radius subplots in four height classes and as an aerial view and (2) measuring tree saplings and seedlings on 6.8-foot-radius microplots. The Pennsylvania Regeneration Study has used ATSR and competing vegetation measurements to evaluate regeneration for 16.7 million acres of northern hardwood and mixed-oak forest. The findings revealed that only about half the State's forest had adequate advance regeneration for replacement of canopy species if the overstory were removed. The ATSR protocols provide estimates of the number of seedlings by species and height class, as well as a flexible method for evaluating regeneration adequacy. The level of detail of the measurements is expected to provide input that has not been available in the past for models that require tree regeneration information.

INTRODUCTION

The Forest Inventory and Analysis Program of the Northern Research Station (NRS-FIA) ceased collection of Phase 3 (P3) data in 2011 for budgetary reasons. Based on an evaluation of costs, time, and efficiencies, a modified suite of existing P3 variables and new Advance Tree Seedling Regeneration (ATSR) protocols were implemented in 2012. The sampling intensity for the modified suite will be as high as 1/24,000 acres, which is between 1/96,000 acres for P3 samples and 1/6,000 for standard Phase 2 (P2) samples, referred to as Phase 2+ (P2+). This intensity is based on the maximum number of plots that can be measured in a 3-month leaf-on summer window. As of this writing, the 2012 field season is just beginning. In 2012, one-eighth of the forested sample conditions are being visited as P2+ samples; in 2013 and beyond, the sample will be expanded to include up to one-fourth of the conditions.

This paper focuses on the ATSR sample methodology. More specifically, ATSR sampling protocols, preliminary results, and applications for assessing forest regenerative capacity are discussed along with the utility for use in eco-process and other models that require regeneration information.

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METHODS

The sampling scheme includes (1) estimating canopy-cover percent for six vegetation growth habits on 24-foot-radius subplots in four height classes (Vegetation Profile) and as an aerial view, and (2) measuring tree saplings and tree seedlings on 6.8-foot-radius microplots. The study design for the P2+ Vegetation Profile was adapted from and integrated with the national P3 Vegetation Diversity and Structure protocols (USDA Forest Service 2012). The seedling protocols were adapted from the Pennsylvania Regeneration Study (PRS)—a 12-year study of regenerative capacity for forests under high deer browse conditions (McWilliams et al., in press; Westfall and McWilliams 2011). The underlying ecological and silvicultural relationships used for evaluating regeneration are described by Brose et al. (2008) and Marquis (1994). The approach for ATSR evaluation was developed during debate within the environmental community over the impact of deer on forest regeneration (Frye 2006).

Tree seedlings are defined as all stems at least 2 inches tall and up to 1 inch in diameter at breast height (d.b.h.) that have survived for at least a year. The ATSR sample provides the number of established and competitive seedlings by length class (2 to 6 inches, 6 inches to 1 foot, 1 to 3 feet, 3 to 5 feet, 5 to 10 feet, and greater than 10 feet). In addition, a browse impact code (five levels from very low to very high) is recorded for accessible forest land for all four subplots. The code was developed for white-tailed deer (*Odecoleus virginianus* Zimmerman) and may be adaptable for other ungulates. Other herbivores (such as hare and rodents) impact tree seedlings, but are not specifically addressed in the estimate of browse impact.

The ATSR protocols recognize that all seedlings are not the same. The study uses an "established" and "competitive" class for heavy seeded species, such as oak, walnut, and hickory (Fig. 1). The determination of seedling establishment and competitive status for

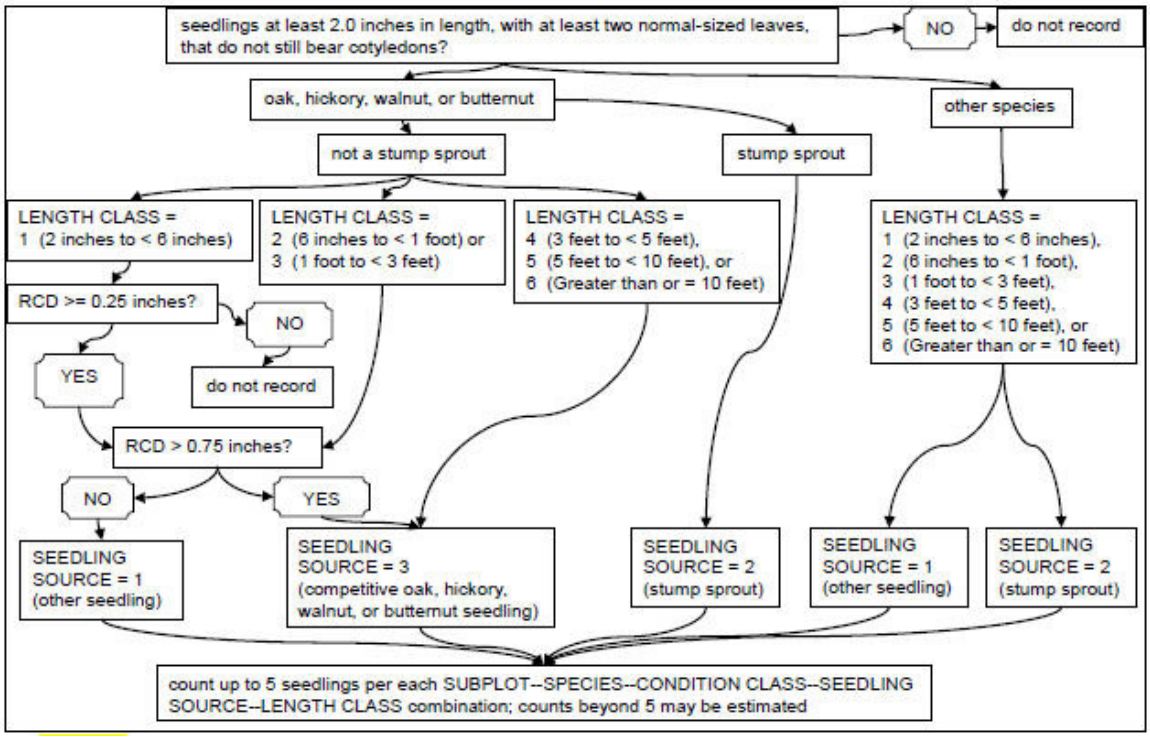


Figure 1.—Advance tree seedling regeneration seedling count guide (USDA Forest Service, Northern Research Station 2012).

large seeded species depends on the diameter at root collar, a better predictor of the future status than height for these species (Brose et al. 2008). Only a single dominant stem is counted when multiple sprouts are encountered. Undetached branches covered with soil, or layered stems, are not counted.

When combined with an estimate of "competing vegetation" from the Vegetation Profile and the browse impact code, the microplots can be evaluated for regeneration adequacy using thresholds for the number of seedlings by length class. The thresholds are determined by the level of browse, i.e., more seedlings are needed when browse impacts are higher. Samples are further screened for light levels conducive to seedling development (from 40 to 75 percent stocked with adult trees).

RESULTS

The underlying assumption for analysis of advance regeneration is that forest stands encountered will eventually have overstory removal or mortality and need advance regeneration to replace adult trees. Past results of the PRS have provided vital information for planners and inter-agency decisions on ameliorating the impacts of deer on forest regeneration. ATSR is used along with the tally of saplings for full evaluation of advance regeneration. Saplings are defined as trees larger than 1 inch d.b.h. up to 4.9 inches. In Pennsylvania, it was found that only about half of the forest land that is receiving adequate light for establishment and development of regeneration had adequate regeneration (Fig. 2) (McWilliams et al., in press). These results are subject to confidence intervals of +/- 4 percentage points at the 95-percent confidence level or +/- 2 percentage points at the 67 percent level.

The results of the 2012 measurements will be the first NRS-FIA-wide dataset containing these new protocols. The full baseline measurements should be complete following the 2017 field season. At that point, full characterization of regeneration adequacy across the NRS-FIA region will be possible.

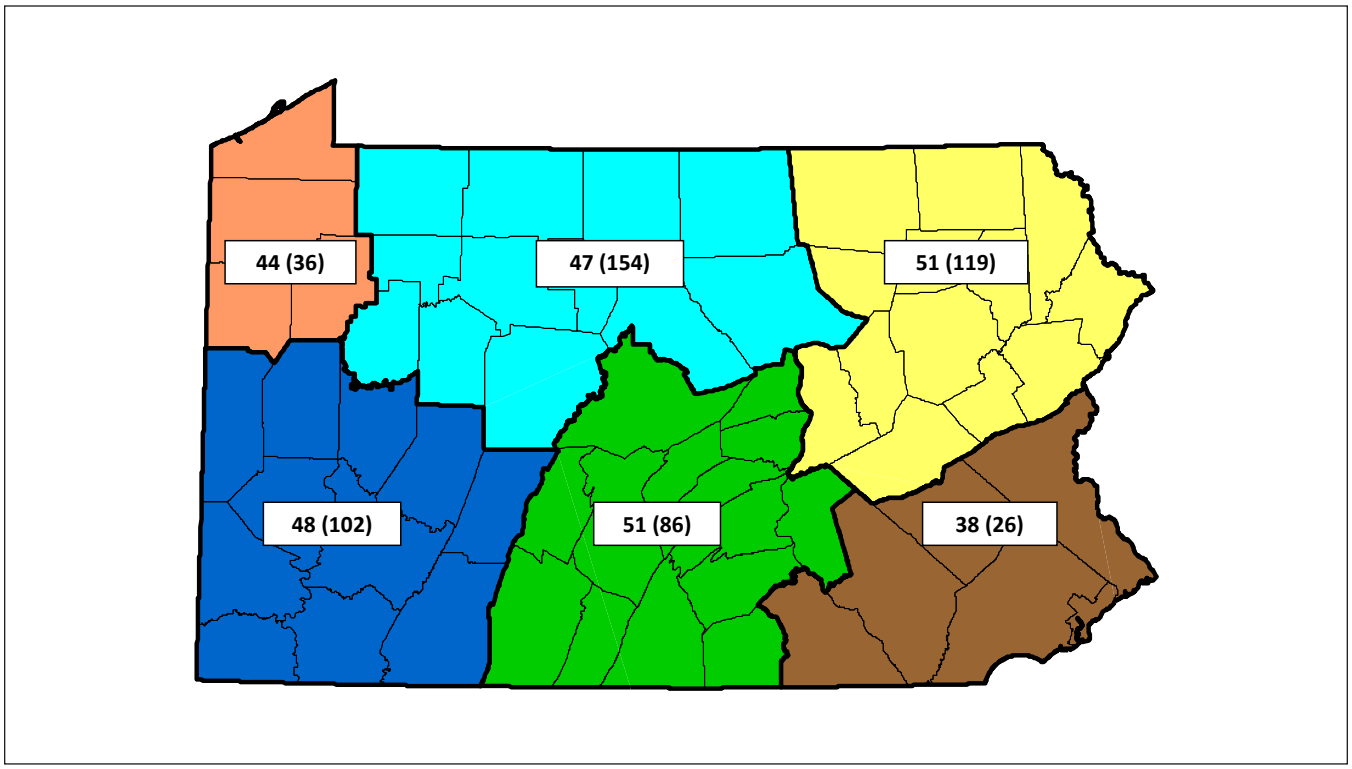


Figure 2.—Percent and number (in parentheses) of samples adequately stocked with advance tree seedling and sapling regeneration for canopy replacement species and samples 40 to 75 percent stocked with trees, Pennsylvania, 2006 to 2010.

DISCUSSION AND CONCLUSIONS

Seedlings less than 1 foot tall have not previously been included as a core variable in NRS-FIA inventories and seedling height has not been recorded. The new sample provides a flexible method for evaluating regeneration adequacy for dominant species subject to study assumptions, e.g., that overstory removal will occur. An advantage of the new P2+ samples is that all vegetation measurements are taken from the 24-foot or 6.8-foot-radius plots. This approach integrates P2 and P2+ measurements together for improved analyses of overstory and understory conditions.

The implementation of P2+ samples across the NRS-FIA region will cover 175.8 million acres of forest compared to 16.7 million acres for Pennsylvania. The expanded study area includes the Central Hardwood, Lake State, Mid-Atlantic, and New England areas; and four Plains States. Needed for regions and forest types outside the Mid-Atlantic are protocols and algorithms for analyzing and applying ecological thresholds for the number of seedlings by height class required for adequate regeneration to replace adult trees. The complexity and diversity of the Pennsylvania experience should provide a useful template for other NRS-FIA areas. For example, spruce-fir forests of Maine will need to use guidelines for size and density of regeneration of various species before overstory removal or destruction, such as those suggested by Seymour (1992, p. 236). The approach should also be adaptable to conditions in the Southern Appalachian Mountains, Piedmont, and Coastal Plain because advance regeneration is important for predicting future stand composition there. Additional research can be incorporated into the analyses to better match forest composition and silvicultural systems of interest.

The level of detail of the measurements is expected to provide input for eco-process and other models that has not been available in the past (Canham et al. 2006). This includes any model that attempts to characterize or project future conditions based on an inventory of vegetation and trees, including regeneration. Seedling height and competitive status are critical for addressing impacts of herbivory and the status of advance regeneration. The study will also provide input for developing regeneration modules for individual tree projection models, such as the Forest Vegetation Stimulator (Crookston and Dixon 2005). Further study by McDill (this proceedings) is addressing the ability to discern reliable trend information from the results.

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INFORMATION FOR FOREST PROCESS MODELS: A REVIEW OF NRS-FIA VEGETATION MEASUREMENTS

Charles D. Canham and William H. McWilliams[1]

Abstract.—The Forest and Analysis Program of the Northern Research Station (NRS-FIA) has re-designed Phase 3 measurements and intensified the sample intensity following a study to balance costs, utility, and sample size. The sampling scheme consists of estimating canopy-cover percent for six vegetation growth habits on 24-foot-radius subplots in four height classes and as an aerial view, and measuring tree saplings and seedlings on 6.8-foot-radius microplots. In the past two years, all of the basic submodels in SORTIE, an individual-tree distance-dependent model, were parameterized for the 50 most common tree species in the eastern U.S. by using FIA data. A significant challenge for modelers is that goodness of fit measures, such as the coefficient of determination, for the resulting growth models are often relatively low. Opportunities for using NRS-FIA data for broad-scale models include use of a non-spatial model of seedlings as a function of basal area of the entire subplot, ability to use a mortality model for seedlings, and improvement in knowledge of the impact of the species of neighboring trees. The major benefit of the new NRS-FIA sample design is a fourfold increase in sample size and integration of all vegetation measurements on the subplot (i.e., adult trees, competing vegetation, and seedlings). The primary limitation of using FIA samples is that the subplots are too small for full analysis of distance-dependent seedling dispersion around parent trees.

INTRODUCTION

Broad-scale models of forest dynamics provide projections of future conditions that are used by policymakers, managers, and scientists to understand and implement major decisions. It is challenging to provide forest modelers with information from forest inventories because model structure requirements vary widely. Prominent approaches include individual-tree distance-independent tree, growth/yield (Crookston and Dixon 2005), individual-tree distance-dependent tree (Pacala et al.1996) and imputation (Wear 2002) models. The Forest Inventory and Analysis Program of the Northern Research Station (NRS-FIA) vegetation measurements are reviewed using SORTIE (Pacala et al.1996) to exemplify complex model needs. SORTIE stands for a model of trees as they "take over" a site (not an acronym). SORTIE is an ecological process model that has been parameterized using NRS-FIA measurements (Canham et al. 2006). Broad-scale models that incorporate or "scale up" finer models of ecosystem processes to the scale of FIA are a critical need expressed by clients, particularly for projecting future conditions. The conclusions should be useful to others working at large scales, such as the Forest Vegetation Simulator (Dixon 2002).

In this paper, we focus on models that "mimic" growth and composition change for forest trees, or "process" models. The goal is to emphasize needs for models of tree recruitment, or regeneration models. The SORTIE model is used here to illustrate requirements for models that operate at finer scale than FIA, because it includes basic components needed for most process models, including a complex set of submodels.

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METHODS

NRS-FIA Vegetation Sample

NRS-FIA ceased collection of Phase 3 (P3) data in 2011 for budgetary reasons. Based on an evaluation of costs, time, and efficiencies, a modified suite of P3 variables and new Advance Tree Seedling Regeneration (ATSR) protocols were implemented in 2012. The sampling intensity for the modified suite will be up to 1/24,000 acres, which is between 1/96,000 acres for P3 samples and 1/6,000 for standard P2 samples, referred to as Phase 2+ (P2+). This intensity is based on the maximum number of plots that can be measured in a 3-month leaf-on summer window. The new P2+ design includes measurement of a Vegetation Profile and adult trees on the 24-foot-radius subplots and seedlings and saplings on a 6.8-foot-radius microplot (USDA Forest Service 2012).

All P2 and P2+ measurements are now integrated in a nested sample for all vegetation, including merchantable trees (greater than 5 inches in diameter at breast height [d.b.h.]) (Fig. 1). The sampling scheme includes estimating canopy-cover percent for six vegetation growth habits on four 24-foot-radius subplots in four height classes and an aerial view canopy cover estimate; measuring tree saplings including total height on 6.8-foot-radius microplots; and measuring tree seedlings on 6.8-foot-radius microplots in six height classes (USDA Forest Service 2012). The P2+ Vegetation Profile measurements are used to characterize vegetation composition and structure, and to develop an estimate of percent cover for competing vegetation. The competing vegetation information is used along with the seedling and sapling measurements to evaluate regenerative capacity.

SORTIE Primer

SORTIE is a spatially explicit, individual-based process model of forest dynamics that emphasizes neighborhood tree dynamics (Pacala et al.1996). Over the past decade, SORTIE has been improved to operate as an object-oriented, open-source platform for simulating forest dynamics. The model can easily be modified, and the source code, executable programs for both Windows and Linux platforms, manuals for programmers and users, sample parameter files, and sample output are all available on the SORTIE Web site (www.sortie-nd.org). Development of the model has been tightly linked to statistical methods to parameterize the model from field data, particularly the landscape-level data available from the FIA sample-plot network (i.e., Canham et al. 2006).

In the past two years, all of the basic submodels in SORTIE have been parameterized for the 50 most common tree species in the eastern U.S. by using FIA data from the entire eastern U.S. (Louisiana north to Minnesota and eastward). This includes functions for seedling recruitment, and growth and survival of seedlings, saplings, and adult trees. The recruitment functions include effects of climate, and indirectly incorporate the effects of shading (using basal area of adult trees within the immediate neighborhood of the seedling microplots within each FIA subplot as a surrogate). Seed production and dispersal are not modeled as separate steps, but as in the original SORTIE model are subsumed within the seedling recruitment functions. The growth and survival functions for saplings and adult trees incorporate effects of competition, climate, air pollution (N deposition) (i.e., Canham et al. 2006).

Regional-scale results are generated for current forest structure, composition, and environmental characteristics of randomly selected FIA plots, using current climate (from bilinear interpolation of PRISM climate data) and N deposition, based on a regional, spatially-explicit model of total wet and dry N deposition (Weathers et al. 2006). Since the FIA plots used to initialize the individual runs represent specific locations and known total areas of forestland, variation in the regional-scale results can be mapped, and can be broken out by sub-region (i.e., states, counties), forest type, or mapped as a function of any of the axes of environmental variation (climate, N deposition, soils) linked to the FIA plots. The model architecture is currently being extended to allow interactions among FIA plots embedded within a region (to allow, for instance, modeling seed dispersal based on regional abundance of tree species).

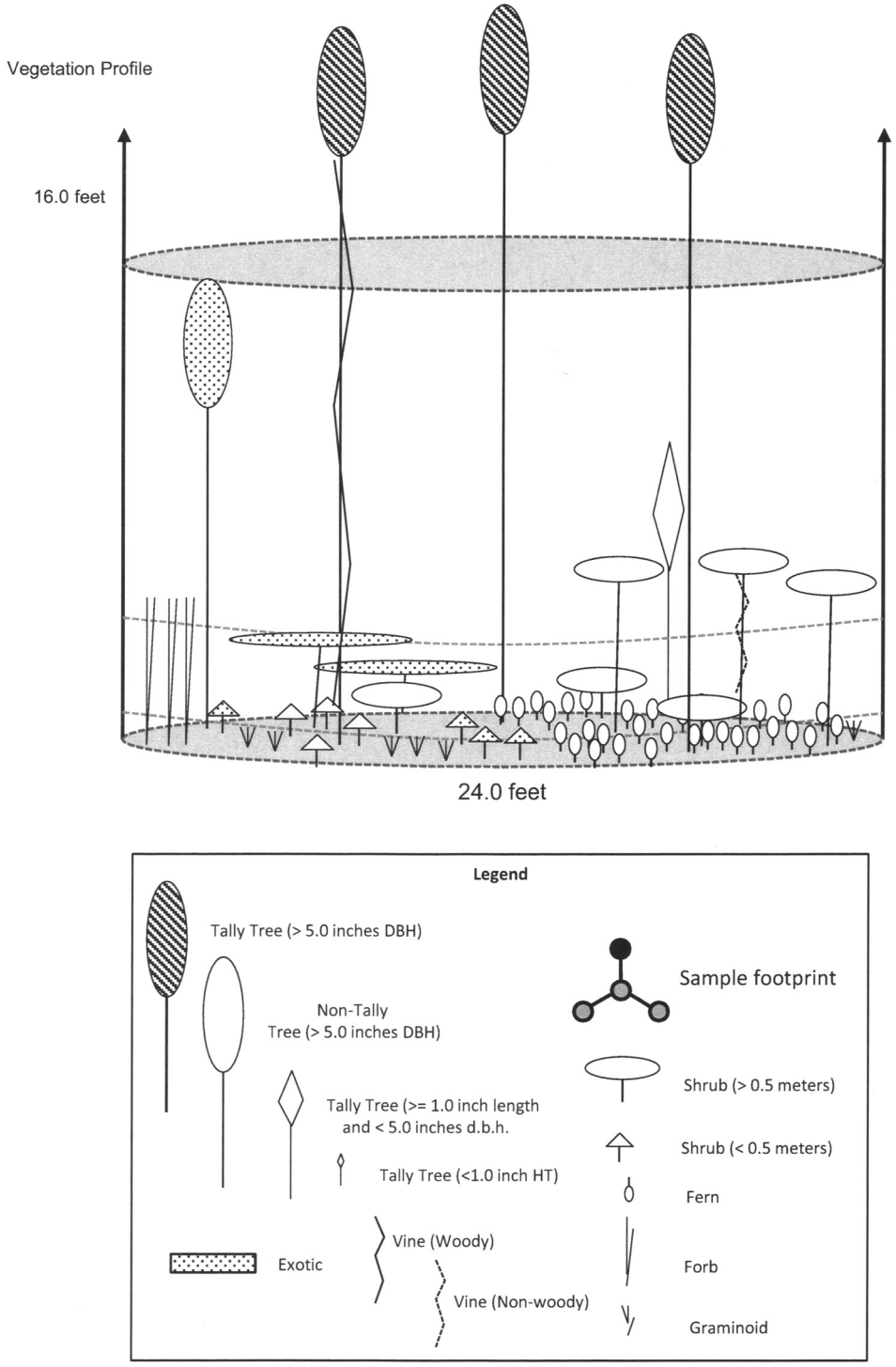


Figure 1.—Example of NRS-FIA forested subplot depicting nested vegetation samples, 2012 (continued on next page).

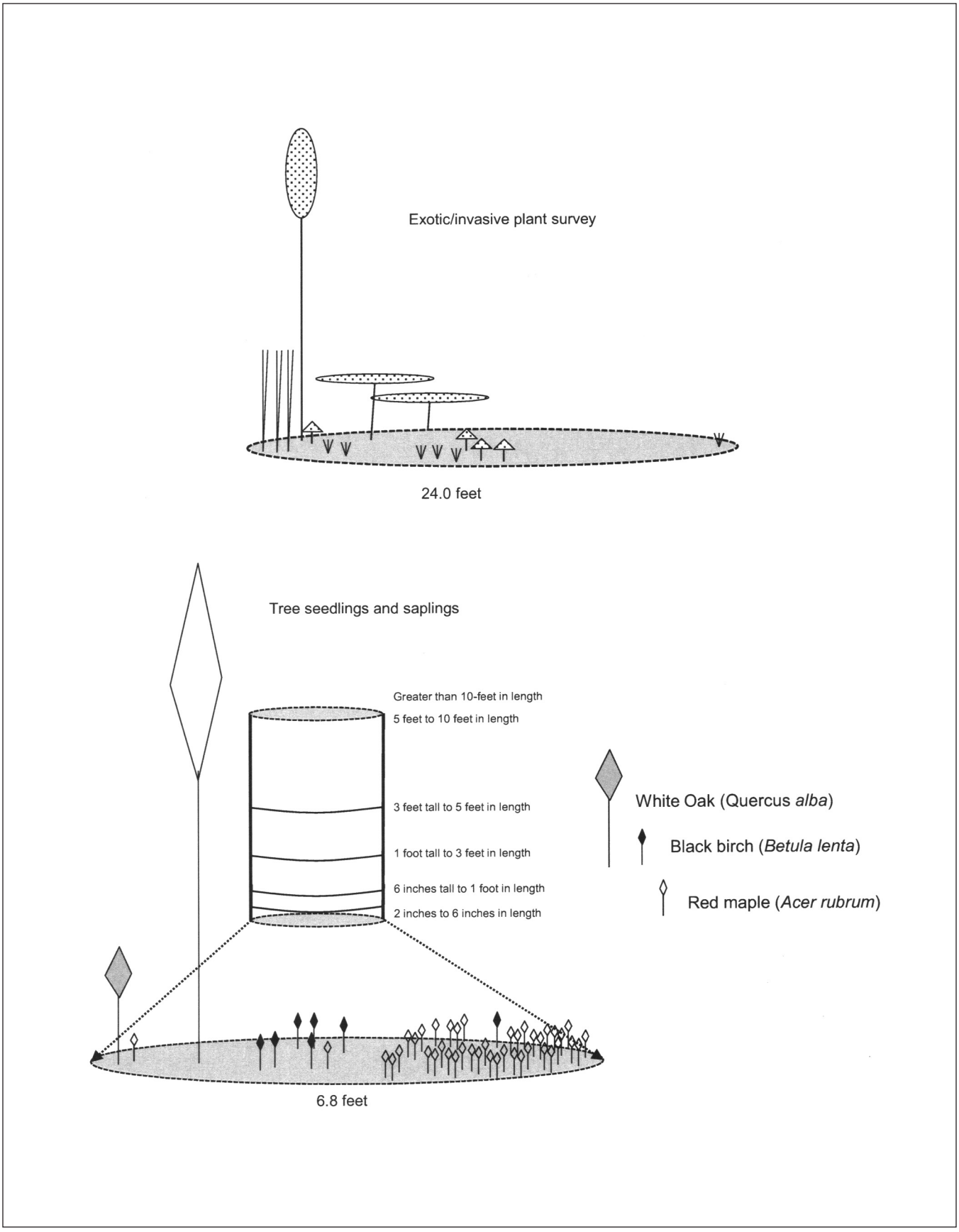


Figure 1 (continued).—Example of NRS-FIA forested subplot depicting nested vegetation samples, 2012.

SORTIE is an individual-tree distance-dependent model that simulates light, tree birth, growth, and mortality for seedlings, saplings, and merchantable trees (Canham et al. 1994). SORTIE consists of four submodels: seedling recruitment (reproduction) function, resource availability (light) (Beaudet et al. 2020), tree growth (Pacala et al. 1994), and tree mortality (Kobe et al. 1996). SORTIE allows development of "behaviors" to fit the user's forest population or eco-type of interest. Canham et al. (2006) parameterized SORTIE for use in New Hampshire and Vermont using NRS-FIA data. Actual tree growth is a function of potential diameter growth using scalars that quantify growth based on initial diameter, local environmental conditions, and crowding by neighbor trees.

The focus for this discussion is the seedling recruitment submodel and associated needs from FIA. Seedling recruitment models can be complicated considering that they track seed production, dispersal, predation, germination, and mortality. To simplify model needs, using seedlings above a minimum threshold allows a focus on seedlings that have germinated in the current year (Ribbens et al. 1994). The FIA minimum size for counting seedlings is 6 inches long for conifers and 1 foot for deciduous species. Canham et al. (2006) modeled seedling dispersion as a function of the proximity of parent trees. Specifically, NRS-FIA seedling counts and adult tree basal area were merged with climate variables with NRS-FIA sample locations.

DISCUSSION AND CONCLUSIONS

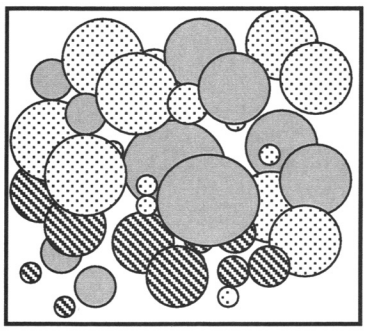
Opportunities for using NRS-FIA data for broad-scale models include use of a non-spatial model of seedlings as a function of basal area of the entire subplot, ability to use a mortality model for seedlings, and improvement in knowledge of the impact of the species of neighboring trees. The NRS-FIA sample design includes several variables associated with SORTIE needs (Figs. 1 and 2).

In the past, the NRS-FIA minimum seedling size threshold included cohorts from multiple years and excluded mortality of seedlings before achieving the minimum size. This threshold is no longer a limitation because the Advance Tree Seedling Regeneration (ATSR) measurement protocols include all seedlings that germinated and survived in the past year. Another challenge for modelers is that the coefficient of determination of the growth models is relatively low. The primary limitation of using FIA samples is that the subplots are too small for full analysis of distance-dependent seedling dispersion around parent trees.

Other benefits of the new NRS-FIA sample design are a fourfold increase in sample size and that all vegetation measurements are integrated on the subplot (i.e., adult trees, competing vegetation and seedlings). Although not utilized yet, the information on seedling height and browse pressure should allow for finer model refinement. The height class breakdown has particular value for refining seedling recruitment models. The information could also be used to improve the seedling component of FIA's stocking and forest type algorithm that uses seedlings to predict future stocking. The basic challenge for modelers is to continue to seek methods for finer scale models to integrate with FIA variables.

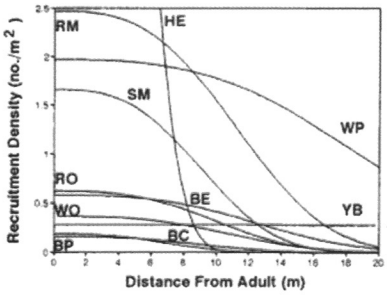
SORTIE

Light



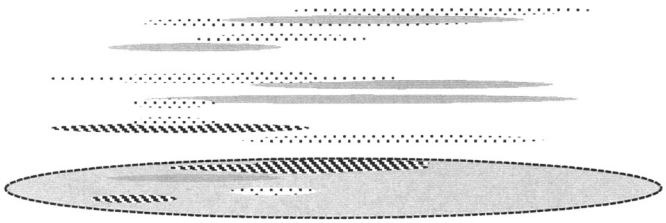
Tree crowns: aerial view

Recruitment



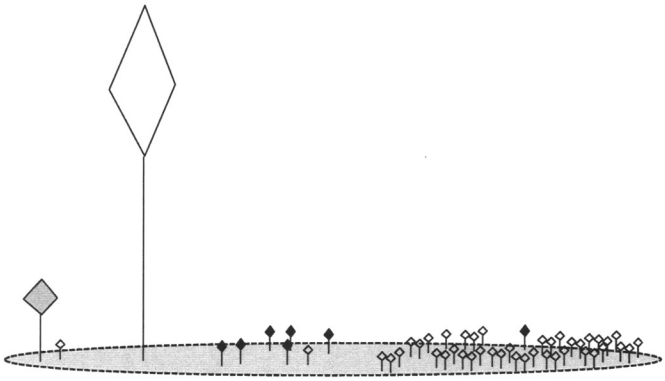
Recruitment densities for nine species (Ribbens and others 1994)

NRS-FIA P2+



Vegetation Profile: percent cover by Growth Habit
percent cover - Aerial View

P2 Tree Tally: Basal Area and Stocking Percent
Canopy Class



Advance Tree Seedling and Sapling Regeneration (ATTSR)

P2: Seedling: Number
Species
Height class
Competitive status
Browse Pressure

P2: Saplings: Azimuth and Distance
Diameter
Height
Crown
Damage

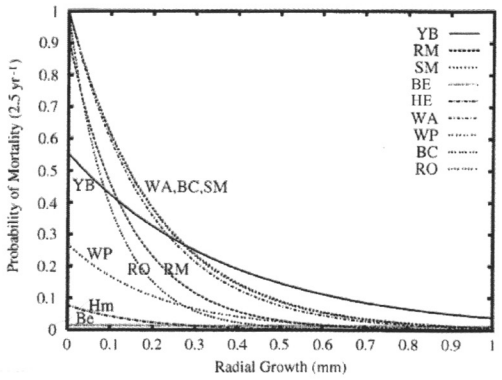
Key to Species Codes: eastern hemlock (*Tsuga canadensis* L.)(HM), red maple (*Acer rubrum* L.)(RM), white pine (*Pinus strobus* L.)(WP), sugar maple (*Acer saccharum* Marsh.)(SM), American beech (*Fagus grandifolia* Ehrh. (BE and BP), white ash (*Fraxinus americana* L.)(WA), black cherry (*Prunus serotina* Ehrh. (BC), white oak (*Quercus alba* L.)(WO), northern red oak (*Quercus rubra* L.)(RO), and yellow birch (*Betula alleghaniensis* Britton.)(YB)

Figure 2.—SORTIE submodels and associated FIA vegetation measurements, 2012 (continued on next page).

SORTIE

NRS-FIA P2+

Mortality

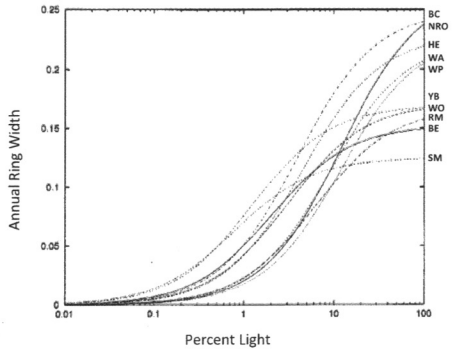


Estimates of growth-related mortality functions (Kobe and others 1995)

P2: Merchantable Tree: Species
Diameter and Tree Length
Azimuth and Distance
Tree History
Damage Code
Crown Density

Down Woody Material

Growth



Sapling growth estimates for 10 species (Pacala and others 1994)

P2: Merchantable Tree: Species
Azimuth
Distance
Diameter
Height
Volume
Weight
Carbon

Key to Species Codes: eastern hemlock (*Tsuga canadensis* L.)(HM), red maple (*Acer rubrum* L.)(RM), white pine (*Pinus strobus* L.)(WP), sugar maple (*Acer saccharum* Marsh.)(SM), American beech (*Fagus grandifolia* Ehrh. (BE and BP), white ash (*Fraxinus americana* L.)(WA), black cherry (*Prunus serotina* Ehrh. (BC), white oak (*Quercus alba* L.)(WO), northern red oak (*Quercus rubra* L.)(RO), and yellow birch (*Betula alleghaniensis* Britton.)(YB)

Figure 2 (continued).—SORTIE submodels and associated FIA vegetation measurements, 2012.

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TRANSITIONING FROM PHASE 3 VEGETATION DATA TO PHASE 2+ VEGETATION DATA IN THE NORTHERN RESEARCH STATION

W. Keith Moser, Katherine Johnson, Cassie M. Kurtz, Cassandra Olson, and William H. McWilliams[1]

Abstract.—Phase 3 (P3) vegetation diversity and structure was measured in the Northern Research Station (NRS), U.S. Forest Service, intermittently between 2000 and 2010. Varying in intensity and location, these data provide a glimpse of native and invasive plants across portions of 24 states. Between 2007 and 2010, all NRS states were sampled largely on the same schedule and intensity. In 2011, an NRS-Forest Inventory and Analysis team evaluated a new sampling protocol (NRS Phase 2+ [P2+]), which includes vegetation composition and structure variables from the Phase 2 vegetation profile and the invasive plants protocols, combined with a regeneration sampling scheme first developed for the Pennsylvania "Regeneration Study." To compare the P3 and P2+ sets of variables, our presentation will apply NRS P2+ vegetation profile, invasive plants, and advance tree seedling regeneration variables to the previously collected P3 vegetation diversity and structure data and we will discuss the implications for customers of these data.

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INTEGRATING NFI DATA WITH REMOTE SENSING AND GIS APPLICATIONS

DEVELOPMENT AND APPLICATIONS OF THE LANDFIRE FOREST STRUCTURE LAYERS

Chris Toney, Birgit Peterson, Don Long, Russ Parsons, and Greg Cohn[1]

Abstract.—The LANDFIRE program is developing 2010 maps of vegetation and wildland fuel attributes for the United States at 30-meter resolution. Currently available vegetation layers include ca. 2001 and 2008 forest canopy cover and canopy height derived from Landsat and Forest Inventory and Analysis (FIA) plot measurements. The LANDFIRE canopy cover layer for the conterminous United States is the first of its kind developed with FIA tree measurements as the source of ground reference data. The mapping process is based on regression tree models with FIA plot values as the dependent variables (canopy cover, canopy height), using predictor variables derived from reflectance, terrain, and a Shuttle Radar Topography Mission-based height metric. Base vegetation maps are updated beginning with a set of annual disturbance maps that combine extant fire severity mapping with Landsat time-series disturbance and polygon data describing management activities on Federal and state lands. FIA plot data are used in the Forest Vegetation Simulator to model disturbance effects on forest vegetation for each disturbance type and severity class. Updated 2010 products are scheduled for delivery during early 2013. The 2010 products include a new tree list layer in which stand structure is depicted explicitly by approximating a representative list of trees occurring at each 30-m pixel. The tree list layer provides a more detailed characterization of canopy fuel structure than is available with standard LANDFIRE products, facilitating new applications and research in fire behavior and fire effects simulation.

INTRODUCTION

The LANDFIRE program, now in its second update phase, produces more than 20 different 30-meter raster layers of vegetation structure and composition, fire behavior, and fire regimes for all of the major ecosystems in the United States (more information is available at www.landfire.gov). The layers describe vegetation and wildland fuel across all lands, and are designed to facilitate national and regional planning and reporting of fire management activities. This program has collaborated closely with the Forest Inventory and Analysis (FIA) Program since 2004 and FIA data are a critical component of several vegetation and fuel layers developed by LANDFIRE.

This paper focuses on a subset of LANDFIRE layers depicting forest structure that were based heavily on FIA field measurements. Forest canopy cover is the proportion of the forest floor covered by a vertical projection of the tree crowns. Canopy height is the representative height above ground level of the taller trees composing the upper canopy layer. Canopy cover and height are key variables required for modeling fire behavior spatially (Finney 2004).

The LANDFIRE canopy cover layer for the conterminous United States is the first of its kind developed with FIA tree measurements as the source of ground reference data, and is paired with

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an integrated canopy height layer. Here we give an overview of the mapping process along with current applications in wildland fire management and research. We also describe a new LANDFIRE layer under development in which stand structure is depicted explicitly by approximating a representative list of trees occurring at each 30-m pixel.

FIELD REFERENCE DATA

Tree canopy cover estimates for FIA plots were based on predicted crown dimensions, using stem coordinates recorded by field crews to map the locations of trees within the subplots and microplots (Fig. 1) (Toney et al. 2009). Canopy height was the basal area-weighted average height of the dominant, codominant, and open-grown trees in each plot. Plot records were filtered based on FIA disturbance attributes and location-specific Landsat image dates to obtain canopy cover/canopy height training sites. Some plots were omitted from the training set if they had significant disturbances (such as cutting, fire, or wind) recorded after the most recent location-specific image date in the multi-temporal Landsat mosaics described below.

PRODUCTION MAPPING PROCESS

Canopy Cover and Canopy Height

Forest canopy cover and height were produced using several dates of Landsat imagery and derived layers as predictor variables. Landsat images from leaf-off, leaf-on, and spring (U.S. Geological Survey 2001) were used, along with texture images derived from tasseled-cap images of the three dates. Elevation, slope, and aspect were also used (U.S. Geological Survey 2005). A Shuttle Radar Topography Mission-derived metric (Kellndorfer et al. 2004) was included in the canopy height modeling.

Regression tree models were fit using Cubist software (RuleQuest [n.d.]). Model predictions were applied to all 30-m pixels within the LANDFIRE forest mask. The output layers were visually checked for seam lines and presence of clouds and other artifacts from the imagery. Problem source data were eliminated or localized revisions were made.

A design requirement for the canopy cover layer was to map a statistical distribution of cover values consistent with the distribution expected for spatial fire

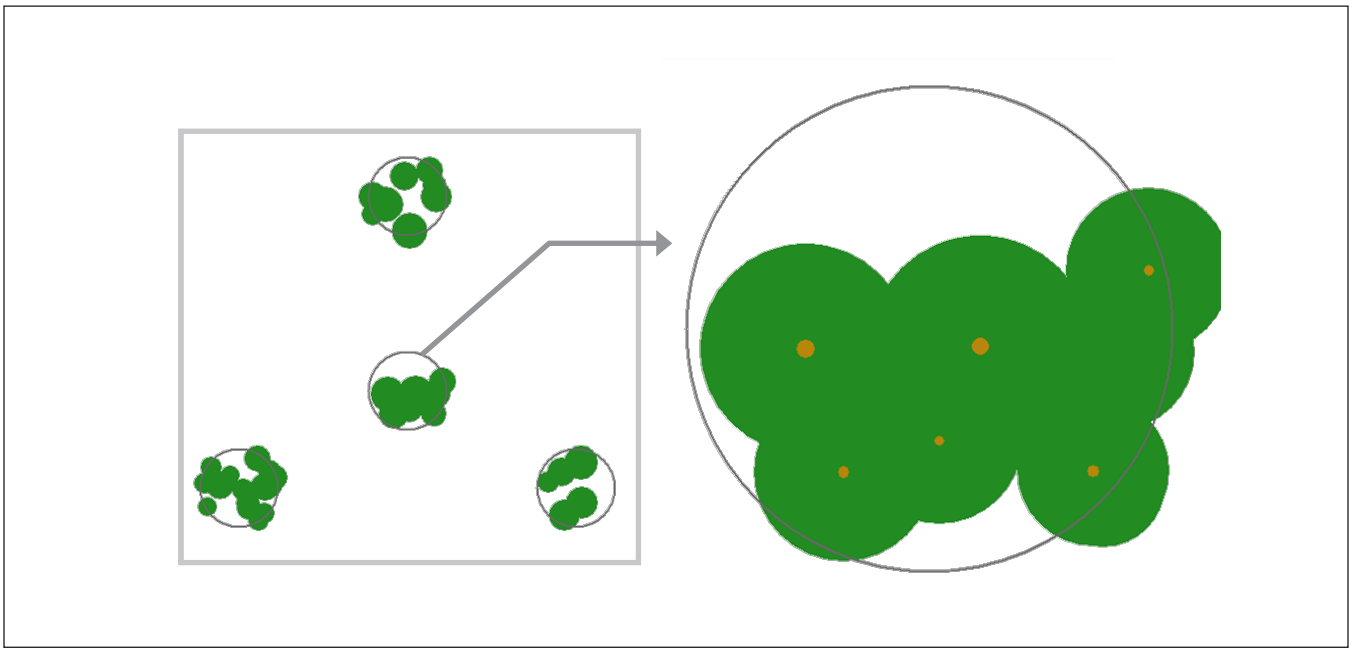


Figure 1.—Example of mapping the modeled crowns of trees in an FIA plot using stem coordinates recorded by field crews.

modeling. Canopy cover rarely exceeds 70 percent in western U.S. forest types (Scott and Reinhardt 2005, Stratton 2006) but is higher in multi-storied forests of the eastern United States. The distribution of stem-mapped FIA canopy cover was consistent with the distribution as evaluated in fire behavior models.

Updating from the 2001 base vegetation maps (Vogelmann et al. 2011) begins with a set of annual disturbance maps that combine fire severity mapping with Landsat time-series disturbance (Huang et al. 2010) and polygon data describing management activities on Federal and state lands. Products available for fire severity mapping include Monitoring Trends in Burn Severity (MTBS) (U.S. Forest Service and U.S. Geological Survey 2012), Rapid Assessment of Vegetation Condition after Wildfire (U.S. Forest Service 2011), and Burned Area Reflectance Classification (U.S. Forest Service and U.S. Geological Survey [n.d.]). Disturbance effects on forest vegetation are modeled for each disturbance type and severity class using FIA plot data in the Forest Vegetation Simulator.

Tree List Layer

The tree list layer is composed of a thematic raster map in which each 30-meter pixel is assigned a tree list identifier, along with a lookup table of tree data for each identifier. The tree list information includes species, size, status, and density from the FIA plot records. Production of the tree list layer involves post-processing the existing classified Landsat (LANDFIRE vegetation type, canopy cover, canopy height) by nearest neighbor imputation within specific landscape strata. The vegetation-based stratification defines subsets of plots eligible for imputation to pixels within each stratum on the map. At each pixel, a nearest neighbor search of the eligible plots is done in a normalized Euclidean space of variables describing geography (x, y coordinates), terrain (elevation, slope, transformed aspect), and vegetation (continuous canopy cover, canopy height). The tree list approach provides much greater detail characterizing forest structure attributes (cf. Wilson et al. 2012). For example, rather than a single canopy height value, a distribution of tree heights is presented, facilitating use of these layers as inputs to specialized models or more in-depth analysis.

PRODUCT AVAILABILITY

Canopy cover (Fig. 2) and canopy height products from LANDFIRE for 2001 and 2008 are currently available for download at www.landfire.gov. Canopy cover and height for 2010 are scheduled for delivery during early 2013. The tree list product for 2010 is also scheduled for early 2013, but availability is by request with an FIA confidentiality agreement.

APPLICATIONS

The LANDFIRE vegetation structure layers have been widely used since 2005 in fire modeling for incident support as well as planning. The layers are used for simulations in the Wildland Fire Decision Support System (http://wfdss.usgs.gov) and the Fire Program Analysis System (http://www.fpa.nifc.gov). Nonfire land management applications are also a major use (e.g., http://www.conservationgateway.org/topic/applications).

The LANDFIRE tree list layer represents a new approach for fuel mapping, providing detail similar to what might be achieved with Light Detection and Ranging mapping, but with the benefit of wall-to-wall coverage consistent with the other LANDFIRE layers. This approach has significant potential for new applications and analysis. For example, the tree list layer can be used to provide realistic inputs to new, physics-based 3D fire behavior models (e.g., FIRETEC), in which canopy fuels can be represented as discrete entities such as individual trees (Linn et al. 2005) (Fig. 3).

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Gretchen Moisen and Mark Nelson provided comments that improved the manuscript.

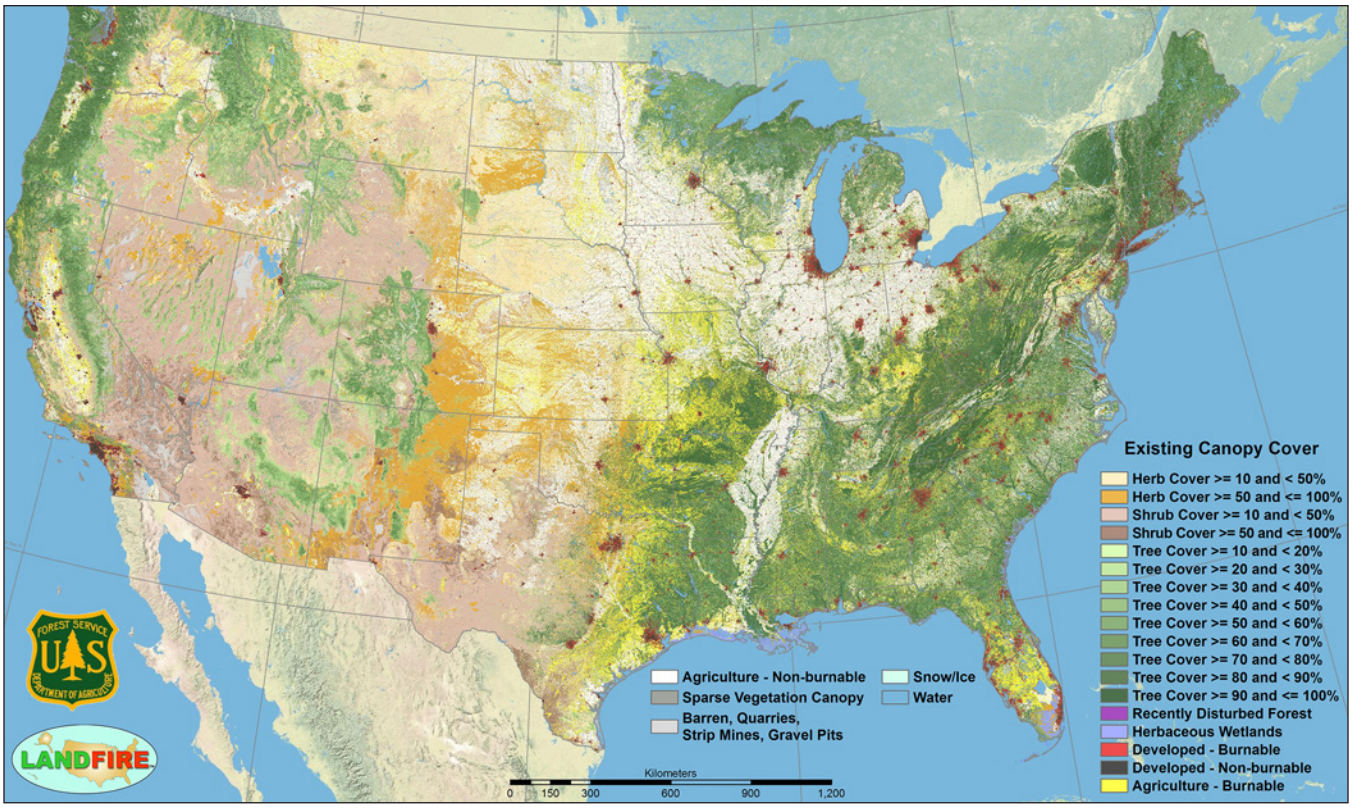


Figure 2.—LANDFIRE 2008 tree canopy cover mapped from FIA plot data and Landsat.

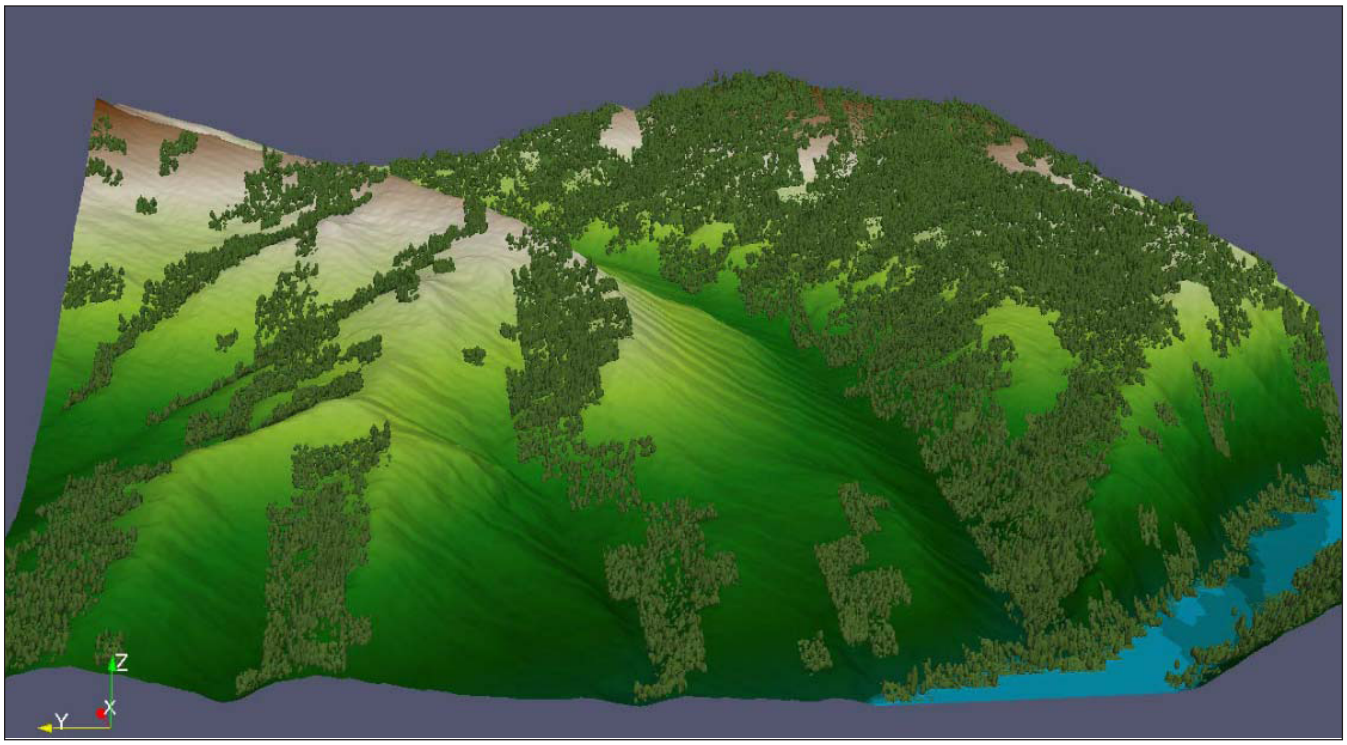


Figure 3.—Application of the LANDFIRE tree list layer as fuels input to the dynamic 3D fire model, FIRETEC. At each forested pixel, tree data from the tree list layer look-up table were expanded to the pixel scale and draped over the LANDFIRE elevation layer. The simulation area is 1 km^2, centered on Mann Gulch in the Helena National Forest, about 25 miles north-northeast of Helena, MT.

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CHARACTERIZING ENVIRONMENTAL CHANGE IN INTERIOR ALASKA (1982-2012) USING MULTI-TEMPORAL, MULTI-SCALE REMOTE SENSING DATA AND FIELD MEASUREMENTS

Hans-Erik Andersen and Robert Pattison[1]

Abstract.—We investigate how vegetation in the Tanana Valley of interior Alaska (120,000 km^2) has responded to a changing climate over the preceding three decades (1982-2012). Expected impacts include: 1) drying of wetlands and subsequent encroachment of woody vegetation into areas previously dominated by herbaceous and bryoid vegetation types, 2) changes in forest composition resulting from succession processes within burned areas, 3) mortality and defoliation from increased insect activity attributable to a warming climate, 4) effects on tree growth attributable to drought stress and/or reduced photosynthetic capacity, and 5) expansion of woody vegetation at the tree line. To characterize and quantify these changes occurring over the full range of environmental conditions present in this vast region, we plan to use a unique resource of multi-temporal and multi-scale remote sensing data to analyze changes observed between 1) field data and large-scale photographs collected in 1982 over a selection of inventory plots within the western Tanana Valley region, and 2) low-altitude airborne digital imagery collected over these same inventory plots in 2012. Detailed stand- and plant-level changes observed over 40-ha remeasured photo plots will be scaled up and used to inform an analysis of changes in vegetation condition observed in spectral trajectories obtained from a time series of Landsat Thematic Mapper/Enhanced Thematic Mapper Plus imagery over this 30-year period.

INTRODUCTION

The impacts of climate change on the condition and productivity of vegetation are likely to be particularly significant in the boreal forest regions of the world, such as interior Alaska, where observed rates of temperature change over the last three decades are significantly higher than in other terrestrial biomes. High northern latitudes have experienced the strongest warming trend during the era of satellite observations (1972-present), leading to a variety of climate-driven changes in vegetation growth and mortality (e.g., Wolken et al. 2011). These impacts are highly varied across the region's wide range of environmental (e.g., hydrological, elevation) gradients. The changes occurring in interior Alaska have important implications for local community subsistence through impacts on wildlife (Kofinas et al. 2010) and biomass for energy (Fresco and Chapin 2009). Due to the vast spatial extent and lack of infrastructure in the region, there has been very little systematic repeated sampling as typified by the permanent plots, such as those of the Forest Inventory and Analysis Program, that can be found in other regions. As a result, insights about changes in interior Alaska have come from localized field studies and broad-scale remote sensing efforts, often carried out independently (Hollingsworth et al. 2010, Parent and Verbyla 2010).

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OBJECTIVES

In this study, we are investigating how vegetation in interior Alaska has changed over three decades (1982-2012) and link those changes to shifts in climate regime during that time. We will develop a hierarchical approach to evaluating vegetation change using a unique resource of multi-temporal and multi-scale remote sensing data along with remeasured field plots over a 17,000-km^2 area in the vicinity of Fairbanks, AK (Fig. 1). We expect changes in climate to be manifested in a variety of ways that will be visible across multiple scales of observation. Expected ecological impacts include: 1) drying of wetlands and subsequent encroachment of woody vegetation into areas previously dominated by herbaceous and bryoid vegetation types, 2) increase in deciduous vegetation postfire due to increased fire severity, 3) tree mortality and defoliation due to increased insect activity attributable to a warming climate, 4) impacts on tree growth attributable to drought stress and/or reduced photosynthetic capacity, and 5) expansion of woody vegetation at tree line. A unique feature of this study will be that we will capitalize on the permanent plot remeasurements to provide more robust insights into changes.

APPROACH

Field data and large-scale photographs collected for a previous inventory of the Tanana Valley in interior Alaska carried out in the early 1980s will be compared with field data and low-altitude airborne digital imagery collected over plots in 2010 in a previous study and in 2012 (Fig. 1). Detailed stand- and plant-level changes observed at field plots and 40-ha remeasured photo plots will be scaled up and used to inform an analysis of changes in vegetation condition observed in spectral trajectories obtained from a time series of Landsat Thematic Mapper/Enhanced Thematic Mapper Plus (TM/ETM+) imagery over this 30-year period.

Remeasurement of Adaptive Infrared Imaging Spectroradiometer Field Data

We plan to revisit a subset of seven Adaptive Infrared Imaging Spectroradiometer (AIRIS) field plots in the vicinity of Fairbanks to confirm and clarify patterns seen at broader scales (repeat air photography and satellite) and to assess feasibility of remeasuring field plots over a broader geographic range in the future (Fig. 1). Revisited plots will be prioritized by those that: 1) are in areas that are near roads (to reduce sampling costs), 2) have undergone the greatest change (increase or decrease) in Normalized Difference Vegetation Index (NDVI) across the study area, and 3) have not been burned (to simplify analyses for this study). Each AIRIS field plot consisted of 19 sample points distributed uniformly throughout the 8-ha photo plot area. Field data from the 1982-1983 inventory are readily available (MS Access database), as are scanned copies of the field manual with detailed sampling notes, and photos taken on the plot. Monuments were placed at all plots to make them easier to find.

Remeasurement of AIRIS Photo Plots

We will refly 30 AIRIS photo plots in the vicinity of Fairbanks with low-altitude (large-scale) digital stereo imagery, to characterize stand- and plant-level processes of change, including shrub and tree establishment, mortality, species replacement or succession, and changes in surface hydrology, for assessment of impacts on carbon flux and habitat. Forest-type polygons interpreted in the 1982 and 2012 photos will provide a large footprint (40 ha) to compare with changes observed in a time series of satellite imagery. Several of the AIRIS photo plots within the proposed study area have already been reflown for a previous project.

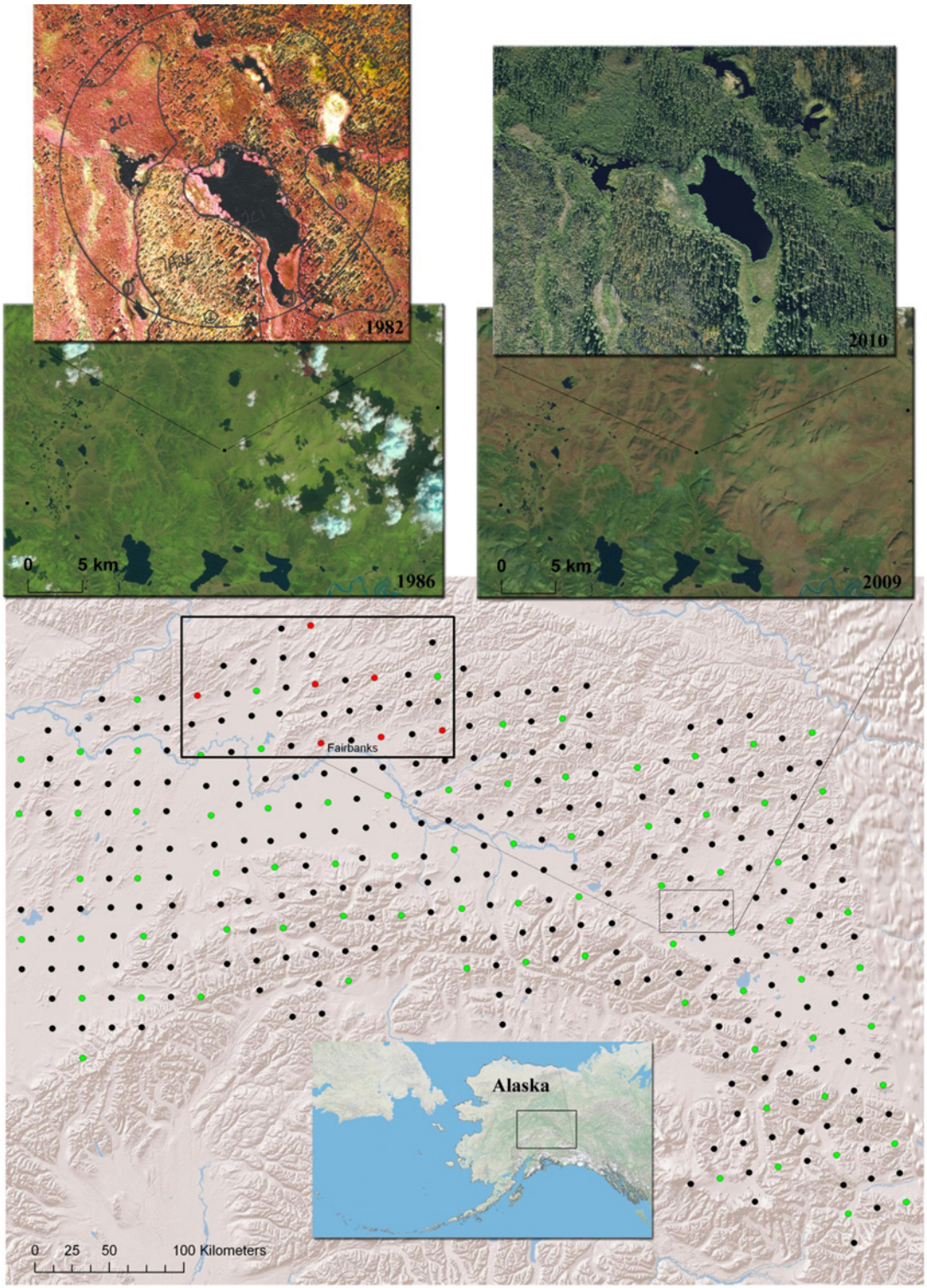


Figure 1.—Location of AIRIS photo plots (black dots) and AIRIS field plots (green) within Tanana Valley, interior Alaska. Black rectangle in upper left area of main map shows proposed 17,000-km^2 study area for this project; red dots indicate the accessible AIRIS field plots to be visited. Inset graphics show Landsat TM imagery and low-altitude aerial photos from the mid-1980s and late-2000s. Photo-interpreted forest type polygons within the 1982 8-ha photo plot are also shown. Note terrestrialization and shrinkage of pond area, as well as burned areas evident in Landsat TM imagery.

Time-Series Analysis of Changes in Satellite Imagery

All field-visited (~7) and reflown photo plots (~30) will be also be examined with a 30-year time- series analysis of changes in key spectral indices (e.g., NDVI) from Landsat TM/ETM+ using TimeSync (Cohen et al. 2010). This analysis will allow us to compare how these field and photo plots fit into other regionwide satellite-based studies of changes in key indices (Parent and Verbyla 2010) and will provide a foundation for regionwide (i.e., "wall-to-wall") assessment of changes to the entire Tanana Valley by using the 30-year Landsat TM/ETM+ record with other approaches such as Landsat-based Detection of Trends in Disturbance and Recovery (LandTrendr) (Kennedy et al. 2010) in the future.

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A MODEL FOR QUANTIFYING FOREST VARIABLES OVER LANDSCAPES WITH UNCERTAIN FOREST AREAS

Andrew O. Finley, Sudipto Banerjee, and David W. MacFarlane[1]

Abstract.—We are interested in predicting one or more continuous forest variables (e.g., biomass, volume, age) at a fine resolution (e.g., pixel level) across a specified domain. Given a definition of forest/nonforest, this prediction is typically a two-step process. The first step predicts which locations are forested. The second step predicts the value of the variable for only those forested locations. Rarely is the forest/nonforest status predicted without error. However, the uncertainty in this prediction is typically not propagated through to the subsequent prediction of the forest variable of interest. Failure to acknowledge this error can result in biased estimates of forest variable totals within a domain. In response to this problem, we offer a modeling framework that will allow propagation of this uncertainty. Here we envision two latent processes generating the data. The first is a continuous spatial process while the second is a binary spatial process. The continuous spatial process controls the spatial association structure of the forest variable of interest, while the binary process indicates presence of a possible nonzero value for the forest variable at a given location. The proposed models are applied to geo-referenced National Forest Inventory (NFI) data and spatially coinciding remotely sensed predictor variables. Due to the large number of observed locations in this dataset, we seek dimension reduction not just in the likelihood, but also for unobserved stochastic processes. We demonstrate how a low-rank predictive process can be adapted to our setting and reduce the dimensionality of the data and ease the computational burden.

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CLIMATE CHANGE AND FOREST HEALTH: INTEGRATING FIA, CLIMATE DATA, AND SPATIAL TECHNOLOGY FOR LONG-TERM MONITORING

RELATIONSHIP BETWEEN CROWN DIEBACK AND DROUGHT IN THE SOUTHEASTERN UNITED STATES

Michael K. Crosby, Zhaofei Fan, Martin A. Spetich, Theodor D. Leininger, and Xingang Fan[1]

Abstract.—Forest Health and Monitoring (FHM) and Palmer's Drought Severity Index (PDSI) data were obtained for 11 states in the southeastern United States to assess the relationship between drought and crown dieback. Correlation analyses were performed at the species group and ecoregion levels within the study area. The results indicate a negative correlation between drought and crown dieback within 3 to 5 years of the onset of drought conditions.

INTRODUCTION

Crown dieback, a crown health indicator collected during Phase 3 sampling by the Forest Health and Monitoring (FHM) Program of the U.S. Forest Service, provides an early indication of tree stress by estimating the amount of death that has occurred in a tree crown (Schomaker et al. 2007). We seek to use crown dieback as a first indication of the impacts of drought on forests in the southeastern United States. Regional differences in crown dieback such as elevated crown dieback in maple species (*Acer* spp.) throughout the northeastern United States and red oak species (*Quercus*, section *Lobatae*) in the Ozark Highlands (Fan et al. 2008, Randolph 2009) indicate that trees may react differently to sources of stress. Typically, hardwood species will shed leaves to avoid drought stress while pine species typically have less leaf area from the outset (Barnes et al. 1998). In the southeast, Randolph (2009) found that oak species had higher levels of crown dieback than pines. Further, denser oak stands exhibit a higher susceptibility to drought in some areas of Alabama, Georgia, and Virginia that could lead to an increase in mortality (Klos et al. 2009) or increased susceptibility to damage from fires or insects.

Monitoring the susceptibility to damage over a large scale is an important first step in understanding the interaction between climate and forests. To this end, we wanted to determine the relationship between crown dieback and drought within various species groups by forest type and ecoregion. Our hypothesis was that relationships will vary among the selected groups and give an overall impression of the impact of drought on southeastern U.S. forests.

METHODS

Crown dieback, plot location (i.e., latitude and longitude), and inventory year were extracted from FHM inventory data obtained from the U.S. Forest Service for all trees with a diameter at breast height (d.b.h.) greater than 5 inches for available states in the southeastern United States (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, North Carolina, South Carolina, Texas, Tennessee and Virginia). PDSI data (Palmer 1965), a commonly used index for assessing drought, were obtained from the National Climatic Data Center of the National Oceanic and Atmospheric Administration to determine the severity and duration of drought across the southeastern United

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States. FHM and PDSI data were then displayed in a geographic information system (GIS) and joined so that PDSI values were extracted to the FHM plot. This allowed for a completed dataset of crown dieback and PDSI for each tree record in the dataset. The data were then extracted by species group within each forest type and then by ecoregion. It was then possible to assess the relationship between crown dieback and PDSI across forest types and ecoregions for each species group.

RESULTS

The pine species group did not yield any significant relationships with PDSI, forest type, or ecoregion. The red oak, white oak (*Quercus* section *Quercus*), and other hardwood species groups all exhibited significant relationships with forest type, with pine, oak/pine, and oak/hickory having elevated levels of crown dieback. PDSI and ecoregion were also significant explanatory variables for red oak and white oak species groups with the highest levels of crown dieback occurring in areas impacted by drought (Table 1). These preliminary findings can be used to further refine models to monitor crown health with indicators of drought.

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Table 1.—The most significant variables for assessing crown dieback in the southeastern United States by species group

Species Group	Significant Variables	Crown Dieback (%)
Red Oaks	Pine, Oak/Pine, and Oak/Hickory forest types	19.7
	Eastern Broadleaf Forest (Oceanic), Outer Coastal Plain Mixed Forest, Lower MS Riverine Forest, Ouachita Mixed Forest/Meadow Ecoregions	26.7
	3-Year Cumulative PDSI ≥1.28	36.8
White Oaks	Prairie Parkland Ecoregion	33.2
	Pine, Oak/Hickory, and Oak/Gum/Cypress forest types	39.6
	7-Year Cumulative PDSI < -1.802	64.8
Other Hardwoods	Pine, Oak/Pine forest types	42.6

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ASSESSING FOREST MORTALITY PATTERNS USING CLIMATE AND FIA DATA AT MULTIPLE SCALES

Michael K. Crosby, Zhaofei Fan, Xingang Fan, Theodor D. Leininger, and Martin A. Spetich[1]

Abstract.—Forest Inventory and Analysis (FIA) and PRISM climate data from 1991-2000 were obtained for 10 states in the southeastern United States. Mortality was calculated for each plot, and annual values for precipitation and maximum and minimum temperature were extracted from the PRISM data. Data were then stratified by upland/bottomland for red oak species, and classification and regression tree (CART) analysis was used to determine the influence of climate variables on mortality at ecoregion province and section levels. The results presented here will provide a basis for future research on the causal factors related to red oak mortality.

INTRODUCTION

Increased mortality in red oak species (*Quercus*, section *Lobatae*) has been attributed to a variety of factors ranging from biotic (e.g., oak borers [Fan et al. 2008]) to abiotic (e.g., drought [Law and Gott 1987]). Such widespread loss of these species could lead to compositional changes in forests across the southeastern United States. While previous studies have sought to relate climatic factors to increased levels of mortality, few have considered the changes in mortality patterns at finer scales of analysis such as the ecoregion province level and section level. Analyzing the relationship between climatic factors and mortality at increasingly finer scales could allow for new insights into changing mortality trends for red oak species across the region. Thus, we assessed changes in mortality for upland and bottomland red oak species by: 1) determining the trends in mortality; and 2) using classification and regression tree (CART) to determine the relationships between mortality and climate variables at ecoregion provinces and sections for both upland and bottomland red oak species. The results of these analyses will help guide future research endeavors across the region as we seek to understand causal factors related to mortality for all species in the southeastern United States.

METHODS

Data including latitude, longitude, species codes, and basal areas of live and dead trees (red oaks) were extracted from the Forest Inventory and Analysis (FIA) database for 10 states in the southeastern United States for which inventory data were available between 1991-2000 (Oklahoma, Arkansas, Kentucky, Tennessee, Mississippi, Alabama, Georgia, Florida, South Carolina, and Virginia). Geographic information system (GIS) software was then used to extract total annual precipitation, maximum temperature, minimum temperature, and temperature range from PRISM (Oregon State University 2012) for 2 years preceding each inventory year as well as ecoregion province and section codes. Mortality was calculated as a percentage of dead basal area for each species type that occurred within each plot by dividing dead basal area by total basal area of the plot. The data were then divided based on sites upon which each species typically

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occurs (e.g., upland or bottomland [Table 1]) for red oak species. This was done in an effort to determine both the scale and degree of difference between the two groups. R statistical software was utilized to perform kernel smoothing using the ”stats” package (R Core Team 2012) to allow for the determination of a spatial trend in mortality, and CART analysis using the “rpart” package (Therneau et al. 2012) to determine the relationship between mortality and climate variables at the ecoregion province and section levels (Table 2).

Table 1.—List of upland and bottomland red oak species extracted from 1991-2000 Forest Inventory and Analysis (FIA) data for 10 southeastern states

	Common Name	Scientific Name
Upland	Scarlet oak	*Quercus coccinea*
	Southern red oak	*Quercus falcata*
	Blackjack oak	*Quercus marilandica*
	Northern red oak	*Quercus rubra*
	Black oak	*Quercus velutina*
	Bluejack oak	*Quercus incana*
Bottomland	Cherrybark oak	*Quercus pagoda*
	Water oak	*Quercus nigra*
	Nuttall oak	*Quercus texana*
	Willow oak	*Quercus phellos*
	Shumard oak	*Quercus shumardii*

Table 2.—Ecoregion sections used in analysis of mortality at the ecoregion province and section levels

Code	Section	Province
A	Arkansas Valley	Southeastern Mixed Forest
B	Atlantic Coastal Flatlands	Outer Coastal Plain Mixed Forest
C	Blue Ridge Mountains	Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow
D	Boston Mountains	Ozark Broadleaf Forest-Meadow
E	Central Ridge/Valley	Eastern Broadleaf Forest (Oceanic)
F	Coastal Plain/Flatwood, Lower	Outer Coastal Plain Mixed Forest
G	Coastal Plain, Middle	Southeastern Mixed Forest
H	Florida Coastal Lowlands, Eastern	Outer Coastal Plain Mixed Forest
I	Florida Coastal Lowlands, Western	Outer Coastal Plain Mixed Forest
J	Interior Low Plateau, Highland Rim	Eastern Broadleaf Forest (Continental)
K	Interior Low Plateau, Shawnee Hills	Eastern Broadleaf Forest (Continental)
L	Mid Coastal Plain, Western	Southeastern Mixed Forest
M	Mississippi Alluvial Basin	Lower Mississippi Riverine Forest
N	North Cumberland Mountains	Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow
O	North Cumberland Plateau	Eastern Broadleaf Forest (Oceanic)
P	Northern Ridge/Valley	Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow
Q	Ouachita Mountains	Ouachita Mixed Forest-Meadow
R	Ozark Highlands	Eastern Broadleaf Forest (Continental)
S	Southern Appalachian Piedmont	Southeastern Mixed Forest
T	Southern Cumberland Mountains	Eastern Broadleaf Forest (Oceanic)
U	Southern Cumberland Plateau	Southeastern Mixed Forest
V	Southern Ridge/Valley	Southeastern Mixed Forest
W	Southern Unglaciated Allegheny Plateau	Eastern Broadleaf Forest (Oceanic)
X	Upper Gulf Coastal Plain	Eastern Broadleaf Forest (Continental)

RESULTS

The highest level of mortality in upland red oak species occurred from coastal areas of southern Alabama northeastward through portions of the Appalachian Mountains. Portions of the Ozark Highlands showed 10-15 percent mortality while coastal areas of South Carolina ranged from 25-30 percent. At the ecoregion province level, CART results showed that the first split occurred at provinces, with the Eastern Broadleaf (Oceanic) province having the highest level of mortality (~25 percent). The second split was for current (inventory year) precipitation where 54 percent mortality levels were associated with precipitation less than 1053 mm, below the minimum value for average annual precipitation within the province. Analysis at the ecoregion section level was similar, with sections located in the eastern portion of the study area being associated with higher levels of mortality. A second split occurred with precipitation values less than 1051 mm (below minimum average values), with a third split indicating a few sections with mortality values approaching 60 percent (Fig. 1).

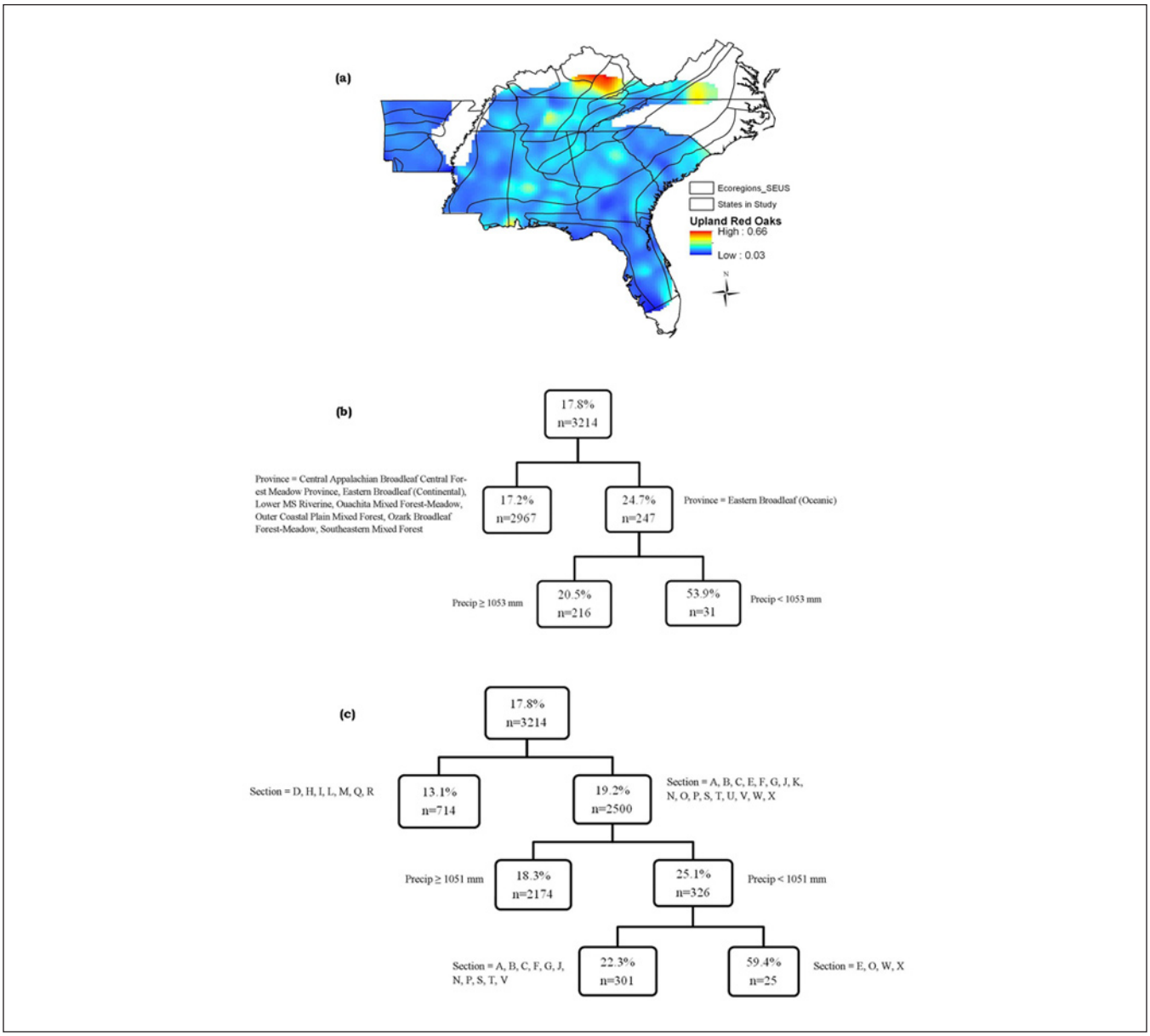


Figure 1.—Upland red oak species (a) spatial trend for mortality, (b) CART model at the ecoregion province level , and (c) CART model at the ecoregion section level.

The north to south spatial trend for bottomland red oak species was similar to the upland species, with the highest mortality values (ranging from 25 to 35 percent) occurring across northern portions of Alabama, across Tennessee and Kentucky, and in south-central portions of Virginia. The first split in the CART analysis at the province level occurred for the previous year's average annual temperature range with higher mortality associated with ranges exceeding 13.16 °C. A second split was associated with minimum average temperatures greater than 12.36 °C, although only 11 samples met this criterion. The CART model for the section level matches the province level but has a split for previous year's temperature range of less than 13.16 °C that shows mortality values near 19 percent for sections in the eastern part of the study area (Fig. 2)

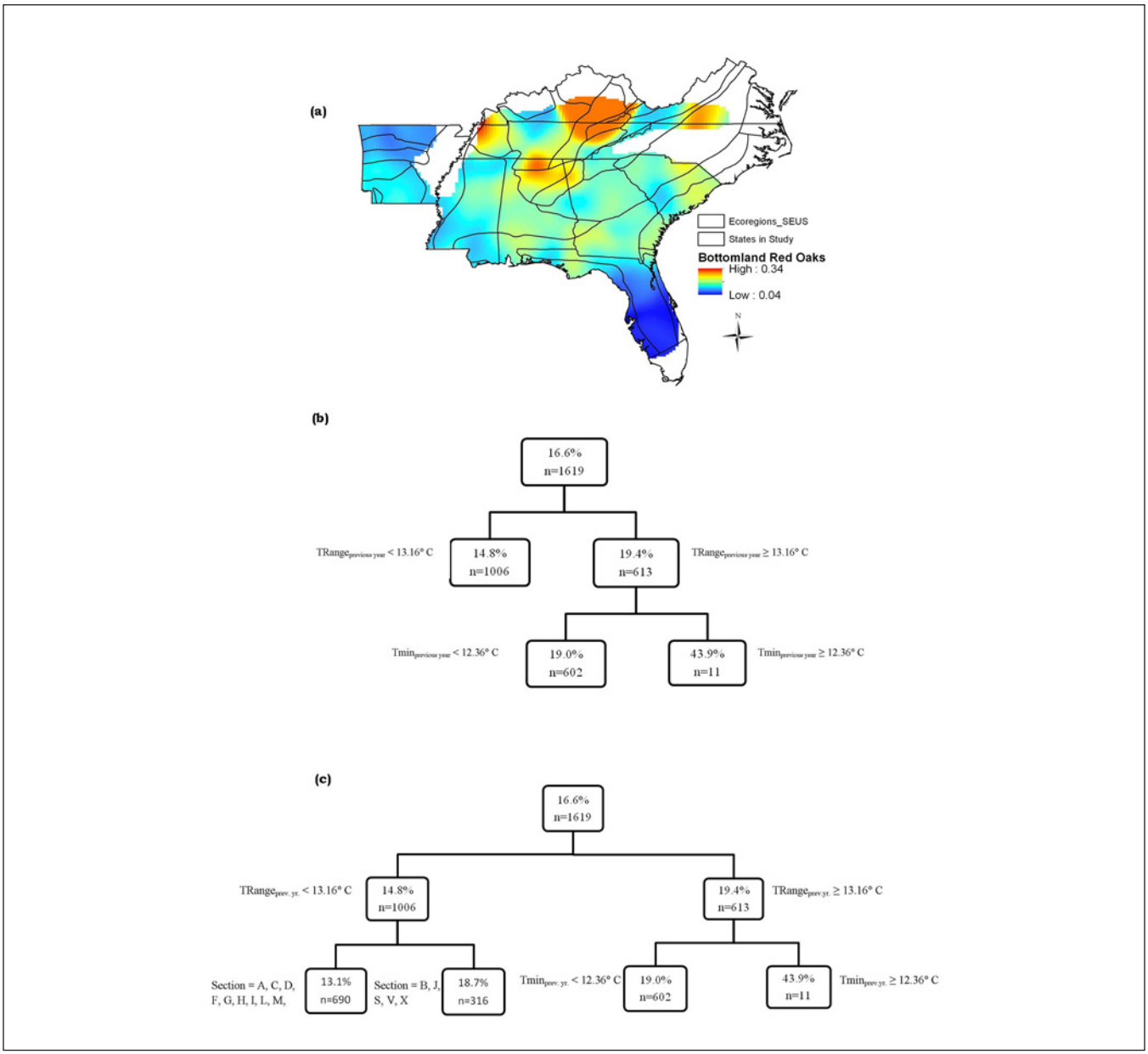


Figure 2.—Bottomland red oak species (a) spatial trend for mortality, (b) CART model at the ecoregion province level, and (c) CART model at the ecoregion section level.

DISCUSSION

The most notable findings are the changes in mortality between the two scales of analysis. The province level analysis for upland red oak species shows a split for which the highest mortality levels are associated with one province; however, when analysis occurs at the section level, many sections across the eastern portion of the study area show higher levels of mortality than those for sections in the west (e.g., Ozark Highlands). The number of sections that appear from within provinces not associated with increased levels of mortality in the province level analysis illustrates the importance of the increased level of detail that occurs at the section level. The sections are associated with detailed environmental and biological features (e.g., dominant forest cover) that provide a means of assessing differences across the region (McNab and Avers 1994). At finer scales, it is likely that micro-climatic influences are having a greater impact on mortality than at larger scales. Kabrick et al. (2007) found that ecological land types, determined at the stand scale, can be useful for determining areas where mortality is likely to be greatest by identifying areas that are less suitable for the support of healthy forests.

Also notable are the differences in mortality between upland and bottomland red oak species. The only climate variable of importance for upland species was average annual precipitation in the same year in which the inventory occurred while for bottomland species, the most influential variable was average annual temperature range. These findings point to the possible importance of extreme temperatures during some months of the year, which could act to stress trees in the impacted areas. The bottomland red oak ecoregion sections with increased mortality indicate some local or possibly regional influences such as associated forest or soil types, elevation, and/or aspect. Oak mortality events related to stand and site factors such as these can also vary across physiographic regions (Oak et al. 1996).

The different variables that influence the level of mortality for upland and bottomland red oaks vary at the scale of analysis but could also vary temporally. It has been established that drought can greatly influence red oak species mortality (Fan et al. 2012). Additional research could also assess variables such as tree age and growing season versus nongrowing season precipitation. The analysis performed here shows that there exists at least some fine scale interaction between mortality and climate variables. Future research will analyze the aforementioned variables as well as compare them to mortality trends in additional time periods.

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INCORPORATING LOCAL STATISTICS BASED SPATIAL WEIGHT MATRIX INTO SIMULTANEOUS AUTOREGRESSIVE MODEL TO PREDICT THE DISTRIBUTION OF NONNATIVE INVASIVE SHRUBS IN THE UPPER MIDWEST

Weiming Yu, Zhaofei Fan, and W. Keith Moser[1]

Abstract.—In this study, we extended the spatial weight matrix defined by Getis and Aldstadt to a more general case to predict the distribution of invasive shrubs among the Upper Midwest counties in a simultaneous autoregressive (SAR) model context. The modified spatial weight matrix performs better than the original spatial weight matrix since it adjusts weights of observations based on the distance from other observations but still maintains the locally adaptive nature of the latter. Both the simulation study and the application to the Forest Inventory and Analysis (FIA) plot data for invasive shrubs collected in 2005-2006 proved that the modified spatial weight matrix outperform its original case in diagnostic statistics (e.g., AIC) and resultant invasion maps. Our results provided further evidence that misspecification of spatial autocorrelation structure in spatial data will result in misinterpretation of real ecological processes and bias estimation of coefficients for important covariates involved. The geographical distribution of invasive shrubs in the Upper Midwest was significantly associated with latitude; local clusters (a group of counties) of high abundance/presence of invasive shrubs was significantly determined by TRPF (a ratio of road density to percent of forest cover at the county level), a variable reflecting the intensity of human disturbance. Both the multiple linear regression model and the SAR model with the original spatial weight matrix incorporated tended to overestimate the effect of forest type (community) on invasive shrubs. However, the SAR model with the modified spatial weight matrix showed that distribution of invasive shrubs among forest types was only marginally different at the significance level of $p = 0.05$. This result conforms to the plot level study and is favorably supported by the data. As a conclusion, the SAR model incorporating the modified spatial weight matrix provides an applicable solution to map spatial data and estimate spatial autocorrelation structure and covariate effect in ecological studies.

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PROJECTING CLIMATE CHANGE IMPACTS ON DOWN WOODY MATERIALS IN THE EASTERN U.S. FORESTS

Zhaofei Fan, Christopher W. Woodall, and Stephen R. Shifley[1]

Abstract.—Down woody material (DWM) is dead biomass that originates from tree/plant mortality in forest ecosystems. DWM is an indicator of forest ecosystem health and can be used to evaluate fire risk, wildlife habitat, and forest carbon stocks. Total DWM and components (coarse woody debris, fine woody debris, litter, and duff) are measured on the Forest Inventory and Analysis (FIA) Phase 3 plots. In this study we employed a two-stage modeling strategy to combine the Phase 2 and Phase 3 plots to map the distribution of major DWM components across the eastern United States. We first used data from the Phase 3 plots to develop a set of semiparametric penalized spline functions to estimate DWM components based on a set of covariates that were measured for both the Phase 3 and the Phase 2 plots. Then we used the derived spline models to estimate DWM components for all Phase 2 plots and map the distribution of DWM components at selected resolutions that are pertinent to management needs. We used multivariate classification and regression tree to evaluate the impact of climatic variables on distributional patterns of DWM components. By integrating design-based information and model-assisted inference this approach improves the efficiency of the estimators of DWM components compared to the design-based estimators. Finally, we explored the ecological implications of current patterns of DWM (by components) for major forest cover types and ecoregions in the eastern United States and discussed the potential impacts of management practices on hardwood forest ecosystems.

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SPREAD OF CHINESE TALLOW IN EAST TEXAS USING FIA DATA

Zhaofei Fan[1]

Abstract.—Chinese tallow tree (*Triadica sebifera* [L.] Small) is an invasive species that is replacing native ecosystems in areas of eastern Texas. It is imperative that the spatial pattern of the spread of this species be identified, as well as causal mechanisms. To that end, we seek to determine factors that contribute to the spread of Chinese tallow using autologistic regression. We also attempt to identify current locations and spread rates across eastern Texas using Forest Inventory Analysis (FIA) data within major forest types. Distance to roads, disturbances (natural and anthropogenic), and low slope were identified as major factors for the occurrence of Chinese tallow. The highest probability of occurrence and spread rate of Chinese tallow were found in the oak/gum/cypress forest type. Continued disturbance, from harvest events or natural disasters will allow the species to continue to spread throughout the region and could threaten overall forest productivity. We also discuss some implications of the continued spread of Chinese tallow on forest management. Forest managers could benefit from this analysis and use it as a guide for monitoring forest types with the highest risk of invasion.

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TEMPO-SPATIAL TRENDS OF OAK DECLINE AND MORTALITY UNDER PERIODIC REGIONAL DROUGHTS IN THE OZARK HIGHLANDS OF ARKANSAS AND MISSOURI

Shirley X. Fan, Zhaofei Fan, W. Keith Moser, Matin A. Spetich, and Stephen R. Shifley[1]

Abstract.—Oak decline and mortality trends for major oak species (groups) was explored in the Ozark highlands of Arkansas and Missouri at the forest landscape/region level, based on annual FIA plot data from 1999 to 2010. Oak decline has elevated cumulative mortality of red oak species to 11 and 15 percent in terms of relative density and basal area of standing dead oak trees, respectively; this rate is two to three times higher than for white oak group and non-oak species.

Oak decline and associated escalating mortality have occurred primarily within red oak species while white oak group maintain a relatively stable mortality rate comparable to non-oak species. Cross-correlation analyses indicate that mortality was significantly correlated with the growing season Palmer Drought Severity Index (PDSI) and usually lagged 2 to 3 years following single drought events. Moreover, based on the past 17 year's PDSI data, it appears that the cumulative impacts of drought may last up to 10 years. The Ozark highlands experienced a severe drought extending from 1998 to 2000 and another milder drought from 2005 to 2006. These drought events triggered the escalation of mortality starting around year 2000. Spatially, high mortality of red oak (hot spots proportional basal area mortality > 0.15) occurred mainly in the central area of the Ozarks. Moderate mortality (proportional basal area mortality of 0.10 to 0.15) was widely dispersed over most of the Ozark highlands, while low mortality was distributed around the outer perimeter of the Ozarks. In contrast, in the white oak group and non-oak species, high mortality was rare and moderate mortality was sporadic. Cumulative mortality of these species was predominant throughout the Ozarks.

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METHODS FOR IMPROVING FOREST INVENTORY

ESTIMATORS USED IN THE NEW MEXICO INVENTORY: PRACTICAL IMPLICATIONS OF "TRULY" RANDOM NONRESPONSE WITHIN EACH STRATUM

Paul L. Patterson and Sara A. Goeking[1]

Abstract.—The annual forest inventory of New Mexico began as an accelerated inventory, and 8 of the 10 Phase 2 panels were sampled between 2008 and 2011. The inventory includes a large proportion of nonresponse. FIA's estimation process uses post-stratification and assumes that nonresponse occurs at random within each stratum. We construct an estimator for the New Mexico inventory and derive an estimated variance based on the missing-at-random assumption.

INTRODUCTION

The national Forest Inventory and Analysis (FIA) Phase 2 grid forms the basis for FIA sampling, yet not all Phase 2 plots can be sampled. When plots are not sampled due to denial of access, logistical constraints, or hazardous conditions, we refer to them as nonresponse following the convention of Patterson et al. (2012). From 2008 to 2011 in New Mexico 8 of 10 panels (more than 5,000 plots) were sampled under an accelerated inventory. For many reasons, there is a large amount of nonresponse in New Mexico, which warrants an examination of how FIA handles nonresponse.

Standard FIA assumptions are that we have a simple random sample of a region, R, which can be post-stratified and whose total area, A_T, is known. The number of acres, A_d, in domain d is of interest, and is equal to $A_T P_d$, where P_d is the proportion of R that is classified in domain d. The FIA post-stratified estimator for P_d is

$$\hat{P}_d = \Sigma_{h=1}^{H} W_h \hat{P}_{dh} \qquad [1]$$

where H is the number of strata, W_h is the weight of the strata, and $\hat{P}_{dh}$ is an estimate of the proportion of stratum h that is in domain d. The definition of $\hat{P}_{dh}$ in chapter 4 of Bechtold and Patterson (2005) contains adjustments for nonresponse plots. The two types of nonresponse are entire plots and partial plots. The adjustment for plots that are entirely nonresponse is to reduce the sample size, while an adjustment factor is used to compensate for plots with partial nonresponse. Both adjustments are based on the assumption that nonresponse is random within each stratum. Patterson et al. (2012) showed by example that substantial bias can occur if the missing-at-random assumption is violated in the case where the nonresponse is restricted to entire plots. Roesch et al. (2012) showed a) why bias occurs when there are plots with partial nonresponse, and b) that if the missing-at-random assumption is correct, then the adjustment factor for the partial nonresponse portion of the estimator is unbiased, given the assumption the sample size is reduced to adjust for plots that are entirely nonresponse. The issue of whether the reduction in sample size, through a non-random process, induces a bias in the estimator is not addressed. Neither is the effect of the reduction in sample size, through a non-random process, on the variance and estimated variance addressed in Bechtold and Patterson (2005) or Roesch et al. (2012).

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Roesch et al. (2012) proposed using partitions of the strata, for which the assumption that the nonresponse is random is tenable for each of the partitions, and then for each partition use ($\hat{P}_{d*}$) to estimate the portion of the partition that is in the domain *d*. In Särndal et al. (1992) the division of the population into groups where the assumption of random nonresponse is valid is referred to as the response homogeneity group (RHG) model.

The purpose of this manuscript is to: 1) construct the estimator used to estimate P_d for the estimation units in the New Mexico inventory; 2) use the statistical framework in Särndal et al. (1992) to construct an estimator equal to the estimator constructed in item 1 and use this equality to investigate the statistical properties of the FIA estimator, namely bias, variance and properties of an estimated variance; and finally 3) discuss the implications for the current FIA estimated variance.

NEW MEXICO ESTIMATOR

Two potential partitioning criteria arise in many FIA estimation units (Patterson et al. 2012). The first is ownership class; denied access is higher among private owners. The second is an aspect of the FIA pre-field procedure, in which high-resolution photos are used in conjunction with old field notes to classify each plot as either "office plot" or "field plot". The office plots are designated as nonforested. The salient point here is that for the office plots the probability of nonresponse is zero, while in most field plots the probability of nonresponse is greater than zero. Whether a stratum needs to be partitioned into office and field domains depends on two factors: first, the agreement between the stratification scheme and pre-field classification and second, the amount of nonresponse in the stratum. If a stratum needs to be partitioned into office and field substrata, the weights for these two partitions must be estimated.

To facilitate the comparison with Särndal et al. (1992) we will develop some notation. It is useful to differentiate between the strata-partitions where the weight is known and partitions where the weight must be estimated. We assume there are *H* strata with known weights. Of the *H* strata, H_1 do not need to be partitioned further and H_2 of the strata need to be partitioned further with the weights for the partitions being estimated. Note that $H_1 + H_2 = H$. Let J_h denote the number of partitions in the *h*th stratum (note: for the first H_1 strata $J_h = 1$). In RHG model terminology (Särndal 1992) there are $J = \sum_{h=1}^{H} J_h$ response groups and each response group is a subset of one of the *H* strata.

In FIA's Interior West region there are typically two strata, Green (G) and Brown (B), representing forest and nonforest, with weights *WG* and *WB*, respectively. Because the nonresponse rate for the New Mexico annual inventory is unusually high on private lands, further stratification into partitions of Private owners (P) and Non-Private owners (NP) must be considered. The four strata weights are W_{GP}, W_{GNP}, W_{BP}, and W_{BNP}, with $W_{GP} + W_{GNP} + W_{BP} + W_{BNP} = 1$, where, for example, W_{GP} is the weight for the stratum which is green and private ownership (see Table 1). Nonresponse rates have been calculated for each stratum based on preliminary data from 2008 to 2011. Nonresponse rates for Private owners within the G and B strata are 47 percent and 19 percent, respectively, while rates for the Non-Private owners are 8 percent and 3 percent. The nonresponse rate for the NP partition is similar among all ownership subclasses (e.g., National Forest system, Bureau of Land Management). In addition, the nonresponse rates for both GNP and BNP are small enough that we can ignore the slight bias caused by blending the field plots and the office plots.

Table 1.—Calculated values of stratum weights W_{GP}, W_{GNP}, W_{BP}, and W_{BNP} for New Mexico, based on spatial intersection of the green/brown stratification and a statewide ownership layer

	Partition	
Stratum	**Private (P)**	**Non-Private (NP)**
Green (G)	0.057	0.155
Brown (B)	0.382	0.406

In contrast, the high nonresponse rates for both GP and BP warrant investigation of further partitioning into "field" (F) and "office" (O), based on pre-field determinations. Preliminary data from New Mexico indicate that nearly all plots in GP stratum were field visits, so there is no further partition of the GP stratum while approximately 40 percent and 60 percent of the BP stratum was field visit and office respectively. Let $w_{F(BP)}$ indicate the estimated weight (or proportion) of F partition within the BP stratum with similar definitions for weights of the O partition of the BP stratum. In terms of the *H* notation, $H = 4$, $H_1 = 3$ and $H_2 = 1$. The estimate is

$$\hat{P}_d = W_{GNP}\hat{P}^o_{d|GNP} + W_{BNP}\hat{P}^o_{d|BNP} + W_{GP}\hat{P}^o_{d|GP} + W_{BP}\left(w_{F(BP)}\hat{P}^o_{d|F(BP)} + w_{O(BP)}\hat{P}^o_{d|O(BP)}\right)$$

where $\hat{P}^o_{d|*}$ is the proportion of the $*$ stratum or partition that is in domain *d* and the superscript o indicates the proportion is based on the observed values and adjusted for the nonresponse in the stratum or partition. The explicit formula for $\hat{P}^o_{d|*}$ is given next.

We will now return to constructing the estimator, using notation consistent with that in Särndal et al. (1992). For the *h*th stratum denote the total number of plots by n_h and the number of partly or fully observed plots by m_h, so the number of entirely nonresponse plots is $n_h - m_h$. In FIA m_h is denoted by n_h (Bechtold and Patterson 2005) and there is no notation for the total number of plots. For the *j*th partition of the *h*th stratum let n_{hj} denote the total number of plots and m_{hj} denote the number of partly or fully observed plots. So $\sum_j^{J_h} n_{hj} = n_h$ and $\sum_j^{J_h} m_{hj} = m_h$. The estimated weight of *j*th partition of the *h*th stratum is $w_{hj} = \frac{n_{hj}}{n_h}$, where if $h = 1, \ldots, H_1$, then $J_h = 1$ and $w_{h1} = 1$.

The estimate of the proportion of the partition *hj* that is in domain *d* is

$$\hat{P}^o_{d|hj} = \frac{\sum_{i=1}^{m_{hj}} a^d_{hji}}{\sum_{i=1}^{m_{hj}} a^o_{hji}} \qquad [2]$$

where a^d_{hji} is the area of observable land in domain d on the ith plot of the jth partition of the hth stratum, and a^o_{hji} is the amount of observable land on the ith plot of the jth partition of the hth stratum. For the H_1 strata that are not further partitioned, this equation reduces to

$$\hat{P}^o_{d|h} = \frac{\sum_{i=1}^{m_h} a^d_{hi}}{\sum_{i=1}^{m_h} a^o_{hi}} \qquad [3]$$

Two points are noteworthy. First, we are using the superscript notation used in Roesch et al. (2012) instead of the notation used in Bechtold and Patterson (2005). Second, equations [2] and [3] are the same as equation [4.1] in Bechtold and Patterson (2005) (with m_h substituted for n_h), where we have simplified equation [4.1] by cancelling terms. Combining all these parts, we have

$$\hat{P}_d = \sum_{h=1}^{H_1} W_h \hat{P}^o_{d|h} + \sum_{h=1}^{H_2} W_h \sum_{j=1}^{J_h} w_{hj}\hat{P}^o_{d|hj} \qquad [4]$$

The denominator in equations [2] and [3] is the adjustment for the partial nonresponse plots.

STATISTICAL PROPERTIES OF ESTIMATOR

We will be using the statistical model presented in section 15.6 of Särndal et al. (1992), which assumes each sample is decomposed into response groups and probability that an element in the kth group responds is a constant. Other technical assumptions are not stated here. The estimator of interest is constructed using the response groups and auxiliary variables (Särndal et al. 1992: section 15.6.4); the auxiliary variable in our case is strata membership. Two assumptions related to FIA merit further discussion.

First, if the adjustment factor is treated as a random quantity, then we have the combination of a ratio estimator and a response model, and the derivation of the statistical properties of the estimator becomes a much more onerous task. However, preliminary data for New Mexico indicate the number of plots with partial nonresponse is less than 1 percent, so treating the adjustment factor as fixed (a constant) rather than random has little effect on the variance.

Second, in section 15.6 of Särndal et al. (1992) the goal is to estimate the population total. Estimates of

the total can be adjusted to proportions by dividing by N, the number of population elements. In using Särndal et al.'s results, we are approximating an infinite population with a finite population (Roesch et al. 2012).

Using these two assumptions, the estimator given by Equation 15.6.16 in Särndal et al. (1992) is equal to $\hat{P}_d$ in Equation [4]. From Result 15.6.2 of Särndal et al. (1992) $\hat{P}_d$ is approximately unbiased and an approximate variance is given. Of interest to us is the formula for a variance estimator. For a plot let the observed sample value be $y_* = a_*^d / \sum_{i=1}^{m_\#} a_{\#i}^o$ where $*$ indicates the index of the plot and # indicates the stratum/partition the plot is in, so the denominator is the adjustment factor for partial nonresponse plots. Let $r_\#$ denote the sample plots in stratum/partition # with either partial or total response. Then the estimated variance is given below. For clarity we have split the equation into three parts; the first part is for strata with $J_h = 1$ and the following two parts for strata with $J_h > 1$.

$$\hat{V}(\hat{P}_d) = \sum_{h=1}^{H_1} \left(w_h^2 (m_h^{-1} - n_h^{-1}) + w_h \frac{1-f}{n} (1 - \delta_h) \right) S_{yr_h}^2 + \quad [5]$$

$$\sum_{h=1}^{H_2} \left(w_h^2 \sum_{j=1}^{J_h} w_{hj}^2 (m_h^{-1} - n_h^{-1}) S_{yr_{hj}}^2 + \right. \quad [6]$$

$$\left. w_h \frac{1-f}{n} \sum_{j=1}^{J_h} w_{hj} (1 - \delta_{hj}) S_{yr_{hj}}^2 \right) +$$

$$\frac{n}{n-1} \sum_{h=1}^{H_2} w_h \sum_{j=1}^{J_h} w_{hj} \bar{e}_{r_{hj}}^2 \quad [7]$$

where $\delta_\# = 1 - \frac{1 - n_\#/n}{m_\#} \frac{n}{n-1}$, with # indicating the stratum/partition, is an adjustment factor for nonresponse; $S_{yr_\#}^2$ is the variance of the y_k for the response portion of the sample contained in stratum/partition #; and $\bar{e}_{r_{h*}}$ is the average of the residuals, $e_k = y_k - \sum_{j=1}^{J_h} w_{hj} \sum_{i=1}^{m_{hj}} y_{hi}$, over r_{h*}.

DISCUSSION

If $H_2 = 0$, then equation [4] is the current FIA estimator. The estimated variance we are proposing would involve only equation [5], which differs from the estimated variance FIA currently uses. The difference between our estimated variance and the one used by FIA is that the latter is derived based on the assumption that a simple random sample of size $m = \sum_h m_h$ is drawn, while our estimated variance is based on two-phase Bernoulli sampling for stratification, that is, a simple random sample s_a is drawn at the first phase and s_a is stratified into the response groups. Then a subsample s_{ah} is drawn from each s_a using Bernoulli sampling, with probability of selection equal to the response probability. This new approach may improve FIA's estimates in situations with high nonresponse where the assumption of missing at random within strata is untenable.

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ESTIMATING ROOT COLLAR DIAMETER GROWTH FOR MULTI-STEM WESTERN WOODLAND TREE SPECIES ON REMEASURED FOREST INVENTORY AND ANALYSIS PLOTS

Michael T. Thompson and Maggie Toone[1]

Abstract.—Tree diameter growth models are widely used in many forestry applications, often to predict tree size at a future point in time. Also, there are instances where projections of past diameters are needed. An individual tree model has been developed to estimate diameter growth of multi-stem woodland tree species where the diameter is measured at root collar. The model was built from radial growth data on trees sampled from plots measured in Utah, Arizona, and Nevada. Individual tree growth can be predicted from the ratio of live woodland stems to all stems and from mean past 10-year radial growth of trees by ecological subsection, section, or province. Coefficients were estimated for four woodland tree species groups that cover most tree species in the Southern Interior West region.

INTRODUCTION

Estimating diameter growth is an important aspect of forest management and inventory. Determining diameter growth is problematic for many western woodland tree species because they are measured at the root collar, are very slow growing, often contain multiple stems, and are poorly suited to measurement methods used for other temperate tree species. Site quality and stand competition in dry arid regions comprised of woodland trees species are not well understood.

Forest Inventory and Analysis (FIA) data on diameter growth are often obtained from repeatedly measuring the same trees over time or by measuring increment cores. Historically, the Interior West FIA (IWFIA) region has had to rely on increment core measurements for estimates of diameter growth because of inconsistent inventories over time or gaps in previous inventories where there were insufficient numbers of previously established permanent plots. When the annual inventory system was implemented in the IWFIA region in 2000, FIA plots were established on a systematic grid (Reams et al. 2005) across the landscape regardless of land use and ownership. Now, those initially established plots are beginning to be remeasured and there will be a need for procedures that reliably and efficiently estimate tree growth from paired plots measured at two points in time.

FIA requires measurements or models of tree diameter growth to estimate individual tree growth. Diameter growth, along with other volume attributes such as total height, is used to calculate growth for every qualifying tree measured on a plot. Individual tree growth is used for compiling inventories made up of tree data because growth can be calculated for each tree and then summarized in many different ways. Therefore, an individual tree modeling approach is used in this analysis.

Multi-stem woodland trees are the most problematic when comparing measurements between two points in time, referred to as time 1 (previous measurement) and time 2 (current measurement). Measurement error can

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be very significant because of extremely high numbers of stems, presence of obstacles that hinder accurate measurements such as thorns and rock outcrops, swelling and irregular form, or extremely degraded stems. The measurement point can change because of a field crew at time 2 disagreeing with where the field crew at time 1 took diameter at root collar (d.r.c.) measurements. Diameters can also change between time 1 and 2 because of stems breaking off due to cutting or mortality resulting in a d.r.c. reduction between time 1 and time 2.

It is because of these inherent difficulties in measuring d.r.c. at time 1 and time 2 that using a change in d.r.c. on multi-stem woodland trees will often yield artificial estimates of diameter growth. Chojnacky (1997) used radial growth data to estimate diameter growth of pinyon and juniper (*Juniperus* spp.) trees in New Mexico. Therefore, for multi-stem woodland trees, a measure of radial growth may be a superior metric for estimating diameter growth than a change in d.r.c. between time 1 and time 2.

STUDY AREAS

The data for this study came from inventory plot data collected by the IWFIA crew in Arizona, Nevada, and Utah. These three states were selected because of the preponderance of multi-stem woodland species and because they are located in the largely arid southern portion of the Interior West region. All data were collected under the annual inventory system that began in 2000 in Utah and covered the following years: Arizona (2001-2009); Nevada (2004-2005); Utah (2000-2009).

DATA

Tree data came from a total of 4,376 inventory plots measured across the three states. The plot design used during the annual inventory is described in Bechtold and Scott 2005. Only multi-stem woodland trees were used in the study because they are measured differently than single-stem woodland trees and are considered to be the most problematic growth form for determining growth. All multi-stem woodland trees used to develop the models had increment cores extracted and 10 years of radial growth measured. The minimum d.r.c. of the study trees was 5.0 inches. There were a total of 7,996 trees used in the analysis.

The woodland trees were grouped into four species groups: (1) common pinyon (*Pinus edulis* Engelm.); (2) Utah juniper (*Juniperus osteosperma* (Torr.) Little); (3) other junipers including redberry juniper (*Juniperus coahuilensis*), California juniper (*Juniperus californica* Carr.), alligator juniper (*Juniperus deppeana* Steud.), Rocky Mountain juniper (*Juniperus scopulorum* Sarg.), and oneseed juniper (*Juniperus monosperma* (Engelm.) Sarg.); and (4) other woodland trees including singleleaf pinyon (*Pinus monophylla* Torr. & Frem.), Mexican pinyon pine (*Pinus cembroides* Zucc.), Arizona pinyon pine (*Pinus arizonica* Engelm), bigtooth maple (*Acer grandidentatum* Nutt.), curlleaf mountain-mahogany (*Cercocarpus ledifolius* Nutt.), western honey mesquite (*Prosopis glandulosa* Torr.), velvet mesquite (*Prosopis velutina* Woot.), gray oak (*Quercus grisea* Liebm.), Emory oak (*Quercus emoryi* Torr.), Gambel oak (*Quercus gambelii* Nutt.), Mexican blue oak (*Quercus oblongifolia* Torr.), silverleaf oak (*Quercus hypoleucoides* A. Camus), and evergreen oaks.

METHODS

Radial growth measurements were converted into an annual change in d.r.c. using the following formula:

$$madc = \frac{2r}{10},$$

where *madc* is mean annual change in d.r.c. in inches of a live stem, and *r* is the length in inches of a radial-growth core representing 10 years of growth. Dividing by 10 converts the periodic estimate of 10 years of diameter growth into an annual estimate, standardizing the time frame so the modeled estimate can be applied to any number of years. This is common practice

in many FIA diameter growth models (Westfall 2006). Differing remeasurement intervals, estimating diameter growth on trees that either died or were cut at various points in time during a measurement interval, and proper assignment of trees to the appropriate growth component are common applications of an annualized change in diameter.

Numerous attributes have been correlated with diameter growth rates. Often, stand and tree-level measurements that are observed or computed are used as predictor variables in diameter growth models. Examples of stand-level predictors often include age, site productivity, and stand density. Several predictor variables were identified for possible inclusion. Least angle regression was used to identify variables thought to be significant for model development and to create model parameters.

Two variables were deemed significant for predicting *madc*: (1) the number of live woodland tree stems divided by the number of live and dead woodland tree stems for an individual tree (lpct), and (2) the mean *madc* for a species group for an ecological subsection assigned to the plot the tree is sampled on ($ecog_{index}$). Ecological subsection refers to areas of unique geomorphology with distinct boundaries (Cleland et al. 2007). All FIA plots nationally are assigned a code that identifies the ecological subsection (Woudenberg et al. 2010). These two predictor variables yielded the following diameter growth equation:

$$madc = \beta_0 + \beta_1 lpct + \beta_2 \ln(ecog_{index})$$

RESULTS AND DISCUSSION

Parameter estimates for average annual change in d.r.c. are given in Table 1. Resulting parameters should be sufficient for most broad-scale inventory needs and can be used to estimate diameter growth on trees that have been cut or have died during the remeasurement interval or trees that need a previous or past diameter predicted because of field crew measurement error. It may even be desirable to use a model developed from increment core measurements to predict diameter growth for all multiple-stem woodland trees because of the high level of d.r.c. measurement error associated with these growth forms.

A more powerful explanatory growth model was not developed because of poor correlation between diameter growth and available FIA site description variables. There are several reasons why the correlation is poor. First, the FIA site description variables are not refined enough for many western forest conditions. For example, physiographic variables for arid woodland tree conditions are very

Table 1.—Parameters for estimating mean annual change in diameter at root collar (d.r.c.) of multi-stem woodland trees in Utah, Arizona, and Nevada

Species Group	Parameter Estimates β_0	β_1	β_2	Number of Trees	Regression Statistics R^2	C.V.
Common pinyon	.071	.021	.053	826	.17	48.0
Utah juniper	.065	.018	.043	3,934	.12	52.2
Other juniper	.067	.027	.060	1,787	.11	54.8
Other woodland species	.079	.00	.050	1,449	.15	57.0

Diameter growth equation (Eq. 2): $madc = \beta_0 + \beta_1 lpct + \beta_2 \ln(ecog_{index})$ where:

madc = mean annual change in d.r.c (inches) based upon 10 years of past radial growth;
lpct = number of live stems divided the total number of live and dead stems for an individual woodland tree;
$ecog_{index}$ = mean *madc* for a species group for an ecological subsection assigned to the plot the tree is sampled on;
R^2 = coefficient of determination;
C.V. = coefficient of variation.

limited. Second, measures to estimate site quality such as site index and site class are not collected on sites dominated by woodland tree species. Site quality studies are limited for many woodland tree species. Third, uncertainty exists for equating growth rates with ring counts for certain species. False and missing rings are known to occur for juniper (Despain 1989). Certain species, such as curlleaf mountain-mahogany, are never cored because of very hard wood characteristics. The inherent slow growing nature of these growth forms can make ring counting difficult.

CONCLUSIONS

The model described is easily applied and uses a minimum amount of field data. What is needed is the proportion of live woodland tree stems for an individual tree (*lpct*) and the mean 10-year diameter growth by species group for the ecological subsection assigned to the plot the tree is sampled on ($ecog_{index}$). The model could be further refined by improving methods to identify growth ring identification such as sanding and magnification and conducting further analysis to determine optimum number of tree samples per species groups for ecological subsection.

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THE IMPROVEMENT OF PRECISION FOR ESTIMATING THE ABUNDANCE OF STANDING DEAD TREES USING AUXILIARY INFORMATION UNDER THE FIA PLOT DESIGN

Hong Su An, David W. MacFarlane, and Christopher W. Woodall[1]

Abstract.—Standing dead trees are an important component of forest ecosystems. However, reliable estimates of standing dead tree population parameters can be difficult to obtain due to their low abundance and spatial and temporal variation. After 1999, the Forest Inventory and Analysis (FIA) Program began collecting data for standing dead trees at the Phase 2 stage of sampling. However, the estimates have relatively large variations compared to the estimates of live trees. The results represent that EZ-Hurdle method shows better precision than the FIA method for both spatial patterns and densities of standing dead trees.

INTRODUCTION

Standing dead trees play an important role in forest ecosystems such as maintaining biodiversity and nutrients, and carbon sequestration. Therefore, reliable estimates of standing dead trees are important to assess and monitor healthy forest ecosystems (Gray 2003). Due to high variation in the abundance of standing dead trees and their spatial pattern, designing sampling schemes for estimating standing dead tree abundance can be challenging. According to previous studies, relatively larger plot sizes or higher sampling intensities than those used for live trees have been applied to estimate the abundance of standing dead trees (e.g., Ganey 1999, Stephens 2004). While intensification of sampling efforts or changing plot designs for estimating standing dead tree attributes is a straightforward solution, ultimately the cost of intensification of sampling must be considered and weighed against the value of increased accuracy (Curtis and Marshall 2005, Gregoire and Valentine 2008).

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One major consequence of surveying too-small an area (e.g., using plot sizes that are too small) is that there may be a large number of zero observations of standing dead trees. Excess zero observations, a.k.a. zero-inflated data, will increase variation in estimates of standing dead tree parameters (Eskelson et al. 2009, Potts and Elith 2006). Because of the tendency for standing dead trees to be aggregated in space and a generally lower abundance of standing dead trees relative to live ones, the problem of zero-inflated data is likely large. The National Forest Inventory and Analysis (FIA) Program collects the attributes of standing dead trees such as species, diameter, and total height, from Phase 2 plots that consist of four 7.32 m fixed-radius subplots (Bechtold and Patterson 2005). About 44 percent of FIA plots observed had no standing dead trees on them (Woodall et al., in press). In a study by An and MacFarlane (N.d.), the Expected-Zero (EZ)-Hurdle method showed better precision than the fixed-area sampling method for estimating the abundance of standing dead trees when there are large proportions of zero observations in fixed-area plot data.

The main objective of this study was to apply the EZ-Hurdle method to the FIA plot design to estimate the abundance of standing dead trees using auxiliary

information describing the distance from each subplot center to the nearest standing dead tree.

METHODS

Data

A simulation study was performed to generate distributions of standing dead trees within a simulated area of 900 ha. In order to collect data for standing dead trees, the FIA plot design was applied, and the number of standing dead trees within 7.32 m (24 ft) radius subplots was recorded. For the EZ-Hurdle method, the distance from each subplot center to the nearest standing dead tree was measured. The maximum search radius for the nearest standing dead tree was 17.95 m (120 ft). Two spatial patterns, random and clustered, and two densities, 30 and 45 standing dead trees per ha, were applied. The number of sample plots in each iteration ranged from 30 to 60 plots in 10-plot increments. For each sampling scenario (spatial pattern, density of standing dead trees, and sampling intensity combination), approximately 3,000 iterations were applied. For each iteration, the number of standing dead trees per ha was calculated. The coefficient variation for the estimated density of standing dead trees was compared.

Estimating Density of Standing Dead Trees

First, the density of standing dead trees per ha was estimated by the published method of the FIA program (see Bechtold and Patterson 2005). Second, the EZ-Hurdle method was applied to estimate the density of standing dead trees. The EZ-Hurdle method (An and MacFarlane, N.d.) is a model-based estimation method which employs a modified version of the Hurdle model (Mullahy 1986) called the EZ-Hurdle model. The main difference between the Hurdle and EZ-Hurdle models is how the zero-proportion (π) is specified in the model. In the case of the Hurdle model, π is estimated directly from the count data it is being fitted to. The zero-proportion in the EZ-Hurdle method is estimated from the detection probability of a standing dead tree, which is modeled from auxiliary data describing the distance from a plot center to the nearest standing dead tree (An and MacFarlane, N.d.).

With counts of standing dead trees from FIA subplots, the EZ-Hurdle method estimates the density of standing dead trees in two steps. The first step is estimating the expected-zero proportion for the given subplot size (radius = r) from the detection probability of a standing dead tree given that plot size. The second step is estimating the contribution of nonzero counts (plots with at least one standing dead tree) to the estimate using zero-truncated count distributions such as the Poisson distribution. The procedure to model the nonzero counts is the same as that in the original Hurdle model (Cameron and Trivedi 1998, Mullahy 1986), and the estimated expected-zero proportion and the contribution of nonzero counts are combined.

When applied to fixed-radius plot sampling y_i, $Y = \{y_i, \ldots, y_n\}$, is the number of standing dead trees in sample plot i and d_i, $D = \{d_i, \ldots, d_n\}$, is the distance from the plot center of i to the nearest standing dead tree; n is the number of samples. In order to estimate the expected-zero proportion, the detection probability of a standing dead tree for the given search radius r is modeled from the auxiliary data D because the expected-zero proportion for the given (fixed) search radius r is:

$$P_ez(r) = 1 - P_dt(r)$$

where P_ez is the expected-zero proportion, P_dt is the detection probability of a standing dead tree, and r is a fixed search radius to find the nearest standing dead trees. A modified Gompertz function was used to estimate the detection probability of a standing dead tree from the distance data (An and MacFarlane, N.d.).

The EZ-Hurdle model is specified as follows:

$$P\{Y=y\}=\begin{cases} P_ez(r) & y=0 \\ (1-P_ez(r))\cdot\dfrac{f(Y=y\mid\mu(r))}{1-f(Y=0\mid\mu(r))} & y>0 \end{cases}$$

where y is the number of trees, $f(Y = y \mid \mu(r)) / (1 - (f(Y = 0 \mid \mu(r)))$ is the zero-truncated count distribution with search radius (plot radius) r, $f(Y = 0 \mid \mu(r))$ is the proportion of zero estimated from a model, and $\mu(r)$ is the estimated expected value from zero-truncated count distributions.

For the EZ-Hurdle with a Poisson distribution (EZP) model, the expected value and variance for the count distribution are:

$$E_{EZP}[Y_c]=(1-P_ez(c,r))\cdot\frac{\mu(c,r)}{1-e^{-\mu(c,r)}}$$

$$Var_{EZP}[Y_c]=(1-P_ez(c,r))\cdot\frac{\mu(c,r)+\mu(c,r)^2}{1-e^{-\mu(c,r)}}-\left[(1-P_ez(c,r))\frac{\mu(c,r)}{1-e^{-\mu(c,r)}}\right]^2$$

where $P_ez(c,r)$ is the expected-zero proportion estimated by the model for the given search radius r and forest condition c, $\mu(c,r)$ is the expected value of the zero-truncated Poisson distribution for the given plot size (radius = r) and forest condition c.

RESULTS

The detection probability increased with increasing density of standing dead trees and was greater with the random pattern than clustered pattern at the same density of standing dead trees. Table 1 shows the estimated density of standing dead trees from 3,000 iterations. The EZ-Hurdle method had smaller standard deviations than the FIA method for all scenarios indicating that the EZ-Hurdle method had better precision than the FIA method. However, the EZ-Hurdle method showed a small bias when standing dead trees were clustered.

ACKNOWLEDGMENTS

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Table 1.—The estimated density of standing dead trees per ha (± standard deviation) by method, spatial pattern, density, and the number of plots. FIA = estimated method by FIA program and EZP = EZ-Hurdle method.

Spatial Pattern	True Density	Number of Plots 30 FIA	30 EZP	40 FIA	40 EZP	50 FIA	50 EZP	60 FIA	60 EZP
Random	30	29.91 (3.96)	30.60 (3.71)	29.94 (3.39)	30.51 (3.17)	30.02 (3.01)	30.53 (2.77)	30.01 (2.72)	30.51 (2.54)
	45	45.12 (4.81)	46.31 (4.49)	44.85 (4.06)	45.98 (3.81)	45.01 (3.64)	46.08 (3.43)	45.03 (3.36)	46.04 (3.17)
Cluster	30	30.56 (5.67)	27.81 (4.90)	29.97 (4.79)	27.57 (4.14)	30.02 (4.48)	27.56 (3.83)	29.97 (4.03)	27.45 (3.42)
	45	45.01 (7.74)	40.83 (6.84)	48.18 (6.68)	40.10 (5.86)	45.07 (6.63)	40.48 (4.89)	45.08 (5.64)	40.48 (4.89)

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The content of this paper reflects the views of the author(s), who are responsible for the facts and accuracy of the information presented herein.

OPTIMIZED ENDOGENOUS POST-STRATIFICATION IN FOREST INVENTORIES

Paul L. Patterson[1]

Abstract.—An example of endogenous post-stratification is the use of remote sensing data with a sample of ground data to build a logistic regression model to predict the probability that a plot is forested and using the predicted probabilities to form categories for post-stratification. An optimized endogenous post-stratified estimator of the proportion of forest has been recently proposed in the literature, but there are no known literature results describing the operating characteristics of this estimator. This study reports the results of a detailed Monte Carlo investigation of the performance of the optimized and another endogenous post-stratified estimator under a variety of realistic scenarios and compares their performance with earlier approaches.

INTRODUCTION

In recent years, estimators have been proposed that use remotely sensed data in conjunction with natural resource inventory sample data to construct land cover or use classifications and then use the classification to post-stratify the sample; Breidt and Opsomer (2008) proposed the term endogenous post-stratification (EPS) to describe the "post-stratification of the sample based on categories derived from the sample data." One example is using forest inventory sample data in conjunction with Landsat Thematic Mapper (TM) imagery to construct a logistic regression model that predicts for each pixel the probability the land associated with the pixel is forested, and then uses a set of strata boundaries so the land associated with the TM image can be stratified. An example of two strata would be as follows: any pixel with probability less than or equal to 0.5 is placed in one stratum, and any pixel with probability greater than 0.5 is in the other stratum. The stratification index (the predicted value from the logistic regression model) was derived using the sample, so the post-stratification is endogenous. Since endogenous post-stratification "violates the standard post-stratification assumptions that observations are classified without error into post-strata and the post-stratum population counts are known" (Breidt and Opsomer 2008), the statistical properties may differ. Breidt and Opsomer (2008) derived statistical properties of endogenous post-stratified estimators (EPSEs) in the case that the stratification index is the logistic regression model, and the stratum boundaries are determined independent of the sample data. McRoberts (2010) proposed an EPSE where the stratification index is a logistic regression model constructed from forest inventory sample data and TM imagery, and the strata boundaries are constructed based on an optimization procedure. To justify certain statistical properties of the optimized EPSE (OEPSE) McRoberts (2010) cites Breidt and Opsomer (2008), which is incorrect because the strata boundaries are derived from the sample data.

The objectives of this study are to (1) construct three EPSEs of the proportion of forest; (2) give a process for constructing populations that can be used in simulation studies to deduce the statistical properties of the three EPSEs; and (3) deduce the statistical properties of the three estimators based on simulation studies for three populations that represent a range of geographical regions and vegetative classes.

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DATA AND ESTIMATORS

Three study areas were used to construct three simulation populations. The three study areas were: (1) the portion of path 27, row 27, Landsat scene in northern Minnesota, which is the study area in McRoberts (2010); (2) the portion of path 37, row 32, Landsat scene in northern Utah; and (3) path 37, row 33, Landsat scene totally within Utah (Fig. 1). These scenes, chosen because they represent differing geographical regions and vegetative classes, have an estimated forest cover of approximately 70, 50, and 30 percent respectively. TM imagery was acquired for three dates corresponding to early, peak, and late seasonal vegetative stages (Table 1). For each date, the normalized difference vegetative index and the tasseled cap transforms (brightness, greenness, and wetness) were used. Forest inventory data for permanent field plots established by the Forest Inventory and Analysis (FIA) Program were obtained for each of the scenes. This study used only the central subplot, which was associated with the image pixel that contains the center of the subplot. The numbers of totally forested, totally nonforested, and partially forested central subplots contained within each scene are in Table 1.

Following McRoberts (2010), the assumptions are (1) there is a finite population consisting of N elements which are 30 m × 30 m Landsat pixels; (2) there is an equal probability sample of n population units (3) with observed characteristic y_i, the proportion of forest for the land associated with each pixel; (4) the ancillary information for each population element, $\mathbf{x}_i$, is 12 Landsat-based spectral transforms; and (5) since the sample consists of FIA central subplots, then the central subplot is assumed to characterize the entire pixel that contains the center of the central subplot. The population parameter of interest is the mean proportion of forest, $\bar{Y} = \sum_i^N y_i / N$.

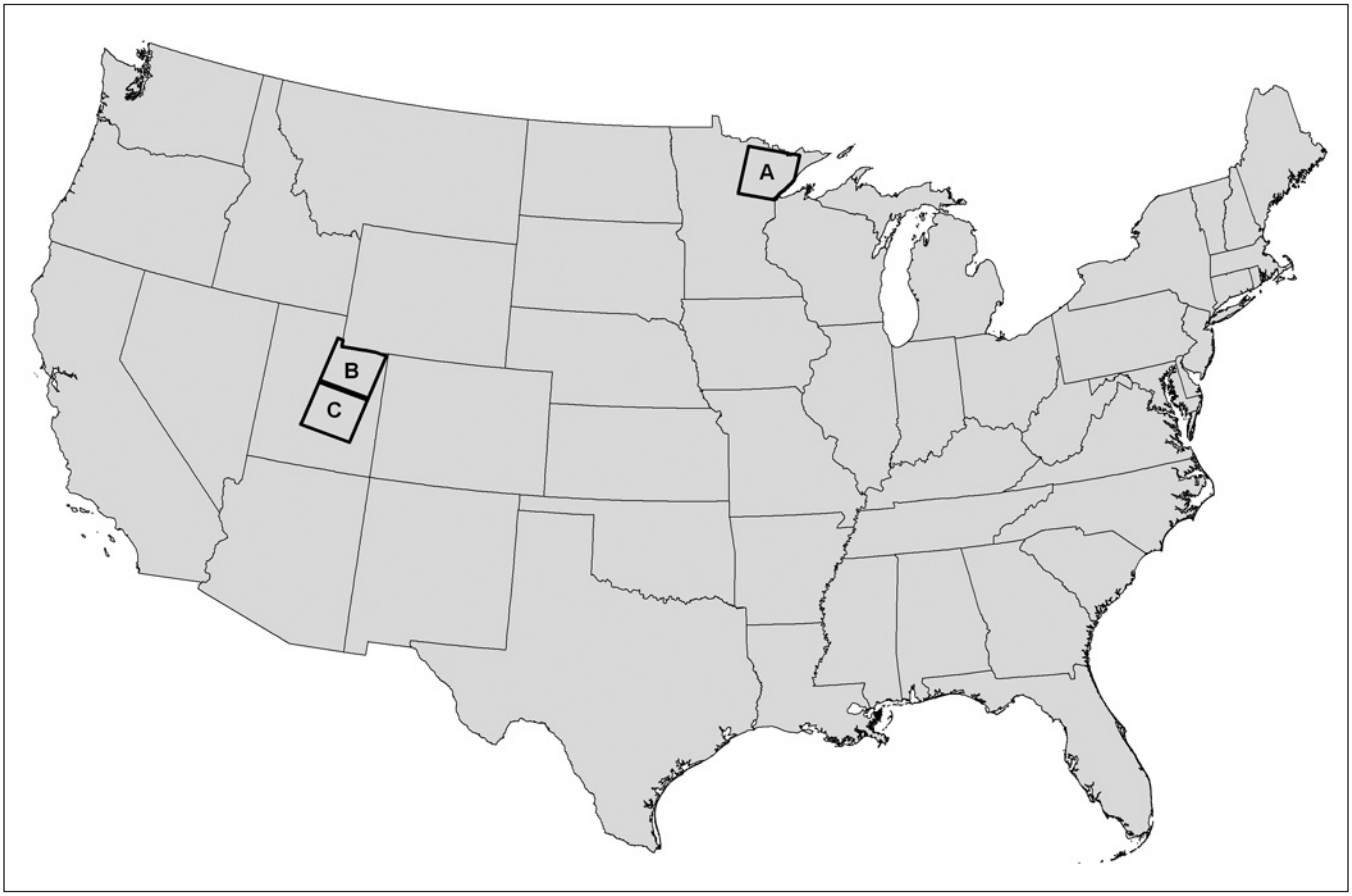


Figure 1.—Study areas: A is path 27, row 27; B is path 37, row 32; and C is path 37, row 33.

Table 1.—Dates for the three Landsat scenes, and number and type of FIA plots, used to construct the simulation populations. Dates represent early, peak, and late seasonal vegetative stages. Plots are those whose center subplot is located in the Landsat scene.

Remotely Sensed Data		Forest Inventory and Analysis Field Plots			
			Number of Plots		
Scene	Three Dates	Field Seasons	Forested	Nonforested	Partially Forested
Path 27, Row 27 within Minnesota	April 29, 2000 July 5, 2001 November 5, 1999	1999 to 2003	1,677	607	34
Path 37, Row 32 within Utah	June 14, 2000 July 30, 2002 October 10, 1999	2000 to 2009	659	620	15
Path 37, Row 33 in Utah	July 4, 2007 August 21, 2007 October 18, 2004	2000 to 2009	447	909	12

Breidt and Opsomer (2008) present post-stratification as a stratification index variable z_i, which along with a set of strata boundaries is used to partition the population into H strata; in endogenous post-stratification (EPS) the stratification index, strata boundaries, or both, are derived from the sample data. For example, the variable z_i is a forest/nonforest indicator, and is observed on a sample but is unknown for the rest of the population. The z_i are assumed to follow a logistic model, that is

$$\mathrm{E}(z_i|\mathbf{x}_i) = \frac{\exp(\boldsymbol{\beta}'\mathbf{x}_i)}{1+\exp(\boldsymbol{\beta}'\mathbf{x}_i)} \quad \mathrm{Var}(z_i|\mathbf{x}_i) = \nu, \qquad [1]$$

where the expectation is with respect to the model. The model parameters $\boldsymbol{\beta}$ are estimated by maximizing the likelihood using the subset of the sample for which the pixel is either completely forested ($\boldsymbol{y_i} = \mathbf{1}$) or completely nonforested ($\boldsymbol{y_i} = \mathbf{0}$). The estimate $\hat{\boldsymbol{\beta}}$ is used to define the endogenous stratification index $\hat{\boldsymbol{z}}_{\boldsymbol{i}} = \exp(\hat{\boldsymbol{\beta}}'\mathbf{x}_i)/\left(\mathbf{1}+\exp(\hat{\boldsymbol{\beta}}'\mathbf{x}_i)\right)$ for all population elements. To complete an EPS we need to specify the strata boundaries, which will be discussed in the following paragraph. Once the boundaries have been specified, the standard post-stratified estimator (PSE) $\bar{\boldsymbol{Y}} = \sum_i^N \boldsymbol{y}_i/\boldsymbol{N}$ can be used, that is,

$$\hat{\mu}_{str} = \sum_{h=1}^{H} W_h \hat{\mu}_h$$

and [2]

$$\hat{V}(\hat{\mu}_{str}) = \left(1-\frac{n}{N}\right)\sum_{h=1}^{H} W_h^2 \frac{\hat{\sigma}_h^2}{n_h},$$

where $\hat{\mu}_h = \frac{1}{n_h}\sum_{i=1}^{n_h} y_{hi}$, $\hat{\sigma}_h^2 = \frac{1}{n_h-1}\sum_{i=1}^{n_h}(y_{hi}-\hat{\mu}_h)^2$, W_h is the weight of stratum h, y_{hi} is the proportion of forest for the ith sample element of stratum h, and $\hat{V}(\hat{\mu}_{str})$ is an approximate estimated variance for the PSE.

Three methods for specifying strata boundaries will be presented and used along with $\hat{\mu}_{str}$ from Equation [2] to define an EPSE of the mean proportion of forest. All three schemes use the endogenous stratification index, $\hat{z}_i$, defined above. The first EPS scheme uses fixed predetermined strata boundaries, $0 = \tau_0 < \tau_1 < \ldots < \tau_{H-1} < \tau_H = 1$; strata assignment given by $\hat{z}_i$ will be denoted as the fixed boundary endogenous post-stratified estimator (FEPSE). The second EPS scheme specifies the strata boundaries using an optimization process. For strata boundaries $\{\tau_h\}_{h=1}^{H-1}$ with values rounded to the nearest hundredth and for which each stratum

contains at least four sample elements, calculate $\hat{V}(\hat{\mu}_{str})$ (Equation [2]). Determine the set of boundaries, over all possible numbers of strata, which minimizes $\hat{V}(\hat{\mu}_{str})$; the OEPSE is calculated using this set of strata boundaries. McRoberts (2010) found little reduction in $\hat{V}(\hat{\mu}_{str})$ when optimizing over two or three strata compared to only two strata. Two strata are defined by a single stratum boundary; a natural choice for that boundary would be the mean proportion of forest, which is estimated by the sample mean, that is, $\hat{\tau} = n^{-1}\sum_{i=1}^{n} y_i$. The third EPSE, which is denoted the estimated endogenous post-stratified estimator (EEPSE), is calculated using the strata boundaries $\{0, \hat{\tau}, 1\}$.

In EPS the classification of observations and the post-stratum population counts depend on the sample and these two aspects add additional sources of variability. Breidt and Opsomer (2008) showed for a class of EPSEs that $\hat{V}(\hat{\mu}_{str})$ converges to the asymptotic variance of the EPSE, as $n,N \rightarrow \infty$. Breidt and Opsomer's assumptions that are germane to our study are: first, the set of stratification indices they consider contains $\hat{z}_i$ defined above; and second, the strata boundaries are fixed. Hence their result on the asymptotic variance applies to the FEPSE, but not to the OEPSE or the EEPSE.

SIMULATION POPULATION AND SIMULATION STUDY

For each of the three Landsat scenes, the population is the landmass covered by the scene; population elements are the land delineated by the image pixels. The FIA reduced sample refers to the set of FIA central subplots which are contained in the scene and are completely forested or completely nonforested. The goal is assign a value of forest or nonforest to each pixel so that the logistic relationship between the values of the 12 Landsat-based spectral transforms and the forest/nonforest values for the entire scene is similar to the logistic relationship between the observed forest/nonforest values for the FIA reduced sample and the value of 12 Landsat-based spectral transforms for pixels associated with the FIA reduced sample.

First, the FIA reduced sample and the associated 12 Landsat-based spectral transforms, $\mathbf{x}_i$, were used to estimate the parameters $\boldsymbol{\beta}$ of the logistic regression model, Equation [1]. Denote the fitted model by $m(\hat{\boldsymbol{\beta}}'\mathbf{x}_i)$ and for $0 < \tau < 1$ define the variable $v_{i\tau} = \begin{cases} 0 \text{ if } m(\boldsymbol{\beta}'\mathbf{x}_i) \leq \tau \\ 1 \text{ if } m(\boldsymbol{\beta}'\mathbf{x}_i) \leq \tau \end{cases}$, which is a forest/nonforest indicator based on the predicted probability of forest from the logistic model and the cutoff τ. For the FIA reduced sample a measure of misfit between $v_{i\tau}$ and the proportion of forest, y_i, was defined as $d_\tau = n^{-1}\sum_{i=1}^{n}|y_i - v_{i\tau}|$, where n is the size of the FIA reduced sample. The measure of misfit d_τ was minimized over the grid $\tau \in \{0.05, 0.10, \ldots, 0.95\}$; denote where the minimum occurred by τ_0. Then a forest/nonforest indicator variable, z_i, was defined for every pixel in the scene so the measure of misfit between z_i and $v_{i\tau_0}$ over the population was the same as the measure of misfit between y_i and $v_{i\tau_0}$ over the FIA reduced sample. For the simulation population the proportion of forest is $\bar{Z} = \sum_i^N z_i/N$.

From the simulation population 4,000 simple random samples of size n were drawn. For each sample, j, four estimates of the proportion of forest were calculated: the simple random sample estimate $(\hat{\mu}_{SRSj} = \frac{1}{n}\sum_{i=1}^{n} z_{ij})$, the FEPSE with boundaries $\{0, 0.5, 1\}$, the OEPSE, and the EEPSE. The estimates for each sample are denoted by $\hat{\mu}_{*j}$, and the value of the proposed estimated variance is denoted by $\hat{V}(\hat{\mu}_{*j})$, where the $*$ is the acronym for the estimator. To determine both the small sample size properties and the asymptotic behavior, sample sizes of 100, 200, … , 700 were used (fitting the logistic model was problematic at smaller sample sizes). For each sample size the statistical properties were evaluated using (1) the empirical bias, EBias(*); (2) the empirical mean squared error, EMSE(*); and (3) the empirical variance, EV(*), where $*$ indicates the estimator.

To measure whether the proposed estimated variances of the three EPSE converge to the variance of the estimator, the actual coverage for 95-percent confidence intervals was calculated, that is, the percentage of the 4,000 replicates where the interval $\mu_{*j} \pm 1.96\{\hat{V}(\hat{\mu}_{*j})\}^{1/2}$ contains the proportion of forest $\overline{Z}$. A standard measure used to compare two unbiased estimators is the relative efficiency between the two estimators. For example, the relative efficiency (RE) between EEPSE and OEPSE is: RE(EEPSE, OEPSE) = (EMSE(EEPSE)) / (EMSE(OEPSE)).

RESULTS AND DISCUSSION

All the EPSEs were empirically unbiased at all sample levels. Hence the variance can be used in lieu of the mean squared error. The acceptance region for n trials of the empirical coverage percentages is $p \pm z_{1-\alpha}\sqrt{p(1-p)/n}$, where p is the stated confidence level, n is the number of simulations, and α is the confidence level for the acceptance region. Figures 2 and 3 show the empirical coverage percentages for two simulation populations; the third was similar. For all three scenes the pattern of convergence is the same: the EEPSE converges at the fastest rate, followed by the FEPSE and then the OEPSE. For sample size 100, the OEPSE empirical coverage percentage is well below the empirical coverage percentages of the other two EPSEs, indicating $\hat{V}(\hat{\mu}_{OEPSEj})$ significantly underestimates the true variance. All the empirical coverage percentages were in the acceptance region when the sample sizes were approximately equal to the number of FIA plots in the scene.

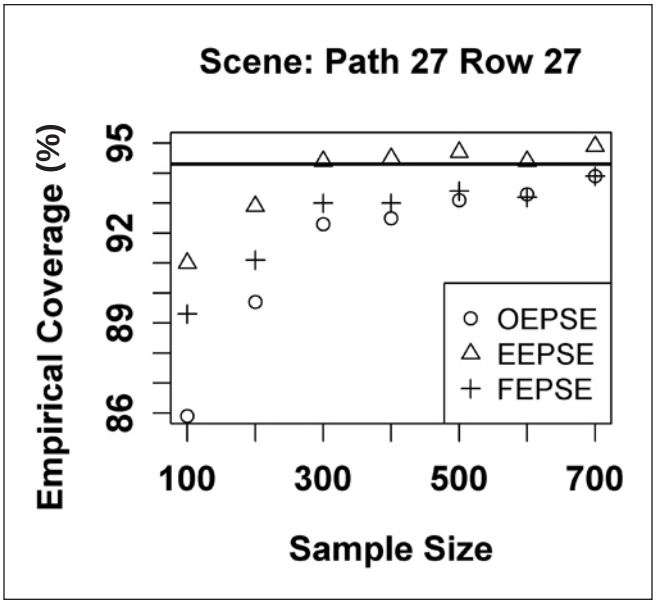


Figure 2.—For the simulation population path 27, row 27 the empirical coverage percentages of the nominal 95-percent confidence intervals for the optimized endogenous post-stratified estimator (OEPSE), the fixed boundary endogenous post-stratified estimator (FEPSE), and the estimated endogenous post-stratified estimator (EEPSE). The empirical coverage percentage is based on 4,000 realizations. The horizontal line y=94.3 is the lower bound for the acceptance region at confidence level of 95 percent.

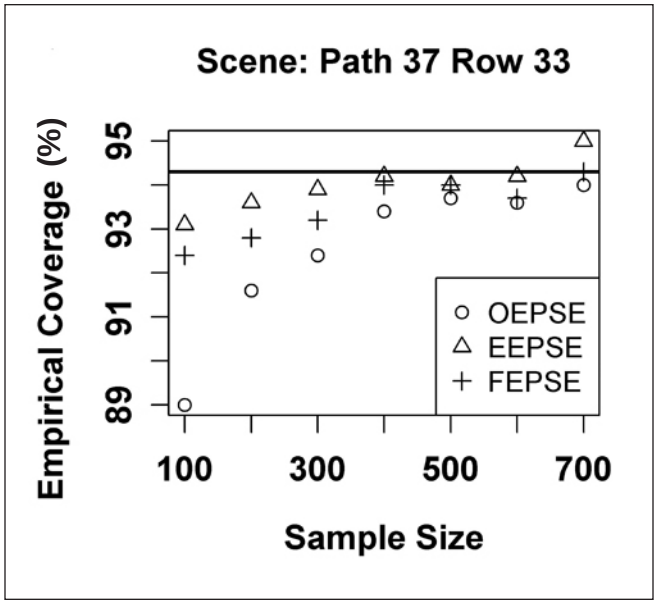


Figure 3.—For the simulation population path 37, row 33 the empirical coverage percentages of the nominal 95-percent confidence intervals for the optimized endogenous post-stratified estimator (OEPSE), the fixed boundary endogenous post-stratified estimator (FEPSE), and the estimated endogenous post-stratified estimator (EEPSE). The empirical coverage percentage is based on 4,000 realizations. The horizontal line y=94.3 is the lower bound for the acceptance region at confidence level of 95 percent.

The pattern for relative efficiencies RE(EEPSE,OEPSE) and RE(SRS,OEPSE) is the same for all three simulation populations: the empirical relative efficiency increases as the sample size increases. Table 2 contains the relative efficiency for sample sizes of 100, either 500 or 700, and the sample size approximately equal to the number of FIA plots. The results indicate the EEPSE appears to be uniformly more efficient than the simple random sample estimator (SRS). The rest of the results paint a mixed picture. In the arid Interior West (Path 37, Rows 32 and 33) the EEPSE is more efficient than the OEPSE at small sizes and slightly less efficient for the larger sample sizes; the EPSEs appear to have around 30-percent improvement in efficiency over the SRS for large sample sizes and no improvement for small sample sizes. In the heavily forested Upper Midwest (Path 27, Row 27) the OEPSE appears to have a gain in efficiency over the EEPSE for large sample sizes and a 50- to 60-percent improvement over SRS.

This study's results are applicable to situations where most if not all of the sample values for the proportion of forest are either 0 or 1. Four conclusions can be drawn. First, the three endogenous post-stratified estimators appear to be unbiased for sample sizes 100 and greater. Second, the standard estimated variance for post-stratified estimators appears to asymptotically converge to an estimate of the true variance for the estimated and optimized endogenous post-stratified estimators. Third, the estimated endogenous post-stratified estimator's asymptotic variance appears to have the faster rate of convergence, followed by the fixed boundary estimator and then the optimized estimator. Fourth, the estimated and optimized endogenous post-stratified estimators appear to have a higher efficiency compared to the simple random sample estimator. Additionally, it appears that for some land cover and large sample sizes the optimized endogenous post-stratified estimator has greater efficiency than the estimated endogenous post-stratified estimator.

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Table 2.—The empirical relative efficiencies (RE) between the estimated endogenous post-stratified estimator (EEPSE), the optimized endogenous post-stratified estimator (OEPSE), and the simple random sample estimator (SRS), for three sample sizes for each of the three simulation populations. The empirical relative efficiencies are based on 4,000 realizations.

	Simulation Population								
	Path 27 Row 27			Path 37 Row 32			Path 37 Row 33		
Sample Size	100	700	2,280	100	500	1,270	100	700	1,350
RE(EEPSE,OEPSE)	1.01	1.15	1.19	0.90	0.97	1.00	0.92	1.03	1.06
RE(SRS,OEPSE)	1.11	1.53	1.59	0.98	1.26	1.35	0.99	1.22	1.28
RE(SRS,EEPSE)	1.10	1.33	1.34	1.09	1.30	1.35	1.08	1.18	1.21

The content of this paper reflects the views of the author(s), who are responsible for the facts and accuracy of the information presented herein.

PROPERTIES OF THE ENDOGENOUS POST-STRATIFIED ESTIMATOR USING A RANDOM FORESTS MODEL

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Abstract.—Post-stratification is used in survey statistics as a method to improve variance estimates. In traditional post-stratification methods, the variable on which the data is being stratified must be known at the population level. In many cases this is not possible, but it is possible to use a model to predict values using covariates, and then stratify on these predicted values. This method is called endogenous post-stratification estimation (EPSE). In this paper, we investigate methods to automatically select the number of post-strata for EPSE. We do this in the context of models fitted by Random Forests with the stratum boundaries set at quantiles of the predicted distribution.

INTRODUCTION

Post-stratification is used in survey sampling designs as a method to improve variance estimates by calibrating to known population quantities (Särndal et al. 2003). In the U.S. Forest Service Forest Inventory Analysis Program (FIA), the stratum categories are often land cover classifications based on remote sensing data. In many cases it is desirable to use the FIA data itself to develop the very maps used for stratification. This method is called endogenous post-stratification estimation (EPSE) and the theoretical properties of this method were first introduced by Breidt and Opsomer 2008, and then extended to a broader class of nonparametric models by Dahlke et al. 2012. The use of FIA data to construct maps and then the subsequent use of these maps as post-stratum to construct estimates has the potential for substantially reducing variance in these estimates. Given the increased use of more complex predictive models in developing forest attribute maps in survey applications, there is an urgent need for simulation studies to investigate the properties of the EPSE method and determine under which conditions the EPSE estimator works and under which it fails.

This paper has three main goals. First is to compare the EPSE estimator properties using a linear model, a spline model, and a Random Forests model (Breimam 2001) to develop post-stratum maps. The second goal is to investigate the effects of using estimated stratum boundaries instead of fixed stratum boundaries. The third aim of the simulation study is to investigate the effects of a minimization of the variance estimate on the EPSE estimator.

THE ENDOGENOUS POST-STRATIFIED ESTIMATOR

Following the EPSE framework described by Briedt and Opsomer (2008), a sample s of size n is taken from a population $U = \{1, \ldots, i, \ldots, N\}$ of size N according to a probability design $p(\cdot)$ where $p(s)$ is the probability of drawing the sample s. For each $i \in U$ a vector of covariates x_i and a response y_i is observed. There is assumed to be a true relationship between x_i and y_i, denoted $m(\cdot)$, where $E[y_i \mid x_i] = m(x_i)$ which is estimated by $\hat{m}(x_i)$.

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The models used for this simulation study are a linear model, a spline model, and a Random Forests model. Details on the models and dataset are omitted from this paper. In EPSE, the model predictions $\hat{m}(x_i)$, $i = 1, \ldots, N$ are sorted into H fixed stratum based on the stratum boundaries $\tau_1, \tau_2, \ldots, \tau_{H-1}$ where $\hat{m}(x_i)$ is in the h^{th} stratum if $I(\tau_{h-1} < \hat{m}(x_i) \leq \tau_h) = 1$. The estimated sample counts in stratum h are given by $\hat{n}_h$ and the estimated population counts in stratum h are given by $\hat{N}_h$. The ratio $\frac{\hat{n}_h}{\hat{N}_h}$ is the estimated stratum weight for stratum h. Using the estimated stratum weights, the stratum mean $\hat{\mu}_h$ is calculated for each stratum h by

$$\hat{\mu}_h = \frac{1}{\hat{n}_h} \sum_{i \in s} y_i I_{\{\tau_{h-1} < \hat{m}(x_i) \leq \tau_h\}}. \quad [1]$$

The EPSE estimator $\hat{\mu}_y$ for the population mean is calculated by

$$\hat{\mu}_y = \frac{1}{N} \sum_{h=1}^{H} \hat{N}_h \hat{\mu}_h. \quad [2]$$

The estimates $\hat{V}(\hat{\mu}_y)$ for $Var(\hat{\mu}_y)$ are calculated using the post-stratified formulas in Särndal et al. 2003 by

$$\hat{V}(\hat{\mu}_y) = (1 - \frac{n}{N}) \frac{1}{N^2} \sum_{h=1}^{H} \hat{N}_h^2 \frac{s_h^2}{\hat{n}_h} \quad [3]$$

where $s_h^2 = \frac{1}{\hat{n}_h - 1} \sum_{i \in s} [(y_i - \hat{\mu}_h)^2 I_{\{\tau_{h-1} < \hat{m}(x_i) \leq \tau_h\}}]$ is the sample variance for stratum h. For the simulation study, fixed stratum values for τ_h are considered following Breidt and Opsomer (2008). Also, estimated stratum values $\hat{\tau}_h$ based on quantiles of the model predictions for the set of population covariates x_i, $i \in U$ are considered.

EMPIRICAL PROPERTIES OF THE ESTIMATOR

The data used for this study are from the pilot study of Utah for the 2011 National Land Cover Data (NLCD) canopy cover map. The study region consisted of 4151 observations in Utah. At each location, aerial photography was interpreted to determine the percentage canopy cover. This is the forest response variable of interest in these simulations. Empirical models of tree canopy cover were then derived by modeling this tree canopy cover as functions of Landsat TM reflectance values and topographic values described in detail in Coulston et al. (2012). These empirical models were then used to predict tree canopy cover and develop the post-strata through a variety of binning rules applied to predicted values.

Comparison of Fixed vs. Estimated Stratum Boundaries

The first simulation study is designed to address two questions. First, how does the EPSE performance compare between the linear model, spline model, and Random Forests model when the stratum boundaries are fixed. This is the case where the theory is well known. And second, how is the EPSE performance affected when the stratum boundaries are estimated by sample quantiles as compared to using predetermined fixed stratum boundaries. To get the fixed stratum boundaries, each empirical model was fit using the full dataset. Assuming the empirical model is correct, the population quantiles of percentage canopy cover are determined. This stratification scheme is fixed and not dependent on the sample (i.e. it is the same value for all samples, or a priori). The strata for the fixed stratum boundaries simulation are $(-\infty, Q_1(y)]$, $(Q_1(y), Q_2(y)]$, $(Q_2(y), Q_3(y)]$, $(Q_3(y), \infty)$ where $Q_1(y)$ represents the 25th percentile of the predicted values of percentage tree cover based on the full population. The second stratification uses estimated quantiles from the empirical model fit using the sample and then the estimated quantiles are used as stratum boundaries. Note that in this second scheme, the quantiles are dependent on the sample s, or a posteriori. The strata for the estimated stratum boundaries simulation are $(-\infty, \hat{Q}_1(y)]$, $(\hat{Q}_1(y), \hat{Q}_2(y)]$, $(\hat{Q}_2(y), \hat{Q}_3(y)]$, $(\hat{Q}_3(y), \infty)$ where $\hat{Q}_1(y)$ represents the 25th percentile of the predicted values of percentage tree cover based on the full population. For both of these strata definitions the behaviour of the EPSE estimator $\hat{\mu}_y$ and its variance estimator $\hat{V}(\hat{\mu}_y)$ at different sample sizes was investigated for the three different models. All models used the full set of covariates as predictors and no model selection was performed. For each iteration of

the simulation, a sample of size *n* was taken from the 4151 observations. The different models were fit using the covariates in the sample and the percentage tree cover values were estimated as the response.

For each iteration of the simulation, $\hat{\mu}_y$ and $\hat{V}(\hat{\mu}_y)$ were calculated using equations (1), (2), and (3). This process was repeated for 1000 iterations and the mean of the variance estimate

$$E\left[\hat{V}(\hat{\mu}_y)\right] = \frac{1}{1000} * \sum_{i=1}^{1000} \hat{V}(\hat{\mu}_y)$$

was compared to the variance of the post-stratified estimator of the mean $Var(\hat{\mu}_y)$.

Results indicate that the EPSE estimator can be extended to include the Random Forests model. This simulation also supports the use of the EPSE estimator when the stratum boundaries are estimated quantiles from the model fits instead of fixed stratum boundaries. The justification for using the quantiles of the model predictions for the set of population covariates is to avoid having to deal with unequal sampling weights if present in the sampling design. The EPSE estimator appears to be robust for different models and under estimated stratum boundaries as long as care is taken to correctly specify the model and no optimization step is performed. There were also some technical issues involving numerical integration methods used in the statistical software not discussed in this paper. For this study, all elements in the population have equal probabilities of being sampled, but this method of using the predictions at the population level should allow for the use of an unequally weighted sampling design. This is an area for further research.

Properties of Minimization of EPSE Variance Estimates

For the second simulation the goal is to construct the smallest variance estimate $\hat{V}(\hat{\mu}_y)$ and to determine if this algorithm is performing well as an estimator for the true variance $Var(\hat{\mu}_y)$. The optimization will be over the number of strata to be used in the EPSE estimator. The model predictions will be split into stratum of equal size by the quantiles of the model predictions based on the covariates for the population.

We start this simulation as before by taking a random sample of size *n* from the population of 4151 sites in the Utah dataset. For each sample we fit a linear regression model, spline regression model, and Random Forests model using covariates to model percentage tree cover. Predictions were made for the sample values based on the model fits.

After computing the model predictions for the population, the strata over which optimization will be performed can be created. For $k = 1$, one stratum is used and is equivalent to simple random sampling. For arbitrary *k*, the predictions are placed into *k* equally spaced quantiles.

For a fixed n, the optimized EPSE estimator using Random Forests has the smallest variances and variance estimates of the three models, the spline model has the next smallest variances and variance estimates, and the linear model has the largest variances and variance estimates. The results also suggest that both the linear model and the spline model are overfitting the data resulting in the variance estimates being too small. This simulation study supports the use of Random Forests in EPSE, but suggests that an EPSE estimator based on linear model or spline model can underestimate the variance when an additional optimization is performed. This statement appears to hold for both the optimized and non-optimized EPSE estimates. This is a reasonable result since no model selection was performed for any of the models and therefore there are too many covariates for the spline model and the linear model.

CONCLUSION

This study has shown that use of the EPSE estimator should not be applied without a simulation study to determine if variance estimates for the EPSE estimator are over- or under-estimating the true variance. Furthermore, care must be taken in implementing

the EPSE method with software that uses numerical integration methods to prevent rounding errors from influencing the results. Caution is needed when attempting to optimize the variance estimates as severe under-estimation of the variance of the EPSE estimator occurred in this study. The use of a model selection step in building the model has been shown to reduce this problem.

This study lends strength to the idea that EPSE can be applied to stratum boundaries that are estimated quanitles of the data rather than fixed stratum boundaries. This is an area for further research as in practice it is easier to implement the EPSE estimator using estimated quantiles and thereby eliminating the possibility of empty stratum. The Random Forests model performed well in each simulation and across all sample sizes considered. This is an exciting result in that there is almost no tuning needed by the user to fit the Random Forests model. This supports FIA's use of maps of land cover and percentage tree cover created by Random Forests as a basis for using endogenous post-stratification as a way to increase precision of FIA estimates.

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IMPROVED PREDICTION OF HARDWOOD TREE BIOMASS DERIVED FROM WOOD DENSITY ESTIMATES AND FORM FACTORS FOR WHOLE TREES

David W. MacFarlane and Neil R. Ver Planck[1]

Abstract.—Data from hardwood trees in Michigan were analyzed to investigate how differences in whole-tree form and wood density between trees of different stem diameter relate to residual error in standard-type biomass equations. The results suggested that whole-tree wood density, measured at breast height, explained a significant proportion of residual error in standard-type allometric equations, but whole-tree form factors explained more. However, such form factors are highly variable from tree to tree and may be difficult to predict with any precision from simple tree measurements. Whole-tree form factors were found to be highly correlated with the percentage of total aboveground mass in tree branches, which likely relates to the allometric scaling of the deliquescent hardwood growth form. These results suggest that further studies are needed to understand whole-tree form factors and incorporate them into tree biomass equations.

INTRODUCTION

The basic problem for accurate forest mass inventory is that standing trees cannot be weighed, so biomass estimates must be derived from allometric scaling principles and dimensional measurements of trees, principally tree stem diameter at breast height (d.b.h.). Since trees with the same basic measurements can have very different form and growth rates, allometric-scaling relationships should vary widely over space and time due to differences in tree form and wood density. In principle, if one could measure tree form and wood density on every standing tree, generalized allometric scaling equations could be made very accurate across diverse ecosystems. Wood density can be determined from tree cores (Williamson and Wiemann 2010) or can be derived from published values (Chave et al. 2005). However, wood density estimates are generally taken at breast height and may not represent the whole tree. While methods for estimating the form of the main stem (a.k.a. the bole) of a tree are available (e.g., Flewelling et al. 1998), methods for estimating the form of a whole tree are lacking (but see Cannell 1984).

Here, data from hardwood trees in Michigan were analyzed to investigate how differences in whole-tree form and wood density between trees of different stem diameters relate to residual error in standard-type biomass equations. Methods of predicting whole-tree form from other tree attributes were also examined.

Data

The study location was Fred Russ Experimental Forest, which is owned by Michigan State University (MSU) and is located in Decatur, MI. Following a major storm event, 32 hardwood trees ranging from 15 to 91 cm in size were selected from a larger group of wind-felled trees for whole-tree measurements and destructive sampling. Tree species included American basswood (*Tilia Americana* L.), American beech (*Fagus grandiolia* Ehrh.), black cherry (*Prunus serotina* Ehrh.), slippery elm (*Ulmus rubra* Muhl.),

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and sugar maple (*Acer saccharum* Marsh.). Beginning at the point where the trunk flares, stem diameter outside bark was measured at 2-meter intervals until the first forking point (defined as the crown base) occurred. From that point, three paths were followed from the first fork to a terminal twig including the dominant path, which was the largest branch leading to an apical control point (i.e., the top of the tree), and two random paths selected using random branch sampling protocols with probability proportional to branch cross-sectional area (Gregoire et al. 1995). In addition to measurements along the path at 2-m intervals, the stem diameter before each forking point and all stem diameters after each forking point were also measured, which allowed for variable probability sampling.

After all measurements were taken, tree discs were removed from all measurement locations starting at d.b.h. The discs were measured and weighed fresh after transport to the laboratory and then dried to a constant mass at 105 °C. Basic wood density was estimated following procedures outlined in Williamson and Wiemann (2010).

Analysis

Whole-tree wood volume (V_W) and mass (M_W) estimates were generated using the sample data and expansion factors derived from random branch sampling (Gregoire et al. 1995), and component volume and mass values were also estimated for branches and the dominant stem. Breast height wood density (ρ) was calculated from the disk removed at breast height, and wood density of the dominant stem, branches, and the whole tree were estimated by dividing the mass by the volume of those components. Diameter of the stem was measured at breast height (D) and stem height (H) was measured. Whole-tree form factor (F) was computed as the ratio of whole-tree volume to a proxy tree volume: $F = V_W / V_P$, where $V_p = ¼\pi D^2 H$.

A standard d.b.h.-based allometric equation was fit to the tree data:

$$M_W = \alpha D^{\beta} \quad (1)$$

where MW is the dry mass of a whole tree (without leaves), and α and β are the scaling and power coefficients of a power function. The coefficients were estimated with least squares regression. Relative error (RE) in biomass estimation (predicted-observed/observed) from equation 1 was related to ρ and F to determine their contribution to RE.

RESULTS AND DISCUSSION

When the RE of biomass prediction from the equation 1 was regressed against breast-height ρ and whole-tree F, it was found that both explained significant fractions of the relative error in biomass estimation from d.b.h., but F explained a greater proportion of the RE than ρ. While several studies have shown that adding ρ can improve allometric equations (e.g., Chave et al. 2005), there has been little attention to F. However, Canell (1984) showed that the allometric scaling coefficients of aboveground biomass equations derived from stand basal area and average tree height were positively correlated with the percentage of total aboveground biomass comprised of branches, and that the percentage of branches was correlated with average stand F. The results presented here suggest that whole-tree F correlates directly with error in individual tree mass estimation and should be a useful addition to allometric equations, where it can be estimated. However, estimation of F requires that whole-tree volume be estimable on standing trees.

Since F was shown to be related to the percentage of whole-tree mass found in the branch component (Cannell 1984), F was plotted as a function of the percentage of mass in branches (Fig. 1a), and they were found to be well correlated (70 percent). MacFarlane (2011) suggested several predictors of

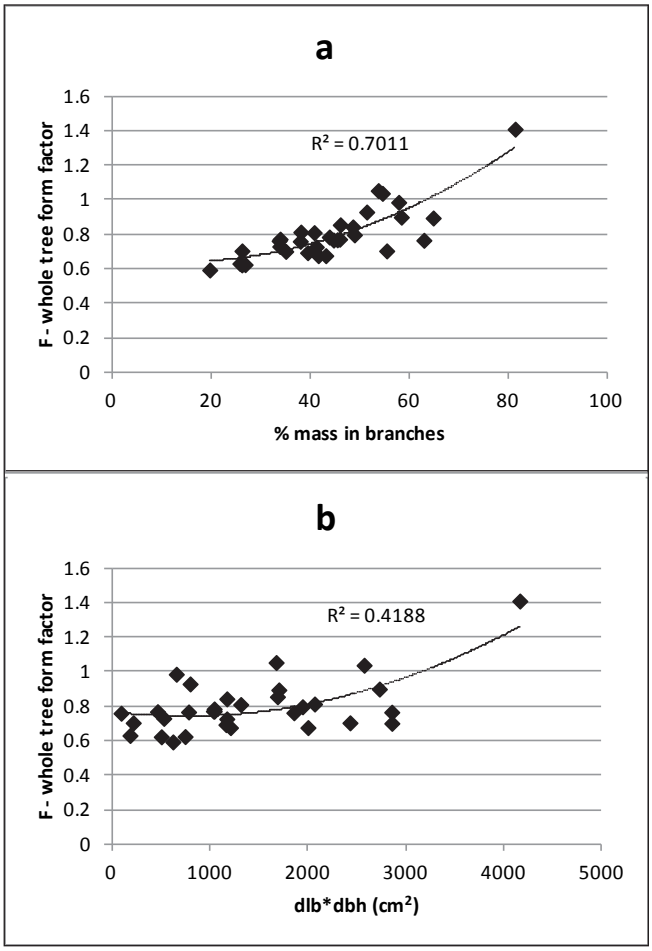


Figure 1.—Whole-tree form factor (F) as a function of: (a) percent mass in branches; and (b) the product of the diameter of the largest branch (d.l.b.) in a tree and the stem diameter at breast height (d.b.h.).

percent branch volume, and these were examined as possible predictors of F. Unfortunately, the best predictor of F, the product of the diameter of the largest branch (d.l.b.) in the tree and d.b.h., explained only about 42 percent of the variation in F (Fig. 1b), which may not be precise enough to improve accuracy of the biomass equation. However, it may be possible to directly estimate whole-tree volume on standing trees (Van Duesen and Roesch 2011) along with standard measurements of d.b.h. and tree height, in which case F could be directly estimated rather than predicted.

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CHALLENGES AND OPPORTUNITIES FOR IMPROVED BIOMASS AND CARBON MONITORING OF U.S. TREE SPECIES

BIOMASS MEASUREMENT AND MODELING CHALLENGES FOR HARDWOOD SPECIES IN THE NORTHERN REGION

James A. Westfall, David W. MacFarlane, and Aaron R. Weiskittel[1]

Abstract.—Biomass models for most commercially important hardwood species in the northern region of the U.S. are often based on data of very limited spatial extent and range of tree characteristics, suggesting uncertain accuracy when applied at regional scales. Also, the current models can have poor predictive ability for the proportions of biomass found in major tree components considered for utilization, namely the merchantable bole, bole tops, tree branches, and foliage. The Forest Inventory and Analysis Program of the U.S. Forest Service is currently undertaking a project to obtain regionally representative data to develop new volume/biomass models. This paper outlines issues related to challenges in data collection and subsequent modeling of biomass components for hardwood species.

INTRODUCTION

A number of tree biomass studies were conducted in the northern region from the late 1970s into the early 1980s (Smith and Brand 1983, Wiant et al. 1977). These studies provided the initial biomass estimation procedures for many hardwood species in the region. However, data collection was often limited to relatively small areas and ranges of tree characteristics. Nonetheless, equations from various sources were adopted by the Forest Inventory and Analysis (FIA) Program (an entity of the U.S. Forest Service) because these equations provided the only opportunity to include biomass estimates in forest resource reports. Due to differences among studies in definitions, data collection protocols, and model forms, predicted values of biomass for trees of a given size could vary considerably. As biomass estimates became increasingly important, FIA implemented a nationally consistent method to estimate individual-tree biomass components (Heath et al. 2009). This change in methodology produced estimates that were sometimes incongruous with those of the earlier models, raising concerns about which method(s) provided the most accurate results (Domke et al. 2012, Westfall 2011). In the absence of data required to make such assessments, FIA has committed to collecting regionally representative biomass data to provide a common basis for biomass estimator development. Although there are several important conifer species in parts of the northern region, the forests are largely dominated by hardwood species. Due to their decurrent form, hardwoods require innovative techniques to appropriately measure and model biomass components.

MEASUREMENT CHALLENGES

Several challenges must be faced when measuring hardwood species for biomass. Foremost, tree form has an unknown effect on allometric scaling relationships and is critical to estimating biomass components. There is an inherent difficulty in recording numerous hierarchical orders of branches and foliage, so a complex measurement and recording system is needed to permit reconstruction of the tree. Measurement protocols should be sufficiently

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prescribed such that no critical information is overlooked or measured incorrectly. Conversely, the detail and cost of measurements should not exceed that needed to meet accuracy objectives in predicting biomass. Also, the protocols must be understandable and intuitive. Theoretically and technically sound protocols are of little use if they cannot be consistently and accurately applied in the field. A related issue is the need to consistently assign tree parts to component categories (e.g., branch vs. top wood), especially as merchantability and utilization standards change over time. Cost (1978) provides examples of field protocols designed for measuring volumes in traditional product categories including sawtimber and pulpwood, but these protocols are not entirely suitable for biomass determination.

To increase efficiency, sampling may be used for branch and foliage components. However, the design of an unbiased, high-precision sampling design is required before widespread implementation. For this study, the first year of data collection will entail a high level of detail for individual-tree measurements, which will allow assessment of various sampling protocols that may be implemented in subsequent years. Obviously, this exercise hinges on successful implementation of the detailed measurement protocols described in the above paragraph. Also, selection of trees that well represent the range of branching and foliage patterns found in the population will be essential.

Unlike many volume attributes, which are based on trees of merchantable size, biomass predictions are needed for smaller trees (e.g., d.b.h. 1.0 inch and greater). Furthermore, current biomass estimates for small trees can be suspect because many existing biomass models are based primarily on trees of merchantable size. Thus, ensuring that sapling-size trees are included in the sample is imperative. However, inclusion of small trees can create measurement challenges because data collection protocols are often specified assuming application to trees of merchantable size (e.g., biomass of the main stem may be defined as that occurring below the 4-inch top diameter). Thus, measurement protocols must be specified such that there is applicability across all tree sizes.

Because prediction models will ultimately be applied to standing trees, a key component in the measurement phase is understanding how measurements of standing trees correlate with more accurate data taken on felled trees. An example would be branch length, which may or may not be needed in addition to branch diameter to accurately predict branch biomass. Perhaps branch allometry suggests that knowledge of branch diameter alone is sufficient to obtain acceptable biomass predictions. Understanding the information needs in this context is important, because branch lengths on standing trees are likely only accurately measured as the linear distance from branch base to tip. However, most branches have some degree of curvature that would not be accounted for in the linear distance measure, and thus recorded branch length would not reflect the actual length. If branch length is vital to branch biomass prediction, differences between linear branch lengths taken on standing trees and the actual length would need to be empirically assessed on trees that are felled. Identifying and accounting for such issues in the data collection process is critical if unbiased estimates of biomass are to be produced based on data elements collected on standing trees (e.g., FIA plots).

MODELING CHALLENGES

Several challenges are also faced when considering biomass model development for hardwood species. First, one must consider the sample size needed to establish statistically significant relationships between predictor variables and biomass values. Due to the wide variation in tree characteristics, more samples are likely needed for hardwoods than for softwoods. Unfortunately, the number of sample trees is often limited due to financial constraints. In these situations, it is advisable to estimate the minimum

sample size deemed necessary and ensure resources exist to attain that base level of sampling. Given that an appropriate number of sample trees have been determined, additional work is needed to specify tree selection processes. For example, it may be desirable to specify numbers of trees to be sampled by size class, form or crown architectural characteristics, and/or spatial distribution. These specifications should be thoroughly evaluated, because substantial effort may be incurred to find and measure certain relatively rare occurrences, e.g., very large d.b.h. trees. On the other hand, one must also consider that sampling trees based on frequency alone would be sub-optimal in that most sample trees would be near the middle of the distribution(s) of selection criteria and relatively little information would be obtained at the lower and upper ranges. Such an approach could lead to poor predictions for trees that do not exhibit characteristics represented in the modeling data. The goal is for the sample to cover the widest range of variation in tree size and form attributes across the geographic range of occurrence; however, this must be balanced within practical cost and time constraints.

Another major issue is that the spatial variation in species-specific allometric scaling coefficients of hardwoods is largely unknown. Due to the high cost of felled-tree data, characterizing changes in biomass parameters across various gradients (e.g., latitude, longitude, and elevation) will require ancillary standing-tree information. The types and amounts of ancillary data needed to capture these shifts in hardwood tree allometry must be determined. Due to the limitations of measuring standing trees from ground-position, the ability to obtain accurate measurements of specified data elements also must be assessed, which includes both unobstructed lines-of-sight and types of equipment required. Finally, a statistically defensible method to incorporate these data into the analysis must be developed.

Potential grouping of species having similar characteristics should also be evaluated. For hardwood species, this may be particularly difficult due to the excessive geographic and phenotypic variation. Typically, such groupings have been accomplished using genera or categorical classification, such as oak/hickory, although different growth habits among species within such groups may make them unsuitable for aggregation when modeling biomass. The best-case scenario is to have pre-determined groupings such that the sampling effort can be lessened by having group-level (vs. species-level) sample size requirements. However, one then assumes the risk of having species within groups that actually are not as similar as expected. In the absence of reliable information on aggregation criteria, caution should be exercised in grouping species before data collection.

A final consideration is the duration of the data collection effort. One option is to set the sample size requirements for model development and cease fieldwork once those requirements are met. An alternative scenario would be to not only develop biomass models from the initial effort, but also to continue to collect data as well. One potential option would be to incorporate needed biomass measurements into existing Timber Products Output (TPO) studies conducted by FIA (Wharton and Birch 1999). This would provide a continual stream of additional information that could be used to periodically update existing models. While the latter approach seems more desirable from a scientific viewpoint, there are programmatic issues for FIA because biomass predictions for trees on inventory plots change over time, which can be problematic for some clients, e.g., reprocessing of older data with newer biomass values will produce different analytical results. Implementation of a continual data collection paradigm would need to be carefully considered before implementation to provide balance between the best scientific practices and program credibility.

CONCLUSION

Measuring and modeling biomass for hardwood species is not a trivial exercise. Due to the decurrent form, substantial effort may be needed to collect multi-level branch and foliage data. The data also need to

be collected consistently across various species, tree sizes/forms, and field personnel. Thus, field protocols must be explicitly defined and consistently interpreted. Obtaining reliable data for hardwoods also requires an understandable and intuitive protocol for recording the extensive measurements, such that the tree can later be accurately reconstructed or re-analyzed as utilization standards change.

A primary difficulty faced in modeling biomass of hardwood species is establishing relationships between biomass and usual mensurational variables such as d.b.h and total height. The wide range of tree forms assumed by hardwood species creates substantial variability, which may require large sample sizes to develop models having acceptable degrees of predictive accuracy. Particularly, it is necessary to empirically describe how relationships between biomass components change in relation to various factors (e.g., tree size and form). Practical constraints on felled-tree data collection suggest that ancillary information from standing trees will be necessary to further refine model predictions for local accuracy and that grouping of species may be helpful in attaining sufficient sample sizes. However, the techniques by which these issues are best addressed must still be developed and evaluated.

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STRATEGIES FOR ASSESSING INTER- AND INTRA-SPECIFIC VARIATION IN TREE BIOMASS IN THE INTERIOR WEST

David L.R. Affleck, John M. Goodburn, and John D. Shaw[1]

Abstract.—Wildfire hazard mitigation and bioenergy harvesting have emerged as forest management priorities throughout the Interior West (IW) of the USA. Regional forest inventory and forecasting applications are therefore increasingly focused on tree biomass, including biomass in traditionally non-merchantable components. Yet accurate biomass equations for the latter components are typically lacking, even for major commercial species. This is because previous assessment efforts have focused on distinct components, have used inconsistent methodologies, or have relied on data with limited spatial or biophysical extents. Here we review and contrast the current state of knowledge of a widely distributed and commercially important species, ponderosa pine (*Pinus ponderosa*), and a locally important species of the southwest, two-needle pinyon (*Pinus edulis*). Owing to high levels of inter- and intra-specific variation in biomass allometry and to the high costs of collecting biomass data, an important element of new data collection efforts will be the development of standardized and accurate subsampling procedures. We describe these subsampling strategies and discuss potential adaptations for two-needle pinyon in the southwest.

INTRODUCTION

Across the Interior West (IW) of the United States, the management of federally administered forest lands is increasingly being shaped by policies related to wildfire hazard mitigation, bioenergy development, and ecological restoration. At the same time, on private lands there is heightened interest in regeneration and the growth dynamics of young stands. As such, there are growing needs for reliable inventory information on submerchantable trees and on forest biomass pools such as foliage, branchwood, and tops. These emerging needs stand in contrast to the considerable biometric knowledge concerning mature tree bole volume and taper that has been developed. Even for commercial species, few biomass models suitable for regional or subregional analyses are available, and many of these are incomplete or inconsistent with one another.

In this paper we review the current state of knowledge concerning tree biomass allometries, focusing on two IW species: the widely distributed ponderosa pine (*Pinus ponderosa*) and the locally important southwestern two-needle pinyon (*Pinus edulis*). We also consider the advantages and limitations of model-assisted subsampling strategies that can be used to augment tree biomass datasets and refine regional allometric models.

CURRENT STATE OF KNOWLEDGE CONCERNING BIOMASS ALLOMETRIES

Ponderosa Pine

Ponderosa pine is found from northern Mexico to southern British Columbia, and from California to

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Nebraska. It is a commercially important species over much of the northern reaches of its range. It generally occupies relatively dry sites but is found over a broad climatic envelope: from the northern Sierras to the adjacent Great Basin it grows on sites with annual precipitation ranging from approximately 1800 mm/yr to 200 mm/yr (Callaway et al. 1994).

Most of our understanding of the biomass allometries of ponderosa pine comes from studies conducted in the northern portion of the species' range. Yet even the relatively intensive field work by, for example, Brown (1978) and Standish et al. (1985), had limited geographic support relative to the species' overall distribution. Moreover, past studies often employed different (and varying) tree biomass measurement protocols and partitioned totals into distinct biomass components. Though not irresolvable, the latter issues do make it challenging to use previously collected data or previously developed models to inform regional or subregional analyses. From smaller-scale studies such as Callaway et al. (1994) and Bouffier et al. (2003), it is evident that this species' biomass allocation patterns and wood density vary within the region owing to environmental and genetic differences; differences in data collection protocols complicate the detection and description of such variations.

Two-Needle Pinyon

In the southwestern United States, two-needle pinyon is a locally important species in terms of forest cover and secondary forest products. It is a woodland species ranging mostly over the states of Utah, Colorado, New Mexico, and Arizona. Two-needle pinyon is found on warmer and drier sites than ponderosa pine. It grows in both single-stem, excurrent forms (on better sites) and with spreading crowns and multiple stems (typical form at lower elevations).

Compared to ponderosa pine, little has been published on the biomass allometries of two-needle pinyon or on its genetic variation or wood density characteristics. Few biomass studies have been conducted and these have been highly localized in terms of geographic extent and have been based on small sample sizes (i.e., 10 to 15 trees) (Darling 1967, Grier et al. 1992).

BIOMASS SUBSAMPLING

Motivations and Challenges

Field assessment of tree biomass is an expensive undertaking in the mountainous and remote regions of the western United States. Besides access costs there are often difficulties associated with the destructive nature of the sampling (e.g., if large d.b.h. trees must be felled or if standard log lengths cannot be maintained). Materials processing costs are also significant with defoliation of branches being particularly time consuming (e.g., defoliation of first-order branches can take more than one person-day for some coniferous species). At the same time, there is a multitude of site and stand factors that can influence the accumulation and apportionment of biomass, investigation of which necessitates the accumulation of relatively large samples of trees for any given species. To collect a large sample in the face of high per-tree costs requires consideration of subsampling strategies and potential sources of auxiliary (non-biomass) information.

The disadvantage of subsampling for tree biomass is that within-tree sampling errors become confounded with among-tree variation. Put differently, residual among-tree variation is inflated by subsampling error, making it more difficult to identify and detect systematic variation in biomass attributable to tree, stand, or site factors. Thus, effective subsampling strategies must allow the size of the sample (i.e., the number of independently selected trees) to increase faster than tree-level uncertainty adds to the overall variance. Specifically, if the subsampling strategy is unbiased then the sample size under subsampling should be greater than the sample size under full measurement by a factor of at least $1 + (\sigma_e/\sigma_t)^2$, where σ_e is the standard deviation associated with the subsampling procedure and σ_t is the conditional standard deviation in biomass across trees with similar characteristics.

Development and Application

Fundamental principles of tree allometry and past empirical work can be brought to bear to devise efficient and practical tree biomass subsampling strategies. As one example, for a given d.b.h. and height much of the tree-to-tree variation in bole biomass can be attributed to differences in bole taper. This suggests using previous taper modeling efforts to minimize costs associated with biomass measurements specific to the bole. Multiple taper studies have been conducted for ponderosa pine in the northwest; particularly noteworthy are multi-point equations such as those developed by Flewelling and Ernst (1996). Though parameterized for specific subregions of the northwest, the latter equations allow for fine calibration of predicted profiles to actual tree taper via the input of multiple upper stem height-diameter pairs (that are easily measured on the downed tree). Point-level predictions (inside- and outside-bark) from the taper profile, together with integrated volumes, can then be used as control variates, allowing for accurate estimation of bole biomass components from a random or systematic sample of discs.

As a second example, numerous field studies (e.g., Monserud and Marshall1999) have shown strong relationships between branch basal area and branch mass for many coniferous species. Less strong are relationships between, on the one hand, branch basal area and, on the other, branch foliar mass or branch woody biomass. Nonetheless, such relationships form an important basis for biomass subsampling strategies because branch basal areas are more easily measured than branch masses (green or dry; whole or by component). Subsampling procedures can draw on these relationships via unequal probability designs (e.g., list sampling or randomized branch sampling, RBS) and at the estimation stage through the use of generalized ratio or regression estimators. Such strategies obviate the need to measure full crown weights in the field, a task that is both time-consuming and fraught with difficulties due to the prevalence of broken and buried branches. As part of an ongoing ponderosa pine biomass study in the northwest (Affleck and Turnquist 2012), RBS of first-order branches has been used to capitalize on the strong quadratic relationship between branch diameter and branch mass while carrying out the crown sampling in a single pass up the stem. The use of generalized regression estimators with RBS is also being studied as initial results have indicated that a number of conifer species do not exhibit area-preserving branching at the first-order level, a characteristic implicitly assumed in RBS.

In developing biomass sampling strategies for two-needle pinyon, there is considerably less mensurational knowledge to draw on. While volume equations have been developed for this species, we are aware of no work on taper. Flexible taper equations for other species might be substituted and used for control variate sampling, though the procedure would need to be modified for multi-stemmed growth forms. Inasmuch as the multi-stemmed growth form is common, it is anticipated that crown subsampling strategies based on branch scaling relationships will be more useful for this species. In particular, RBS strategies could be applied in different ways to estimate crown characteristics on single stems or across multiple stems.

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ESTIMATING BIOMASS AND CARBON IN FORESTS OF THE PACIFIC STATES: STATISTICAL ISSUES

Andrew N. Gray and Hailemariam Temesgen[1]

Abstract.—Increasingly, large-scale estimates of biomass and carbon play significant roles in providing critical information to forest resource management and policy decisionmaking. Biomass and carbon estimates are required to monitor CO2 mitigation projects, characterize forest productivity, and estimate carbon flux. Yet, estimating biomass and carbon for large-scale inventory and monitoring is a difficult task. The amount of bias introduced by using locally developed equations to estimate biomass and carbon across large regions is not known. Equations are either not available or poorly developed for important species and important components of carbon storage like standing dead trees. In addition, the Pacific states are characterized by some of the largest trees and most remote landscapes in the country, which complicates sampling and measurement.

Using ground data collected from across a range of major forest types in Pacific Northwest, we demonstrate selected approaches that might improve regional biomass and carbon estimates. In this presentation, we discuss 1) the suitability and predictive abilities of selected methods to quantify biomass and carbon in different forest types of the Pacific Northwest; 2) the use of selected methods to quantify types and frequency of dead trees/snags and their contributions to biomass/carbon pools; and 3) the challenges and opportunities in estimating biomass and carbon. In addition, we will discuss existing gaps and emerging technologies that might offer opportunities to quantify biomass and carbon inventories.

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ROLE OF FIA DATA IN EVALUATING FOREST ECOSYSTEM RESPONSES TO AIR QUALITY STRESSORS

IMPACTS OF NITROGEN AND SULFUR DEPOSITION ON THE GROWTH OF RED SPRUCE AND SUGAR MAPLE IN THE UNITED STATES

Jennifer N. Phelan, Paramita Sinha, George Van Houtven, Marion Deerhake, Randall G. Waite, Anne W. Rea, and Ginger M. Tennant[1]

EXTENDED ABSTRACT

Total nitrogen (N) and sulfur (S) deposition in forest systems can have either positive or negative impacts on tree growth. The growth of many forests in North America is limited by N availability (Chapin et al. 1993, Killam 1994). Therefore, N fertilization is often a key component of forest management (Allen 2001), and in areas of N deposition, tree growth may be stimulated. However, N additions can sometimes be greater than what trees require and can negatively impact tree health and growth (Aber et al. 1995, Driscoll et al. 2001, McNulty et al. 2005). Systems where atmospheric deposition of N and S is greater than the critical load may be examples of such forest conditions. When critical loads are exceeded, tree health and growth may be compromised both directly and indirectly due to soil nutrient imbalances caused by leaching of base cations from the soil. Trees may have an increased susceptibility to drought and pest damage, aluminum (Al) toxicity in roots, reduced tolerance to cold, and a greater susceptibility to frost injury (Cronan and Grigal 1995, Driscoll et al. 2001, Fenn et al. 2006, McNulty et al. 2005, Ouimet et al. 2008). In the context of acidifying deposition of N and S, whether deposition has a positive or negative impact on tree growth may depend largely upon whether the critical load is exceeded by the deposition level, and it may follow an inverted U-shaped relationship similar to that which was hypothesized by Aber et al. (1995) for temperate forest systems that receive chronic, long-term N additions (Fig. 1).

To examine the relationships between N and S deposition and tree growth, preliminary analyses comparing the growth of sugar maple (*Acer saccharum* var. *saccharum*) and red spruce (*Picea rubens*) and critical acid load exceedances (positive and negative) were conducted for the full geographical ranges of both species in the United States. Sugar maple and red spruce were selected as the test species because both have experienced decline in areas of high N and S deposition (Ouimet et al. 2008, Shortle et al. 1997, Watmough 2002). Annual tree growth estimates for sugar maple and red spruce were obtained from the Forest Inventory and Analysis (FIA) database, and critical acid loads were calculated using the simple mass balance model (United Nations Economic Commission for Europe 2004) and three different levels of protection to tree health (base cation/Al soil solution ratio = 0.6, 1.2, and 10.0). The critical loads were compared against 2002 N and S deposition to estimate critical load exceedances. A series of multivariate ordinary least squares regressions were then conducted to examine the

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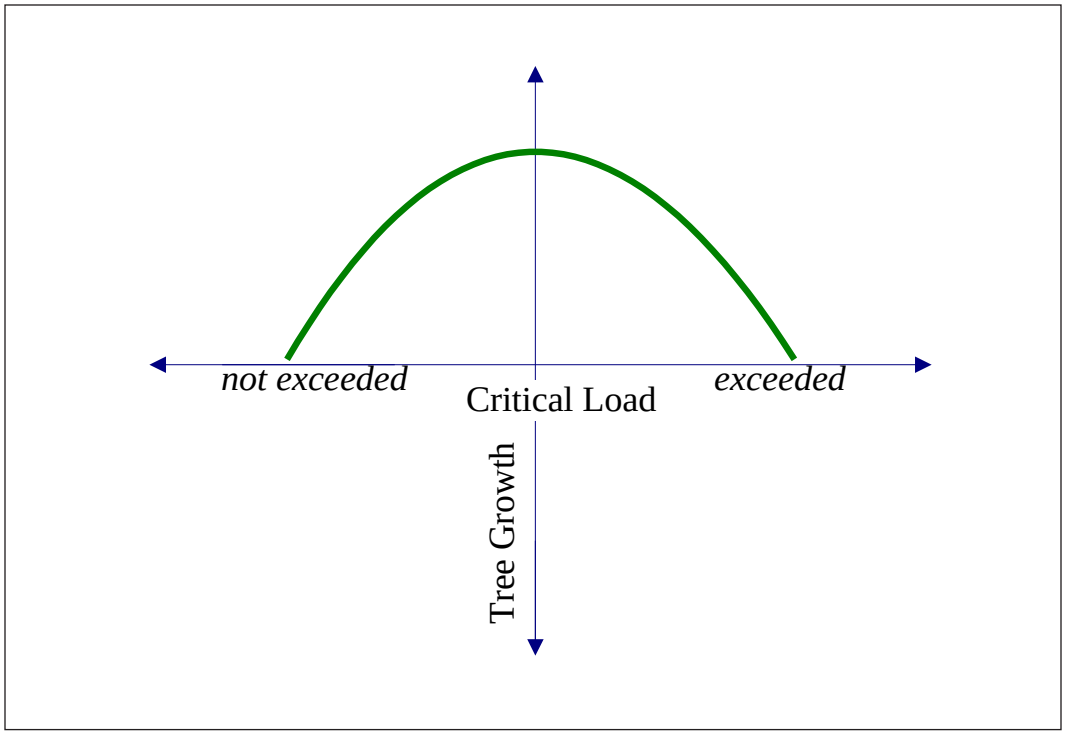


Figure 1.—Hypothetical relationship between tree growth and critical load exceedance (based on curve describing forest productivity as a function of long-term chronic N additions outlined in Aber et al. [1995]).

relationship between tree growth and N and S deposition. A quadratic functional form was used to test for evidence of the inverted U-shaped relationship between critical load exceedance and tree growth represented in Figure 1.

In addition, we conducted separate linear regression analyses relating N deposition and tree response in plots where critical load exceedance values were negative (i.e., plots where deposition levels did not exceed the critical loads), and analyses evaluating critical load exceedance and volume growth on plots where N and S deposition levels exceeded the critical loads. These separate analyses were conducted to test the hypotheses that tree growth is stimulated or "fertilized" by N when critical loads are not exceeded, and tree health and growth are impaired when the benefits of N deposition are replaced by the negative acidifying impacts of N and S deposition. The statistical results suggested that both species exhibited a quadratic functional form relationship between critical load exceedance and growth, although not significant at the $p = 0.05$ level. Based on critical loads determined using the base cations/Al ratio of 10.0, the linear regressions showed that growth of sugar maple was stimulated by N deposition on plots where critical loads were not exceeded ($p = 0.0013$), and red spruce growth was reduced on plots where 2002 N and S deposition levels exceeded the critical loads ($p = 0.0223$).

The objectives of this study will be to expand and improve on the preliminary analyses and further our understanding of the relationships between N and S deposition and red spruce and sugar maple growth. Parameters including initial tree volumes, plot elevation, stand basal area, and plot latitudes and longitudes will be included in the analyses to account for other sources of variation in the growth response. The ability to indirectly

determine species-specific soil solution base cation/Al ratios will also be explored. It may be possible to calculate the base cation/Al ratio critical limit for red spruce and sugar maple based on the point of inflection in the quadratic relationship determined for each species. Previous comprehensive synthesis efforts have reported that the growth of red spruce and sugar maple seedlings was reduced by 20 percent, relative to controls at base cation/Al ratios of 1.2 and 0.6, respectively (Sverdrup and Warfvinge 1993). To date, however, the ability to test or confirm these species-specific critical limits for trees in the field has been limited. Furthermore, these exposure-response models of red spruce and sugar maple growth to N and S deposition may potentially be applied to evaluate the impacts of altered deposition levels on tree growth, and consequently, on provisioning ecosystem services through the use of the Forest and Agricultural Sector Optimization Model—Green House Gas version. If successful, these analyses and novel approach may prove to be a very effective way to evaluate the current condition of U.S. forests in response to N and S deposition, and how forest health could be improved with decreased deposition levels.

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YELLOW BIRCH AND ACID DEPOSITION IN THE SOUTHERN APPALACHIANS

Kenneth W. Stolte, Walter C. Shortle, Kevin T. Smith, Michael Amacher, Charles H. Perry, Lindsay Majer, and Owen Carson[1]

Abstract.—Aerial observations of small clusters of large, standing dead trees in higher elevations of the southern Appalachians (SoApps) in 2005 were later identified as yellow birch (YB) growing in areas of low soil pH and calcium. Yellow birch is a common tree in the maple-beech-birch forests of the northeast United States and higher elevations of the SoApps. It cannot move calcium from older to newer growing tissues and low soil-calcium conditions cause reduced growth and increased vulnerability to damage and mortality from drought, insects, fungi, storms, and other stressors. Black cherry is a common associate with yellow birch but can translocate Ca within tissues and therefore is relatively tolerant of low soil calcium. We used FIA Phase 2 data to locate 48 survey sites in parts of ecoregion subsections M221Dc and M221Dd where larger diamater (>15 inches at breast height) YB were found. At each site we established polygons based on randomly located 5+ YB in each of three target size classes (5-12, 12-15, and >15 inches d.b.h.) in 2010. Yellow birch was evaluated for crown condition (dieback, transparency, ratio, position); damage (type, location, and severity); d.b.h and height; and seedling and sapling regeneration. We also recorded sites that had associated black cherry with d.b.h. >8 inches. Mineral soil samples from 2 depths (0-4 and 4-8 inches) were collected under three randomly selected largest diameter class YB trees and analyzed by the Northern Research Station Forest Inventory and Analysis soils laboratory. We found low soil pH and calcium, and high aluminum, Fe, S, and other toxins correlated with higher elevation sites. The largest diameter yellow birch trees had the highest damage index scores. Seedling and sapling regeneration was highly variable with little or no regeneration at many sites. In late summer of 2011, we obtained tree ring cores from a subset of 26 sites with large diameter yellow birch and black cherry trees for growth of the outer 1 inch of the largest diameter trees of both species, and created shallow wound holes in the same trees to evaluate would response over time. On average, 33 years were required to add 1 inch diameter of growth to yellow birch trees (n=126) and 14 years for black cherry trees (n=62). Shallow wounds on most black cherry had filled with sap, while most of the yellow birch wound holes remained dry 3 months later. A second evaluation of wound response and collection of soil humus for chemical analysis in autumn 2012 is scheduled.

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MODELS FOR ESTIMATING CARBON AND BIOMASS

VERIFICATION OF THE JENKINS AND FIA SAPLING BIOMASS EQUATIONS FOR HARDWOOD SPECIES IN MAINE

Andrew S. Nelson, Aaron R. Weiskittel, Robert G. Wagner, and Michael R. Saunders[1]

Abstract.—In 2009, the Forest Inventory and Analysis Program (FIA) updated its biomass estimation protocols by switching to the component ratio method to estimate biomass of medium and large trees. Additionally, FIA switched from using regional equations to the current FIA aboveground sapling biomass equations that predict woody sapling (2.5 to 12.4 cm d.b.h.) biomass using the Jenkins et al. (2003) equations (Forest Science 49 (1): 12-35) and then multiplying predictions by species-specific adjustment factors. The new equations have not been verified for saplings in Maine where sapling-dominated stands make up nearly 24 percent of the forest land. We verified the FIA sapling equations and Jenkins et al. (2003) equations for naturally regenerated hardwood species from an experiment in eastern Maine. Results demonstrate the FIA sapling equations underestimated observed aboveground woody biomass by between 15 and 37 percent. Our results suggest that the current species-specific sapling adjustment factors were inadequate for the trees in this study, and we propose a new set of adjustment factors based on the observed data.

INTRODUCTION

In 2009, the Forest Inventory and Analysis (FIA) Program updated its protocols for estimating biomass across the United States by switching to the component ratio method (CRM). The CRM was designed to provide consistent national-level biomass estimates similar to the current FIA volume estimates. In particular, the CRM uses specific gravity conversions to estimate bole wood and bark biomass and component proportions from Jenkins et al. (2003) equations to estimate biomass of tops and roots (Heath et al. 2009, Woudenberg et al. 2011). FIA also switched from using regional equations to predict sapling (i.e., trees between 2.5 and 12.4 cm diameter at breast height [d.b.h]) biomass to the current FIA aboveground sapling biomass equations (Heath et al. 2009). The new sapling equations predict oven-dry woody biomass (stem, stump, and woody crown) of saplings using the estimates from Jenkins et al. (2003), and then multiplying the estimate by a species-specific adjustment factor to ensure a smooth transition into estimates obtained for larger size classes of trees. The species-specific adjustment factors are the ratio of estimated biomass by the CRM and predictions by the Jenkins et al. (2003) equations for all 12.5 cm d.b.h. trees of a particular species.

Although the FIA sapling equations conform to biomass estimation techniques of larger trees, the switch to the new equations resulted in a decrease of sapling biomass in Maine by 34 percent between 2003 and 2010, even while corresponding stem densities increased by 11 percent during that time period (McWilliams et al. 2005, USDA FS 2012). The likely reason for the drastic reduction in sapling biomass in the region was the shift to the FIA sapling equations because the species-specific adjustment factors range between 0.7 and 0.8 for the common species in

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Maine. Unfortunately, biomass predictions using the FIA sapling equations have not been well verified in Maine where nearly 24 percent of the 7 million hectare forested area is dominated by sapling-size stands.

In this investigation, we verified the Jenkins et al. (2003) and FIA sapling equations for biomass estimation of hardwood saplings common in Maine, including red maple (*Acer rubrum* L.), paper birch (*Betula papyrifera* Marsh.), gray birch (*Betula populifolia* Marsh.), bigtooth aspen (*Populus grandidentata* Michx.), and trembling aspen (*Populus tremuloides* Michx.) from an experiment in eastern Maine.

METHODS

Experimental Design and Sampling

As part of a larger study, saplings of red maple, paper birch, gray birch, bigtooth aspen, and trembling aspen were destructively sampled in summer 2011 from a controlled experiment installed in a post-clearcut stand dominated by early successional hardwood species on the Penobscot Experimental Forest in eastern Maine. The experimental design is a 3 x 3 +1 factorial of silvicultural intensity (thinning, thinning plus enrichment planting, and intensive plantations) and species compositional objectives (hardwood, mixedwood, and conifer), plus an untreated control. A full description of the experiment can be found in Nelson et al. (2012, In press). Sample tree d.b.h. ranged from 2.7 to 12.0 cm and oven-dry woody biomass ranged from 0.88 to 48.25 kg (Table 1).

Trees were cut at the root collar and dried at 65 °C for a minimum of 2 weeks (foliage and branches) or 6 weeks (bole) to constant mass. Foliage and branches were weighed separately to the nearest 10 mg, while boles were weighed to the nearest 10 g.

Analytical Approach

Oven-dry woody (branch, bole, and stump) biomass estimates of the Jenkins et al. (2003) and FIA sapling equations were compared to the observed data for the sample trees. Paper birch and gray birch were combined due to low sample sizes and because both the Jenkins et al. (2003) equation and sapling adjustment factor were the same for both species. Root mean square error (RMSE), bias (observed–predicted), and the minimum negligible difference (MDND) equivalence test (Radtke and Robinson 2006), where the null hypothesis is that the observed and predicted values are not equal (Robinson and Froese 2004), were used to assess model accuracy and precision.

RESULTS

The FIA sapling equations substantially underestimated aboveground woody biomass for all of the hardwood species in the investigation (Fig. 1). The predicted means were between 15.0 percent for paper birch and gray birch combined to 36.6 percent for trembling aspen lower than the observed means. RMSE of the FIA sapling predictions ranged from 1.0 kg for red maple to 6.7 kg for trembling aspen, and bias ranged from 0.8 kg for red maple to 3.7 kg for trembling aspen (Table 2). Because the predicted

Table 1.—Descriptive statistics of destructively sampled trees used to verify the Jenkins et al. (2003) and FIA sapling equations. The number of individuals (n), and median values and ranges of d.b.h. (cm) and woody biomass (branches and bole) in kg are shown.

Species	n	D.b.h. Median (cm)	D.b.h. Range (cm)	Woody Biomass Median (kg)	Woody Biomass Range (kg)
Red maple	6	3.4	2.7 - 6.0	2.75	1.19 - 8.10
Birch species	5	5.2	3.2 - 8.4	7.03	2.20 - 23.40
Bigtooth aspen	13	6.5	2.7 - 9.5	7.85	0.97 - 19.10
Trembling aspen	15	5.2	2.6 - 12.0	4.78	0.88 - 48.25

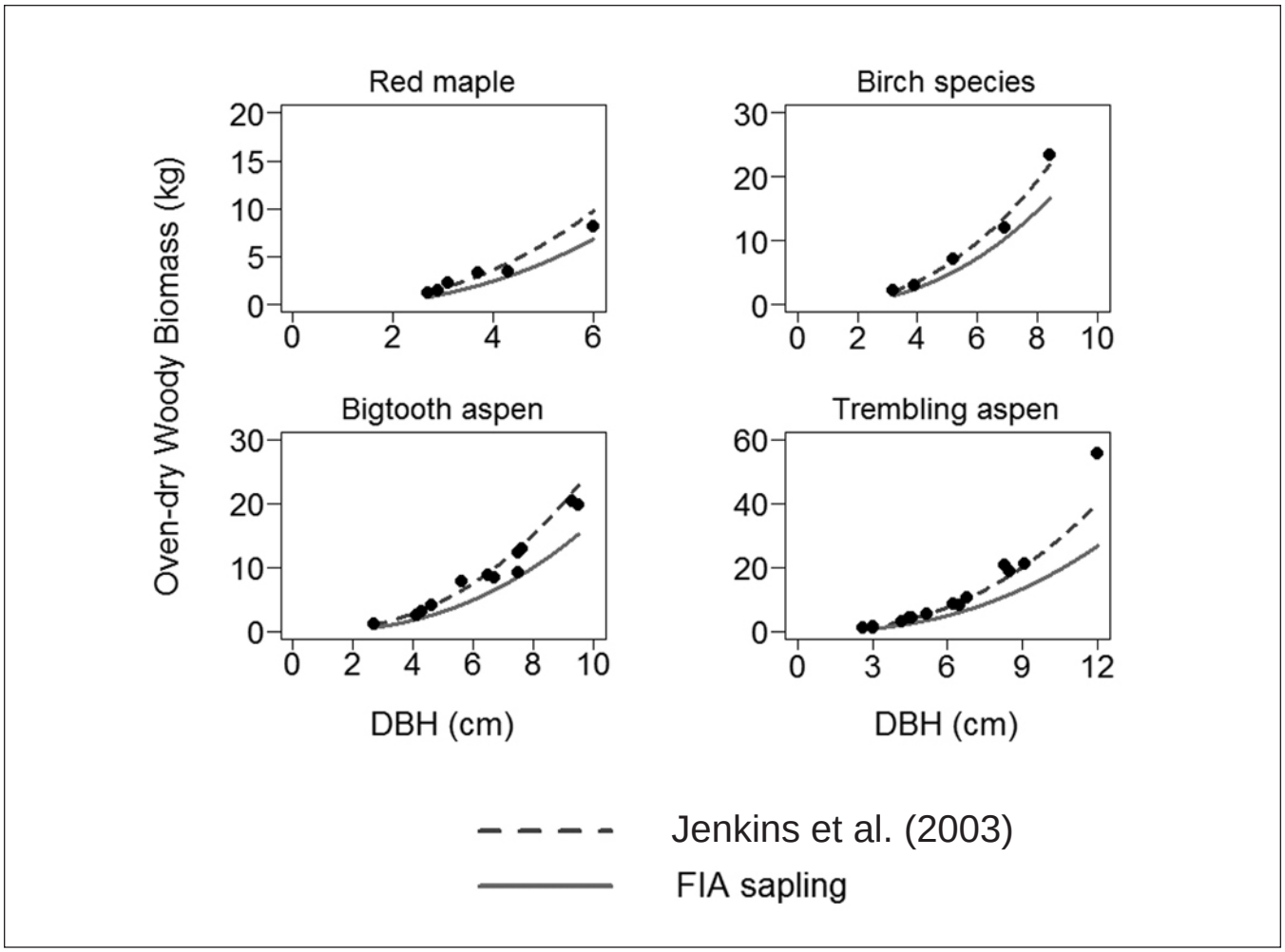


Figure 1.—Oven-dry woody biomass (kg) versus d.b.h. (cm) for the five naturally regenerated hardwood species (paper birch and gray birch combined). The solid circles represent the observed data, the dotted line represents estimates by the Jenkins et al. (2003) equations, and the solid line represents estimates by the FIA sapling equations.

Table 2.—Root mean square error (RMSE), bias (observed-predicted), prediction relative to observed (PRO), minimum detectable negligible difference (MDND), and equivalence test results for the Jenkins et al. (2003) equations (Jenkins) and FIA sapling equations (FIA Sapling)

	RMSE (kg)	Bias (kg)	Observed Mean (kg)	Predicted Mean (kg)	PRO (%)	MDND (%)	Null Hypothesis
Red maple							
Jenkins	0.88	0.57	3.28	3.65	11.31	31.89	reject
FIA Sapling	0.99	0.82	3.28	2.46	-25.13	14.00	not reject
Birch species							
Jenkins	1.33	0.86	5.66	6.52	15.16	38.16	reject
FIA Sapling	1.11	0.85	5.66	4.81	-14.98	1.19	not reject
Bigtooth aspen							
Jenkins	2.15	1.51	8.12	9.51	17.02	26.83	reject
FIA Sapling	2.42	1.89	8.12	6.23	-23.25	14.54	not reject
Trembling aspen							
Jenkins	2.41	1.21	10.18	9.83	-3.41	7.31	reject
FIA Sapling	6.71	3.72	10.18	6.45	-36.57	11.88	not reject

relative to observed values were all larger than the MDND for the FIA sapling equations, the null hypothesis of the equivalence test was not rejected. This suggested that the predicted mean was outside the range of the observed mean ± MDND and there was not enough evidence to reject that the two means were different.

Comparatively, the predicted means of the red maple, birch species, and bigtooth aspen Jenkins et al. (2003) equations were 11.3 percent, 15.2 percent, and 17.0 percent greater, respectively, than the observed mean, while the predicted mean was 3.4 percent lower than the observed for trembling aspen. RMSE error was 12.1 percent, 11.3 percent, and 64.0 percent lower for the red maple, bigtooth aspen, and trembling aspen Jenkins et al. (2003) equations, respectively, than the FIA sapling equation, but was 16.3 percent greater for the birch species.

DISCUSSION

The FIA sapling equations substantially underestimated woody biomass of the hardwood species in this investigation. Although the equations are used to facilitate a smooth transition of biomass estimates to larger trees estimated with the CRM, the substantial underestimation relative to observed values of sapling biomass is the likely cause of a 34 percent decrease in sapling woody biomass estimates for Maine, where nearly 24 percent of the forest land is dominated by sapling-size stands. Our investigation had small sample sizes, but the 15 percent and 37 percent underestimation corroborates the reported decreases in sapling biomass in Maine.

Comparatively, the Jenkins et al. (2003) equations overestimated sapling woody biomass for three of the species. Because the observed data typically occurred between the estimates of the Jenkins et al. (2003) equations and the FIA sapling equations, it may be useful in the future to modify the species-specific sapling adjustment factors to conform to observed field data. For instance, the current adjustment factor for red maple is 0.74, but using the data from this investigation, we find an adjustment factor of 0.90 multiplied by the Jenkins et al. (2003) estimates would provide estimates identical to the mean observed woody biomass. Other potential species-specific sapling adjustment factors calculated using the observed data in this investigation are shown in Table 3. Of course, more field data will be necessary to calibrate the sapling adjustment factors across sites and regions and include more species, but this may be a worthwhile venture given the poor estimates of sapling woody biomass found in this investigation and the drastic reductions in sapling woody biomass in Maine.

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Table 3.—Species-specific sapling adjustment factors calculated as the ratio of the observed mean woody biomass and predicted mean from the Jenkins et al. (2003) equations

Species	Sapling Adjustment Factor
Red maple	0.90
Birch species	0.87
Bigtooth aspen	0.85
Trembling aspen	1.03

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ASSESSING THE UNCERTAINTY OF FOREST CARBON ESTIMATES USING THE FVS FAMILY OF DIAMETER INCREMENT EQUATIONS

Matthew B. Russell, Aaron R. Weiskittel, and Anthony W. D'Amato[1]

Abstract.—Serving as a carbon (C) accounting tool, the Forest Vegetation Simulator (FVS) is widely used by forest managers and researchers to forecast future forest C stocks. Assessments of the uncertainty that FVS equations provide in terms of their ability to accurately project forest biomass and C would seemingly differ, depending on the region and scale of interest to the user. This analysis used permanent sample plot data obtained from the annual Forest Inventory and Analysis (FIA) Program database to assess the performance of the diameter at breast height (d.b.h.) increment function in the Northeast and Lake States variants of FVS. Up to three measurements of FIA plots were recorded, representing more than 10 years of observed growth. Total aboveground biomass and C were estimated using the FIA's component ratio method, which served as a field-based measure of forest biomass/C. After initial FIA measurements were forecasted with the species-specific d.b.h. increment equation from the appropriate FVS variant, biomass/C was calculated and compared with the field-based measure. Results found that d.b.h. increment was generally underpredicted across both regions, which resulted in deviations when comparing model- and field-based predictions of biomass. Generally, a 10 percent error in predicting d.b.h resulted in a 25 percent error in predicting total aboveground biomass and C. Assessing the amount of uncertainty as predictions from FVS are used by managers and researchers will continue to provide information for those attempting to quantify the intricate processes of forest C dynamics.

INTRODUCTION

Growth models like the Forest Vegetation Simulator (FVS) provide predictions for individual trees, but forest managers typically make decisions at the stand level. Because error begins to compound as one scales from the individual tree to the plot and stand, quantifying the uncertainty associated with this scaling would have a direct impact on stand-level estimates. For example, some argue that a 10 percent bias in measuring diameter at breast height (d.b.h.) can result in a 25 percent error in predicted basal area (BA) (Gertner and Dzialowy 1984). BA is a relatively straightforward calculation, but for measures such as aboveground biomass and C, computations are much more complex. This complexity can be seen in the component ratio method (CRM) administered by FIA, which estimates total aboveground C for individual trees (Woodall et al. 2011).

FVS is a distance-independent growth model that projects future forest conditions, composition, and stand structure. A key determinant of future forest stocks in FVS lies in its diameter increment (Δdbh) function. Similarly, national biomass equations (Jenkins et al. 2003, 2004) rely heavily on d.b.h., and d.b.h. is widely used in the CRM to calculate aboveground C (Woodall et al. 2011). Increasingly, FVS is being used to estimate forest C into the future, yet little is known about the uncertainty of forest C estimates that might arise from a potential bias inherent in the Δdbh equation used. The goal

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here was to use Forest Inventory and Analysis (FIA) remeasurement data from the Northeast and Lake States to quantify the uncertainty of plot-level C stocks using different implementations of d.b.h. increment equations in FVS.

METHODS

FIA Data

Tree and plot records were obtained from the U.S. Forest Service's FIA Program. Many of these inventory plots were remeasured but some were not. Data were obtained from the online FIA database at http://apps.fs.fed.us/fiadb-downloads/datamart.html (accessed November 11, 2011). Compiled data spanned eight ecoregions. Plots began measurement in 1998.

Diameter Increment in FVS

Diameter increment is estimated differently in the Lake States (FVS-LS) and Northeastern (FVS-NE) variants of FVS. Key differences in the Δdbh equations used in the two regions are (1) diameter increment is predicted in FVS-LS, whereas BA increment is predicted in FVS-NE and then converted to diameter, (2) in the competition modifier, tree crown ratio, species maximum and plot BA, and quadratic mean d.b.h. are used in FVS-LS, whereas BA is used in larger trees in FVS-NE, and (3) an adjustment factor is added to Δdbh predictions in FVS-LS.

FVS-LS

The Δdbh for trees ≥5.0 inches in FVS-LS is predicted using a potential-modifier approach and adjustment factor. First, potential diameter growth is estimated using tree d.b.h., crown ratio, and species site index (Hahn and Leary 1979). Second, a competition modifier is estimated using tree d.b.h., maximum species BA, plot BA, and quadratic mean d.b.h. (Holdaway 1984). Predicted annual Δdbh is assumed to be the product of the potential and modifier components and is then corrected to the cycle length. Lastly, an adjustment factor is predicted based on tree d.b.h. and d.b.h. squared, and is added to Δdbh Equation coefficients for the three components of Δdbh are provided for 28 species groups (Dixon and Keyser 2008a).

FVS-NE

The Δdbh for trees ≥5.0 inches in FVS-NE is also estimated using the potential-modifier approach (Teck and Hilt 1991). First, potential BA growth is estimated using tree d.b.h. and species site index. Second, a growth modifier is estimated using the BA in larger trees. Lastly, predicted annual BA growth is estimated by multiplying the potential and modifier components. Basal area growth is added to current tree BA and converted to a tree diameter. Equation coefficients are provided for 28 species groups (Dixon and Keyser 2008b).

Analyses

This analysis was limited to all trees with d.b.h. ≥5.0 inches because (1) it is the threshold for measurement trees on FIA Phase 2 plots, and (2) it is the threshold for the large-tree Δdbh equations within FVS. Increments for d.b.h. were standardized to a 5-year interval for each tree that survived a remeasurement period, given that most FIA plots were remeasured on a 5-year time step. So, Δdbh_5 represents 5-year d.b.h. increment.

Volume, biomass, and C were estimated for each initial measurement on each individual tree using the CRM (Woodall et al. 2011). Predictions were made separately for growing stock and cull trees. Summaries of these variables were made for each FIA plot. Plot-level summaries were calculated using the predicted Δdbh_5 from FVS, representing a "predicted" plot condition. Plot-level summaries were then calculated using actual FIA measured d.b.h., representing the "observed" value. Only surviving trees in Y2 measured in Y1 were used, and FIA plots with no observed treatment (e.g., silviculture or harvesting) since the last measurement were used. Percent accuracy within 15 percent and bias were computed for each FIA plot and summarized by ecoregion.

RESULTS AND DISCUSSION

Lake States

Mean Δdbh_5 bias (observed-predicted) provided by FVS-LS was as low as 0.01 inch/5 years for the trees in the Laurentian mixed forest ecoregion and as high as 0.25 inch/5 years for trees in the prairie parkland ecoregion. This slight underprediction of Δdbh_5 differs somewhat from Pokharel and Froese's finding (2008) of a general overprediction of the FVS-LS model for trees in Michigan. The differences could arise because Pokharel and Froese (2008) employed data from FIA inventory cycles in the 1980s and early 1990s, whereas this analysis employed data from the annual inventory design beginning around 2000. Similarly, 5-year increments were used here, whereas 10-year increments were used by Pokharel and Froese (2008). The degree that biomass/C predictions are influenced by a Δdbh equation for a specific species of interest is a subject for further investigation.

Northeast

Underprediction of 5-year diameter increment was similarly observed using FVS-NE. Mean Δdbh_5 bias provided by FVS-NE was as low as 0.05 inch/5 years for the trees in the outer coastal plain mixed forest ecoregion and as high as 0.40 inch/5 years for trees in the eastern broadleaf (continental) ecoregion. A more substantial underprediction was generally observed for those ecoregions with fewer FIA plots located on the fringes of the northeastern geographic range (e.g., Western Allegheny plateau).

Uncertainty in Plot-level Carbon

Adding the predicted Δdbh_5 to initial d.b.h. and scaling to the plot level, FVS predicted basal area, volume, and biomass/C well for some ecoregions in the Northeast (e.g., Laurentian mixed forest and eastern broadleaf [oceanic]) and Lake States (Laurentian mixed forest) (Table 1). For Northeast plots, percent accuracies were generally similar for the three variables. For the Lake States, however, percent accuracies decreased as one scaled from basal area to volume and biomass. This result for FVS-LS as opposed to FVS-NE likely arises because of the adjustment factors used and the differing volume equations employed in the two regions.

Generally, a 10 percent error in predicting d.b.h. resulted in a 25 percent error in predicting total aboveground biomass and C (Fig. 1). Although the CRM uses a myriad of calculations to arrive at aboveground biomass and C, initial results do not seem to show that errors in individual tree predictions lead to larger uncertainties of forest C when compared to plot-level basal area predictions.

Table 1.—Ecoregions examined, number of FIA plots, and evaluation statistics for basal area, volume, and biomass/carbon

Ecoregion	Code	Plots (n)	Mean Δdbh_5 Bias (inches)	Percent Accuracy (±15%)		
				Basal Area	Volume	Biomass/C
Northeast						
Laurentian mixed forest	212	3,212	0.09	91	90	91
Eastern broadleaf (oceanic)	221	2,262	0.14	64	64	64
Eastern broadleaf (continental)	222	262	0.40	38	38	39
Western Allegheny plateau	223	12	0.19	17	25	25
Adirondack-New England mixed forest	232	115	0.19	12	14	14
Central Appalachian broadleaf forest	M211	2,329	0.09	96	96	96
Outer coastal plain mixed forest	M221	1,062	0.05	61	61	61
Lake States						
Laurentian mixed forest	212	2,376	0.01	97	64	61
Eastern broadleaf (continental)	222	581	0.20	92	43	41
Prairie parkland	251	10	0.25	90	50	50

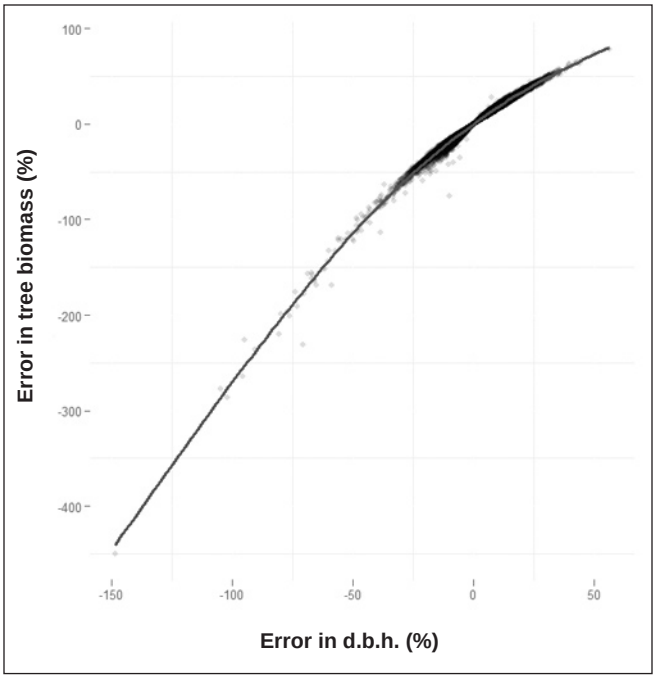


Figure 1.— Percent error in predicting 5-year diameter increment with associated uncertainty in predicting tree biomass using the FIA component ratio method.

CONCLUSIONS

Using FIA data from the northeastern U.S. and Lake States, this analysis found that the current implementation of FVS underpredicted tree diameter increment throughout the two regions. Previous work in the Lake States (Pokharel and Froese 2008) and ongoing work in the Northeast suggest that recalibrating the diameter increment functions in FVS may not prove effective, suggesting new Δd.b.h. models be engineered. As managers will continue to rely on C accounting tools like FVS to project future forest C stocks, assessing the level of uncertainty as these models scale output to upper level hierarchies will help provide more information for those seeking improved methodologies for quantifying forest C dynamics.

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ANALYSIS OF TRACHEID DEVELOPMENT IN SUPPRESSED-GROWTH PONDEROSA PINE USING THE FPL RING PROFILER

C. Tim Scott and David W. Vahey[1]

EXTENDED ABSTRACT

The Ring Profiler was developed to examine the cross-sectional morphology of wood tracheids in a 12.5-mm core sample. The instrument integrates a specially designed staging apparatus with an optical imaging system to obtain high-contrast, high-resolution images containing about 200-500 tracheids. These images are further enhanced and analyzed to extract tracheid cross-sectional properties such as shape, double-wall thickness, and lumen area. Subsequently, localized density can be calculated for specific regions of interest (e.g., earlywood and latewood), as it varies throughout the tree.

We showed that tracheid development in trees can be closely examined with the Ring Profiler. In particular, we showed that for the same core sample, recent periods of "suppressed" growth result in very narrow growth rings containing as few as 2-10 radial fibers/year (Fig. 1). In contrast, normal periods of growth may contain 20 or more radial fibers/year, resulting in dramatically different tracheid development (Fig. 2). This was observed in ponderosa pine (*Pinus ponderosa* Dougl. Ex Laws.) trees of various diameters harvested from an even-aged, high density stand in the Pringle Falls Experimental Forest near Bend, OR. For this study, sample disks were extracted from each tree at diameter at breast height (d.b.h.) and every 6 m up the tree. Radial strips (Fig. 3) were then prepared for examination by the Ring Profiler. The entire strip was scanned and image algorithms were applied to calculate tracheid cell wall area, relative proportion of earlywood and latewood, and local density in select growth rings. A calculation of yearly mass accumulation was made by assuming that the tree volumetric growth can be approximated by a sequence of concentric cones. Measures of stored carbon were then estimated based on the chemical composition of the wood.

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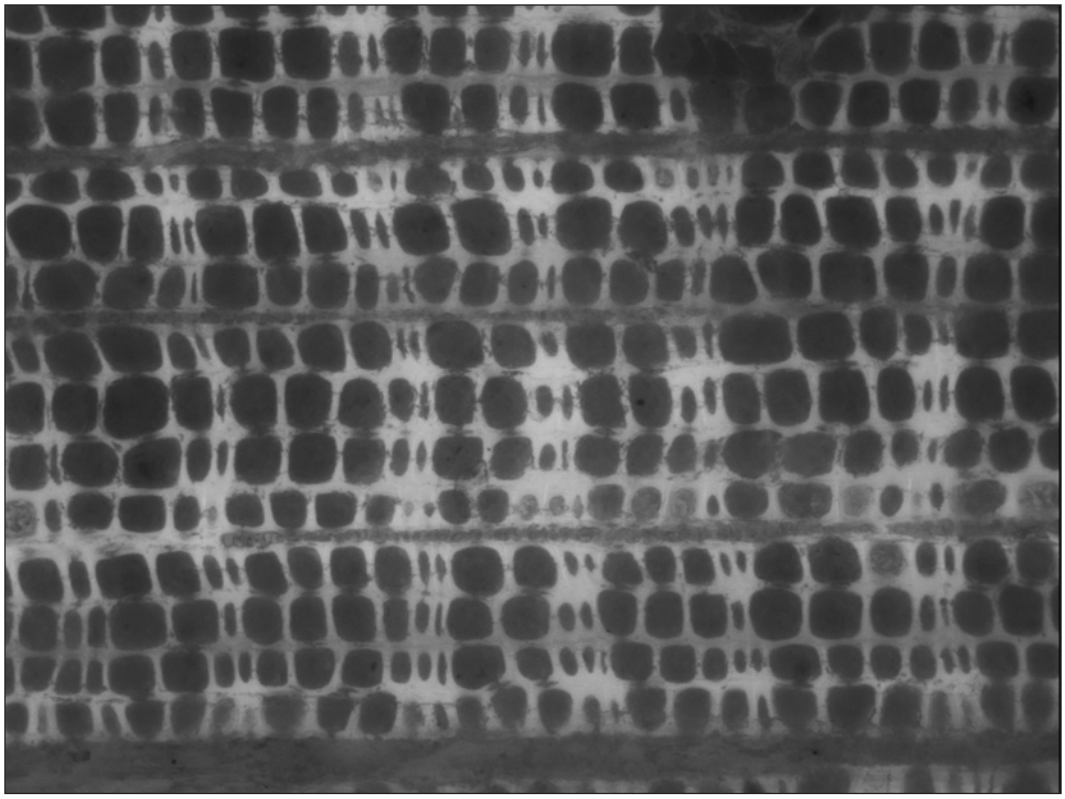


Figure 1.—Narrow growth rings circa 1992.

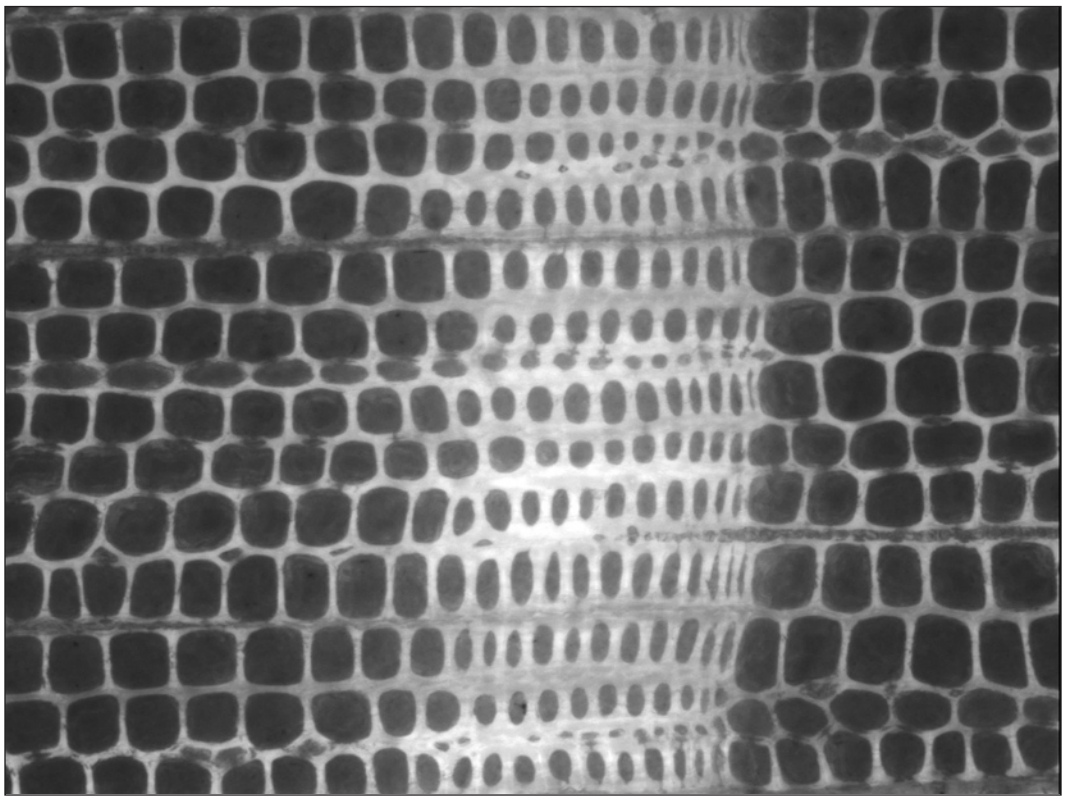


Figure 2.—Wide growth ring circa 1957.

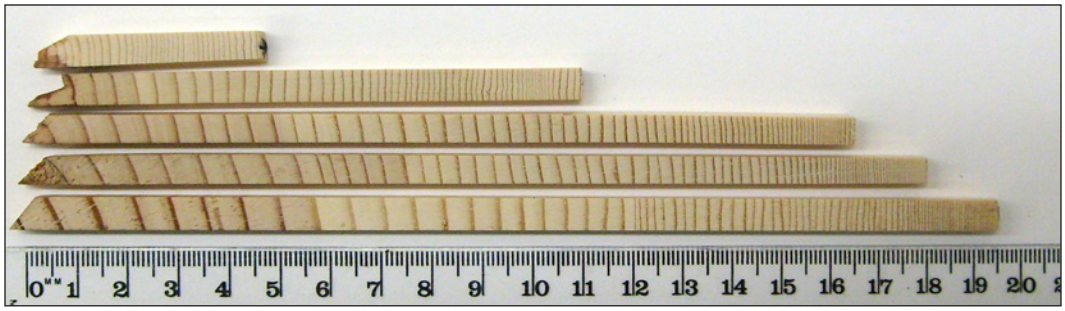


Figure 3.—Five radial samples from a century-old, 33-m ponderosa pine. The bottom strip was prepared from the diameter at breast height (d.b.h.) disk with the rest taken at 6-m intervals up the tree.

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RING PROFILER: A NEW METHOD FOR ESTIMATING TREE-RING DENSITY FOR IMPROVED ESTIMATES OF CARBON STORAGE

David W. Vahey, C. Tim Scott, J.Y. Zhu, and Kenneth E. Skog[1]

Abstract.—Methods for estimating present and future carbon storage in trees and forests rely on measurements or estimates of tree volume or volume growth multiplied by specific gravity. Wood density can vary by tree ring and height in a tree. If data on density by tree ring could be obtained and linked to tree size and stand characteristics, it would be possible to more accurately predict changes in density and weight of tree biomass with projected changes in tree size and stand characteristics. Ring Profiler is a patented method for characterizing the structure of softwood tracheids and their changes from one tree ring to another over time. Measurements can be converted to density and can be multiplied by volume to estimate total weight and weight of carbon by ring. A sample displaying pith-to-bark ring structure is prepared from a radial core and scanned beneath a microscope as images are taken. Despite the sample's thickness (up to 6mm) it is possible to image it with light transmitted from below using a single light-emitting diode (LED) for illumination. Near-infrared radiation (NIR) from the LED is captured by tracheid walls and travels efficiently to the viewing surface, much as light travels through an optical fiber. NIR captured by lumens tends to be absorbed by particulate matter introduced during sample preparation. The result is a high-contrast image in which tracheid walls are bright, lumens are dark and the interface is sharp. Images containing approximately 400 tracheids each are processed by ImageJ, public software available from the National Institutes of Health (NIH). Measurements include the distribution of radial and tangential diameters and wall thicknesses, from which local density can be estimated and applied to improved estimates of carbon storage. Over time, measurements from Ring Profiler can increase our understanding of tree response to stress.

INTRODUCTION

Forests have been a strong carbon sink in the United States in recent decades. Forest policy makers and forest managers have a keen interest in monitoring and projecting how forest carbon stocks will change and learning how alternate management practices can influence carbon accumulation.

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Current methods to estimate weight of total biomass or weight of growth in biomass rely in large part on estimates of wood volume in trees and estimates of average density of trees by species. Wood density can vary by tree ring (age) and height in a tree. The density associated with volume growth can change as the tree ages and can be influenced by stand and site conditions. The weight increase associated with a volume increase will depend on the changing value of density.

To what degree is wood density in a tree ring affected by tree characteristics, stand characteristics, and site characteristics? If data on density by tree ring

could be obtained and linked to tree size and stand characteristics, it would be possible to more accurately predict changes in density and weight of tree biomass with projected change in tree size and stand characteristics.

With ongoing joint Forest Service and university efforts to revise tree biomass equations, information will be collected on tree volume and wood weight by tree part. With the collection of cross section samples for trees of varying sizes, species, and stand conditions there is an opportunity to collect density for some subsamples by tree ring (age or radius from the center). Modeling this link could allow for more accurate estimates of tree density associated with a given volume or with given volume changes under certain species, stand, and site conditions.

More detailed models could make it possible to answer additional questions about managing for carbon accumulation. Is it possible that forest treatment recommendations to increase carbon weight may differ from treatment recommendations to enhance tree volume? To what degree is slower volume growth in a denser stand offset by higher density in slower growing rings? How does this tradeoff differ by forest type, stand conditions, or site conditions?

The gold standard for measurement of tree-ring density from cores is the SilviScan™ instrument developed by the Commonwealth Scientific and Industrial Research Organization (CSIRO) in Melbourne, Australia (Evans 1994). Using robotic control of optical microscopy, X-ray densitometry, and X-ray diffraction, a complete picture is presented of density, tracheid structure, and microfibril angle over the life of the tree. At present, SilviScan™ is not an instrument for purchase but rather a service. The response time for results may be long for FIA requirements.

At the other extreme is the Haglof Tree Core Reader (Haglof Sweden AB, Langsele, Sweden). This field-worthy device accepts a standard core and provides a 6x magnifier to measure the narrowest growth rings. Though providing much less information than SilviScan™, and no information archiving, it has advantages of lower cost, no core preparation, and rapid field response.

Ring Profiler is intended to fill a niche midway between that of SilviScan™ and the Haglof device (Vahey et al. 2007). Like SilviScan™, it requires a processed core for measurement and produces archived results in a computer-based instrument. Like SilviScan™, it has an optical microscopic component for measuring tracheid structure. Unlike SilviScan™, it avoids the need for an X-ray component by producing a density measurement based on a near-infrared image of tracheid cross-sections. It lacks SilviScan™'s measurement of microfibril angle, but this information is not needed for FIA applications. In final implementation, it would be an instrument for sale rather than a service, allowing the owner-user control of turn-around time.

RING PROFILER CONCEPT

The Ring-Profiler concept is illustrated by Figure 1, showing an LED illuminating a portion of a radially cut sample prepared with the growth direction parallel to the light beam. Both exit and entry surfaces are sanded to a 1200 grit finish and polished with paper. A microscope objective collects transmitted light from the sample and images it on a charge-coupled device (CCD) camera array. Figure 2 shows a more rugged implementation of the optics, along with a representative camera image. Light travels through and along tracheid walls which show up as bright, while the lumens filled with debris from the sanding operation show up as dark. The field-of-view in the radial direction is 0.7 mm. After the image is generated, a scanning mechanism moves the sample 0.7 mm so that the next image aligns with the first. The process continues until the entire radial length is examined, or at least a portion of interest nearest the bark. This may take a matter of minutes.

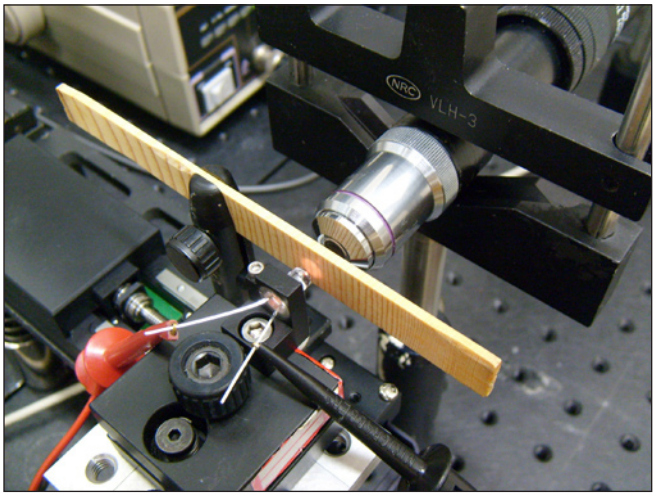


Figure 1.—The Ring Profiler concept.

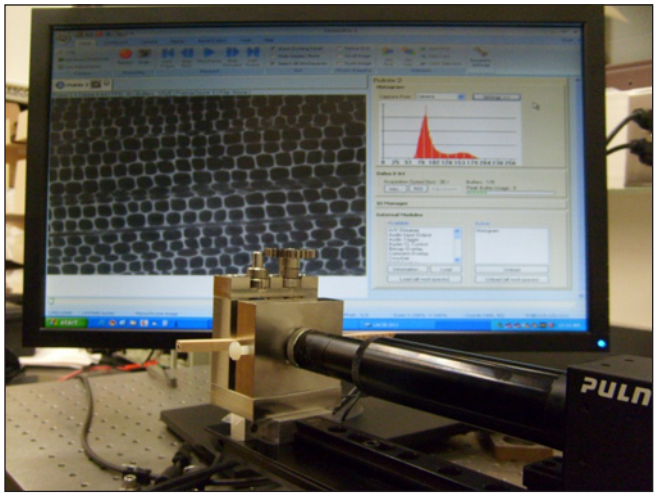


Figure 2.—A current version of Ring Profiler with example image.

The 0.7 mm field of view (FOV) was chosen with suppressed growth in mind. There might be three complete suppressed growth rings captured within this FOV, while for normal growth only a partial growth ring is captured. Image processing must be flexible enough to deal appropriately with each situation. Our focus to date has been on suppressed and intermediate growth, such as shown in Figure 3. A single latewood (LW) band near the center of the image is flanked on the right by the last earlywood (LEW) from the same growth year, and on the left by the earliest earlywood (EEW) from the next growth year.

Image Processing

By blurring the image and thresholding, we created masks for the three distinct bands of the image. The masks allowed us to optimally digitize portions of the original image. For example, Figure 3b shows processed LW, LEW and EEW bands containing lumens and rays as all black, and other material, mostly cell walls, as all white. By taking the dark area density to be 0 kg/m^3 and the white area density to be 1500 kg/m^3, the commonly accepted density of cellulose, we estimated the overall densities of the LW,

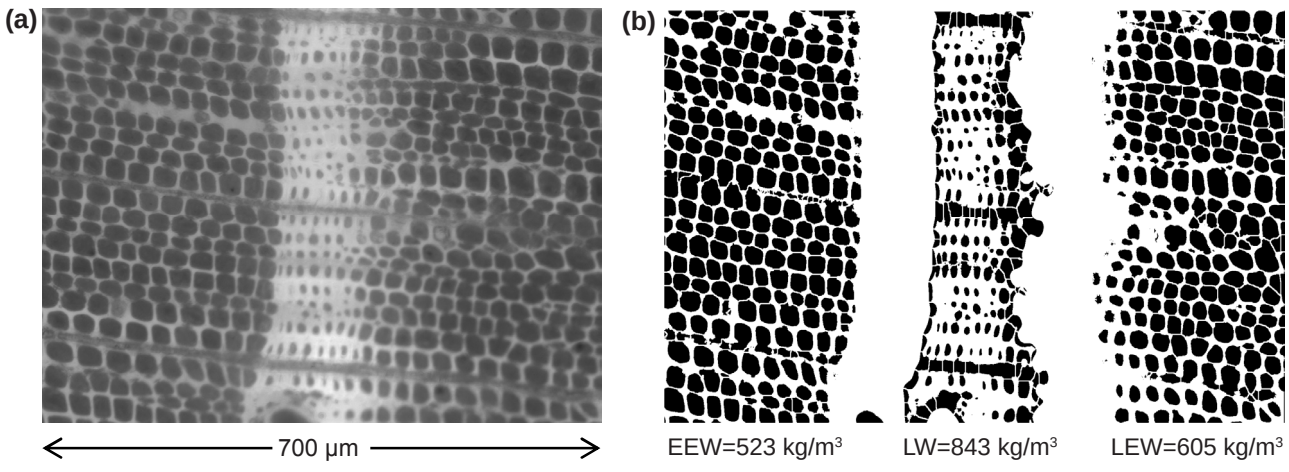


Figure 3.—(a) Latewood (LW)- centered image showing early earlywood growth of the next year (EEW, left) and last earlywood growth of the current year (LEW, right); (b) Binary images of the three sections, showing calculated densities.

LEW and EEW bands of the original image. An added benefit is that we can piece together the annual growth of the tree from the radial dimensions of the bands. This allows the calculation of accumulated mass.

Comparison with SilviScan™

This information may be sufficient for FIA applications. However, further processing of the lumen images of Figure 3b leads to measurements of the radial and tangential diameters and cell-wall thickness, such as are available from SilviScan™. The main point of differentiation from SilviScan™, with regard to measurement capability, is that the SilviScan™ measures density using X-rays and calculates cell wall thickness from density and tracheid diameters. Ring Profiler measures wall thicknesses and tracheid diameters and calculates density. The SilviScan™ approach allows for measurements of more tracheids, producing greater statistical accuracy of results. Finally, SilviScan™ X-ray technology is applied to the measurement of microfibril angle as well as density.

Both SilviScan™ and Ring Profiler require sample preparation from wood cores. This results in the greatest time delay between gathering the core and learning results. There are three SilviScan™ units to serve the world's needs, so there is an additional delay in shipping samples and waiting for prior customers to be serviced. At a targeted cost of ~$20,000, Ring Profiler will be within purchasing range of most testing laboratories, and should become much more widely distributed than SilviScan™. Future marketing directions for SilviScan™ are unknown; however, Ring Profiler has obtained patent protection in the United States (Vahey et al. 2011).

RING PROFILER AND FIA

In the near term, Ring Profiler could be a stationary lab instrument to process and measure cores provided by FIA. Information would be delivered in rough proximity to other FIA information for the same lands to inform management decisions. The information appears comparable to that which would nominally be obtained when the lands are revisited in later years. Suppose a course of remediation prompted by revisiting a forest in year 10 could be prompted by use of Ring Profiler in year 0. This would result in double the expanded growth in biomass in year 20. A quick calculation suggests that if the unmanaged forest grew 25 percent in 20 years, the forest remediated in year 10 would grow 27 percent in 20 years, and the forest remediated in year 0, based in part on Ring Profiler, would grow 29 percent in 20 years. This calculation assumes that remediation improves the content of normal-growth trees from 70 to 90 percent. More careful determination of these "back-of-envelope" numbers provides a starting point for discussion about the relevance of Ring Profiler to FIA.

RING PROFILER IN THE WOODS

In the longer term, Ring Profiler could be qualified for use in the woods. The essential imaging hardware weighs in the vicinity of 2kg, and much has already been accomplished with respect to merging the light source, camera, and sample holder into a stable, precision mechanical unit. Required computing power is commensurate with modern laptops, which adds additional weight and battery power requirements. However, the downloading of images to remote computers by cell or satellite phone is an active area of interest in many fields.

The greatest challenge appears to be producing an acceptable sample from the green core. This is known to be an area of active interest to law enforcement charged with detection of contraband trees, so work by others toward this end may be to the benefit of Ring Profiler.

ACKNOWLEDGMENTS

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CUMULATIVE VOLUME AND MASS PROFILES FOR DOMINANT STEMS AND WHOLE TREES TESTED FOR NORTHERN HARDWOODS

Neil R. Ver Planck and David W. MacFarlane[1]

Abstract.—New models were presented to understand the relationship between the dominant stem and a whole tree using cumulative, whole-tree mass/volume profiles which are compatible with the current bole taper modeling paradigm. New models were developed from intensive, destructive sampling of 32 trees from a temperate hardwood forest in Michigan. The species in the sample were primarily American beech (*Fagus grandifolia* Ehrh.) and sugar maple (*Acer saccharum* Marsh.). The new profile models allowed for both mass and volume of both the dominant stem and branches to be estimated from ground level to the top of the tree. Nonlinear mixed effects models were used in the model development to account for the correlations among multiple measurements of an individual tree. Allometric scaling relationships between the dominant stem and branches can be directly derived from the new models and can be used to define sampling approaches to localize predictions of generalized whole-tree models via measurements of simple branch parameters.

INTRODUCTION

Integrated whole-tree biomass and volume equations are in great demand due to the simultaneous need to improve estimation of forest carbon stocks and to quantify the distribution of wood volume within trees for estimating whole-tree utilization potential. While the volume of the dominant stem in a tree, generally referred to as the bole, has been extensively studied, the relative mass and volume of branches has received much less attention. It is particularly challenging to quantify the branch volume and branch mass in trees with a deliquescent branching architecture (i.e., hardwoods), and it is even more difficult to model the bole for such trees because the lack of apical dominance makes definition of the bole more obscure. Here, a dominant path through a tree's branch network is defined as the cumulative bole profile and other nondominant branches contribute to cumulative volume and mass along the dominant path.

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METHODS

Study Site and Tree Selection

The study site included 20.8 ha of a 36-ha second-growth maple-beech stand at the Fred Russ Experimental Forest in southwestern Michigan owned by Michigan State University. The Fred Russ Experimental Forest is located in Cass County, in Decatur, MI, with a total area of 381 ha that supports a diverse range of species and stand conditions. Kalamazoo, Ormas, and Oshtemo are the three primary soil series. The Kalamazoo and Oshtemo soil series are fine-loamy and coarse-loamy, mixed, mesic typic hapludalfs, respectively. The Ormas soil series is a coarse-loamy, mixed, mesic arenic hapludalfs on an outwash plain landform with a level topography (USDA NRCS 2011). The 30-year average annual precipitation is 1035 mm (NOAA 2011). The residual basal area of the stand is 22.1 m^2/ha.

In the spring of 2010, wind-thrown trees with intact crowns were sampled following a windstorm that uprooted more than 200 trees. Sampling began in late spring of 2010 and included as wide a range of diameter at breast height (d.b.h.) as possible, irrespective of species, with at least one individual in each 10 cm size class ranging from 10-95 cm. Selected trees were relatively isolated from other fallen trees so that the branches were easily measurable. The 32 sample trees had a mean d.b.h. of 50.9 cm and mean height of 29.4 m with 87.5 percent of the trees being American beech (*Fagus grandifolia* Ehrh.) or sugar maple (*Acer saccharum* Marsh.).

Volume Profiles

The dominant stem in this study was defined by following the largest and most vertical branch at each fork to an apical control point. For each tree, circumference was measured at stump height, 37 cm above ground level, followed by d.b.h. Additional circumference measurements were taken at 2-m length intervals up to the first branch junction. Upon encountering the first branch, circumference measurements were taken at the before fork (BF) location of the stem and then at the after fork (AF) location of each branch based upon functional branch analysis protocols (van Noordwiijk and Mulia 2002). The BF was defined as the location where bark due to branching was no longer visible, as this is most likely the origin of the branches off the dominant stem. The AF was the location immediately after the point at which the fork occurred. The length from the BF to the AF was also recorded. The process of length and circumference measurements continued by following the dominant stem until the terminal bud was reached. The volume of each section was determined by Smalian's formula for volume (Avery and Burkhart 2002). The cumulative dominant stem volume profile is the accumulation of consecutive sections as a function of height.

An estimate of the total aboveground volume outside bark of an entire tree was obtained by random branch sampling (Gregoire and Valentine 2008). The same measurement methods as for the dominant stem were used, but a segment was selected based on probability proportional to size at each branch junction. The sectional volume for the random path was used to compute the volume of the whole tree using the inverse of the cumulative selection probability as expansion factors for a section in the random path (Gregoire and Valentine 2008). The volume of branches was found by subtracting the total dominant stem volume from the whole tree volume. A second random branch path was sampled on each tree to determine mean whole tree volume and the variation of whole tree volume estimates between the two different selected paths. The mean total branch volume determined from the two random paths was then distributed back to each first order branch immediately off the dominant stem. The volume for each first order branch and all higher order branches were incorporated into the profile at the height at which the first order branch connected to the dominant stem. The redistribution of the branch volume ensured that the final observation of the cumulative whole tree volume profile was the same as the mean total whole tree volume outside bark from the two random branch paths.

Density Profiles

To obtain a dominant stem mass profile, a profile of density for each tree was developed by harvesting tree discs. Discs were harvested at every circumference measurement location below crown height. Above crown height, discs were collected at every AF along the dominant stem path. Approximately 5- and 10-cm-thick discs were harvested for smaller and larger circumferences, respectively. Each disc was measured for green mass and green volume immediately after transportation to the laboratory. Mean disc thickness was calculated by averaging the thickness of eight locations at 45° angles. Green volume was calculated as the product of mean disc thickness and cross-sectional area of the disc. After being oven-dried at 105 °C until constant mass was reached, each disc was reweighed to calculate moisture content, dry mass, and basic specific gravity (Williamson and Wiemann

2010). The basic specific gravity of each disc was assumed to be constant in the radial direction of the disc. The basic density, in units of kg/m^3, of each disc is the basic specific gravity of the disc multiplied by 10^3.

Whole tree cumulative mass profiles were developed by harvesting tree discs. To reduce costs, discs were collected at every AF for only the second random branch path, and the density along the path length was assumed to vary equally along the first random branch path and the second random branch path.

The statistical analysis was performed using the R statistical environment (R Development Core Team 2010). The nlme package was used to fit the linear and nonlinear mixed effects models of the volume and density profiles (Pinheiro et al. 2011).

RESULTS

Figure 1a shows an example of a cumulative volume profile for a sugar maple using nonlinear mixed effects modeling for the dominant stem and whole tree. For this particular tree, most of the whole-tree volume is in the dominant stem, but a significant amount of additional volume accumulates in branches above relative crown height (RCH), although slowly at first, as the first branch encountered is not of large size compared to branches encountered later in the vertical profile. The difference between the dominant stem and whole-tree profiles gives the volume of branches in the tree.

Figure 1b shows the basic density profile for the same sugar maple which oscillates around the average wood density of sugar maple as determined by the Forest Products Laboratory (USDA FS 2010). Stem wood is dense at the base of the tree then density declines to a point about half-way to the base of the crown, increases into the middle of the crown and then decreases again toward the tip. The model for the basic density shows that after the relative path length at which the random path diverges from the dominant stem (RHD), the branches are denser at higher relative heights of the dominant stem. By combining the cumulative volume and basic density profiles, a cumulative mass profile can be attained. For this example tree (Fig. 1a and b), the branch mass fraction of whole-tree mass would be somewhat higher than the branch volume fraction of whole-tree volume.

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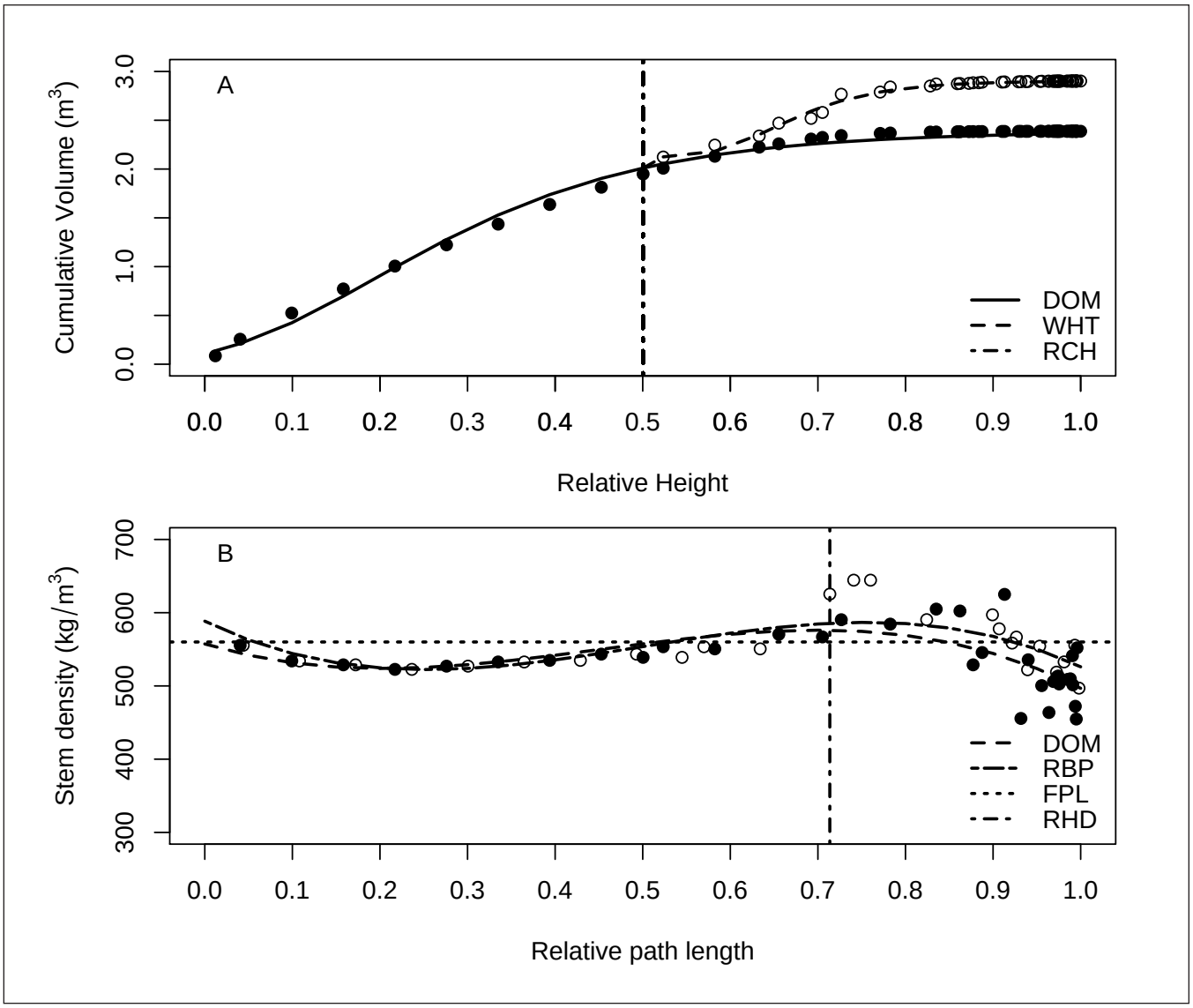


Figure 1.—(A) The cumulative volume profile for the dominant (DOM) stem and whole-tree (WHT) of a sugar maple with d.b.h. = 42.8 cm, total height = 34.0 m, and relative crown height (RCH, vertical line) of 0.500. The measured DOM locations are represented by filled circles, and WHT locations are represented by open circles. (B) The mixed-effects vertical stem density (wood plus bark) profile for the DOM stem and the random branch path (RBP) of the same sugar maple tree with relative path length at which the random path diverged from the dominant stem (RHD, vertical line) of 0.714. The average wood density of 560 kg/m^3 for sugar maple trees (USDA FS 2010) is shown as a horizontal dashed line.

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FIA'S VOLUME-TO-BIOMASS CONVERSION METHOD (CRM) GENERALLY UNDERESTIMATES BIOMASS IN COMPARISON TO PUBLISHED EQUATIONS

David C. Chojnacky[1]

Abstract.—An update (Chojnacky et al. in preparation) of the Jenkins et al. (2003) biomass estimation equations for North American tree species resulted in 35 generalized equations developed from published equations. These 35 equations, which predict aboveground biomass of individual species grouped according to a taxa classification (based on genus or family and sometimes specific gravity), generally predicted higher biomass than estimates from the U.S. Department of Agriculture, Forest Service Forest Inventory and Analysis Program (FIA). FIA uses a conversion approach called the component ratio method (CRM) (Woodall et al. 2011) to generate biomass estimates. This method converts cubic volume estimates to biomass using constant specific gravity values and auxiliary information for branches, bark, and stumps. FIA tree biomass data were grouped by the same taxa as used for the 35 equations, biomass for the same trees was also predicted with the equations, and then diameter-class averaged values were compared. FIA estimates excluded foliage, but the amount of biomass by which the equation predictions exceeded FIA's estimates generally suggested more than a foliage discrepancy. The equations predicted 2 to 28 percent higher biomass (at 30-cm d.b.h.) for most conifer and hardwood taxa. Exceptions were *Larix* and western *Tsuga* genera which predicted 10 to 12 percent lower for trees at 30-cm d.b.h. Equations for woodland taxa predicted biomass 45 to 53 percent higher than FIA estimates (at 30-cm d.r.c.) but FIA's woodland biomass definition may have confounded comparison. In a similar study, Zhou et al. (2011) found that a volume-to-biomass conversion method (resembling FIA's approach) underestimated biomass by 6.3 to16.6 percent—supporting the idea that CRM may inherently underestimate biomass.

INTRODUCTION

The generalized Jenkins et al. (2003) biomass equations came from an effort to produce standardized, consistent, and well-documented tree estimation equations on a national scale, through compilation and synthesis of equations published in the literature, for use in the forest sector (Heath et al. 2011) of the Inventory of U.S. Greenhouse Gas Emissions and Sinks (EPA 2012). A meta-analysis was used to develop 10 generalized species-group-specific equations for estimating biomass from only diameter measurements using regression and log-transformation.

Current work (Chojnacky et al. in preparation) updated the Jenkins et al. (2004) database and refined biomass modeling. Generalized equations were developed based on allometric scaling theory (Chojnacky 2002); taxonomic groupings (genus or family) and wood specific gravity were used as surrogates for scaling parameters that could not be estimated. The update resulted in 35 biomass equations for a taxa classification described below. The purpose of this paper is to compare the biomass predictions from the new equations to estimates of live-tree biomass from the U.S. Department Agriculture, Forest Service's Forest Inventory and Analysis Program (FIA).

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UPDATED EQUATIONS

The initial database for Jenkins et al. (2003) included 2,626 total biomass and component equations; the new study brought the total to 3,464 equations for North American tree species from 206 source studies. These included published equations up to May 2011 developed in the United States or Canada that estimated total bone-dry biomass for individual trees and/or components thereof, based on diameter alone or on diameter and height. The published equations were used (as in Jenkins et al. [2003]) to generate biomass values (pseudodata) for diameters at equally spaced, approximately 5-cm intervals within the diameter range of the trees used for each original equation.

The pseudodata from the published equations were classified into what we defined as "taxa" based on genus or family and sometimes specific gravity for finer separation (Table 1). The classification was mostly genus-based for conifer species, but family-based for hardwood and woodland species.

Biomass equations were developed from pseudodata by using logarithmic regression for a 2-parameter model [$\ln(\text{biomass}) = \beta 0 + \beta 1 \ln(\text{diameter})$, where diameter = diameter at 1.37 m (d.b.h.) for conifer/hardwood species and diameter near root collar (d.r.c.) for woodland species]. Parameters for the 13 conifer, 18 hardwood, and 4 woodland taxa are listed in our more detailed manuscript in process of publication (Chojnacky et al. in preparation).

COMPARISON TO FIA DATA

FIA generates biomass estimates with a biomass expansion factor approach called the component ratio method (CRM) (Heath et al. 2009, Woodall et al. 2011). Cubic volume estimates are converted to biomass using constant wood and bark specific gravity values and auxiliary information for branches, bark, and stumps (Miles and Smith 2009). We expected the new equation estimates to exceed FIA estimates because FIA excluded foliage, but the magnitude of the differences found suggested more than just a foliage discrepancy.

The comparison was complicated both by having to sort through FIA definitions to delineate a reasonable biomass without excessive deductions and by FIA's exclusion of foliage, which particularly underrepresents total biomass for small coniferous trees. We considered using our database to devise an adjustment for foliage but this seemed to further confound comparison. Instead, we defined an estimate of FIA biomass as follows, using USDA Forest Service (2010) variables as listed in uppercase: Live trees (STATUSCD=1) were defined as "growing stock" if measured at d.b.h. (TREECLCD Eq 2 and DIAHTCD Eq 1) or defined as "rough cull" if measured at d.r.c. [TREECLCD In(2,3) and DIAHTCD Eq 2] with no additional CULL coded. From this subset of 2.2 million trees (≤50 cm diameter) for the entire United States, total bone-dry biomass (excluding foliage) was calculated for trees ≥12.7 cm diameter (biomass=DRYBIO_BOLE + DRYBIO_TOP + DRYBIO_STUMP), and selected for saplings (DRYBIO_SAPLING) and for trees measured at d.r.c. (DRYBIO_WDLD_SPP). FIA biomass data for these trees (between 2.5 and 50 cm diameter) were then grouped by our taxa and averaged into 2-cm diameter classes generally based on about 100 to more than 1,000 trees per diameter class. For completeness, FIA data for families (excluding alien species) not included in our 35 taxa classes were grouped as follows: Taxaceae grouped with *Pseudotsuga*; Aquifoliaceae, Ebenaceae, Lauraceae, Moraceae, Styracaceae and Theaceae grouped with the mixed hardwood group (except a few species exceeding specific gravity 0.60 grouped with deciduous Fagaceae taxa); and woodland families Boraginaceae, Rhamnaceae, and Ericaceae grouped with Fabaceae/Rosaceae taxa. (Although we suggest woodland Aceraceae be estimated from Aceraceae <50 hardwood taxon, it was not included in this comparison). We also predicted biomass with the 35 equations for the same FIA trees, averaged them within 2-cm diameter classes, and then subtracted FIA biomass for comparison.

Table 1.—North American tree species grouped into 35 taxa for biomass equation development. Taxa derivation and further description included in Chojnacky et al. (in preparation).

Group	Taxa name	Description
Conifer	Abies <35	*Abies* species with specific gravity <0.35, eastern species & *A. lasiocarpa*
	Abies ≥35	*Abies* species with specific gravity ≥0.35, western species
	Cupressaceae <30	Cupressaceae family with specific gravity <0.30, eastern *Thuja* species
	Cupressaceae 30-39	Cupressaceae family with specific gravity 0.30-0.39, western *Calocedrus*, *Sequoiadendron*, *Thuja* species
	Cupressaceae ≥40	Cupressaceae family with specific gravity ≥0.40, *Chamaecyparis* species & *Juniperus virginia*
	Larix	*Larix* species
	Picea <35	*Picea* species with specific gravity <0.35, western species
	Picea ≥35	*Picea* species with specific gravity ≥0.35, eastern species & *P. abies*
	Pinus <45	*Pinus* species with specific gravity <0.45, western & northeastern species
	Pinus ≥45	*Pinus* species with specific gravity >=0.45, southern species
	Pseudotsuga	*Pseudotsuga* species
	Tsuga <40	*Tsuga* species with specific gravity <0.40, eastern species
	Tsuga ≥40	*Tsuga* species with specific gravity ≥0.40, western species
Hardwood	Aceraceae <50	*Acer* species with specific gravity <0.50
	Aceraceae ≥50	*Acer* species with specific gravity ≥0.50
	Betulaceae 39<40	Betulaceae genera with specific gravity <0.40, primarily *Alnus* species
	Betulaceae 40-49	Betulaceae genera with specific gravity 0.40-49, primarily *Betula* species
	Betulaceae 50-59	Betulaceae genera with specific gravity 0.50-59, primarily *Betula* species
	Betulaceae ≥60	Betulaceae genera with specific gravity ≥0.60, including *Betula* & *Ostrya* species
	Fabaceae/Juglanaceae, Carya	*Carya* species only
	Fabaceae/Juglandaceae, other	Fabaceae & Juglandaceae genera except *Carya*, including *Robinia*, *Juglans* species
	Fagaceae, deciduous	Deciduous Fagaceae genera, including *Fagus*, *Quercus*, *Castanea* species
	Fagaceae, evergreen	Evergreen Fagaceae genera, including *Quercus*, *Chrysolepis*, *Lithocarpus* species
	Hamamelidaceae	Hamamelidaceae genera, primarily *Liquidambar styraciflua*
	Hippocastanaceae/Tiliaceae	Hippocastanaceae &Tiliaceae genera, primarily *Aesculus* & *Tilia* species
	Magnoliaceae	Magnoliaceae family, primarily *Liriodendron tulipifera*
	Oleaceae <55	Oleaceae genera with specific gravity 0.55, primarily *Fraxinus* species
	Oleaceae ≥55	Oleaceae genera with specific gravity ≥0.55, primarily *Fraxinus* species
	Salicaceae <35	Saliaceae genera with specific gravity <0.35, primarily *Populus* species
	Salicaceae ≥35	Saliaceae genera with specific gravity ≥0.35, primarily *Populus* & *Salix* species
	Mixed hardwoods*	Cornaceae, Ericaceae, Lauraceace, Platanaceae, Rosaceae, Ulmaceae famlies or other hardwood families not listed in this table with specific gravity between 0.45 and 0.65
Woodland	Cupressaceae	Cupressaceae genera, primarily *Juniperus* & *Cupressus* species
	Fabaceae/Rosaceae	Fabaceae & Rosaceae genera, primarily *Cercidium*, *Prosopis*, *Cercocarpus* species
	Fagaceae	Woodland Fagaceae genera, primarily evergreen *Quercus* species
	Pinaceae	Pinyon pine species

*Mixed hardwood equation also appropriate for species not included in table, unless specific gravity of the species more closely related to another taxon.

RESULTS

For conifers (Fig. 1), the new equations predicted 5 to 24 percent higher biomass (at 30-cm d.b.h.) than FIA estimates for most taxa, and predicted even higher for saplings. Exceptions were *Larix* and *Tsuga* ≥0.40 predicting 10 to 12 percent lower at 30-cm d.b.h. The small trees showed an interesting biomass pattern with a peak (or mode) between 10 and 15 cm d.b.h. This peak corresponds to a discontinuity in FIA methodology where tree (d.b.h. ≥12.5 cm) biomass is estimated from volume conversion but sapling (d.b.h. <12.5 cm) biomass is actually estimated from Jenkins et al. (2003) equations (Woudenberg et al. 2010) with some additional adjustment (JENKINS_SAPLING_ ADJUSTMENT). Because foliage can be quite large for small trees—ranging from 13 percent (median) to more than 30 percent (90th percentile) of total biomass for our conifer pseudodata for trees ≤12.5-cm d.b.h. (Chojnacky et al. in preparation), it is not surprising that our equations overpredict FIA biomass (with foliage excluded) for small trees. However, the percentage of conifer foliage to total biomass in our pseudodata drops to 4 to 12 percent (depending on species) for trees larger than 12.5-cm d.b.h., indicating some other explanation for the overall 5 to 24 percent larger biomass estimates from our conifer equations.

Comparison of the woodland equations (Figs. 1 and 2) to FIA data (Fig. 3) revealed a pattern similar to that for conifer and hardwood except differences were much greater—45 to 53 percent for trees at 30-cm d.r.c. However, FIA's definition of woodland biomass (DRYBIO_WDLD_SPP) could be excluding much branch material less than 3.8 cm in diameter. Although the definition of DRYBIO_WDLD_SPP (Woudenberg et al. 2010) mentions exclusion of tree top above 1.5 inches diameter (3.8 cm) in addition to foliage exclusion, this could mean all branch biomass smaller than 3.8 cm in diameter is excluded, as is typical for estimating woodland volume for these bushy multi-stemmed species (Chojnacky 1994). Otherwise, FIA exclusion of only a single top branch less than 3.8 cm in diameter—and not the rest—makes little sense.

DISCUSSION

Why did the updated Jenkins et al. (2003) equations (Chojnacky et al. in preparation)—based on all biomass equations in the literature—generally produce estimates higher than those generated by the FIA CRM method? One possibility is volume-to-biomass methods simply underestimate. For example, Zhou (2011) demonstrated for green ash (*Fraxinus pennsylvanica*), ponderosa pine (*Pinus ponderosa*), and eastern redcedar (*Juniperus virginiana*) that volume-to-biomass conversion (using specific gravity similar to FIA's CRM method) consistently and significantly underestimates biomass from 6.3 to 16.6 percent. However, we cannot determine whether the pseudodata are accurate biomass estimates nor whether volume-to-biomass conversion approaches (as utilized by the FIA) inherently underestimate. These questions can only be answered from measuring new biomass data. We simply offer this comparison that FIA biomass estimates are generally 2 to 28 percent lower (at 30-cm d.b.h.) for most conifer and hardwood taxa than results from a meta-analysis of published biomass equations.

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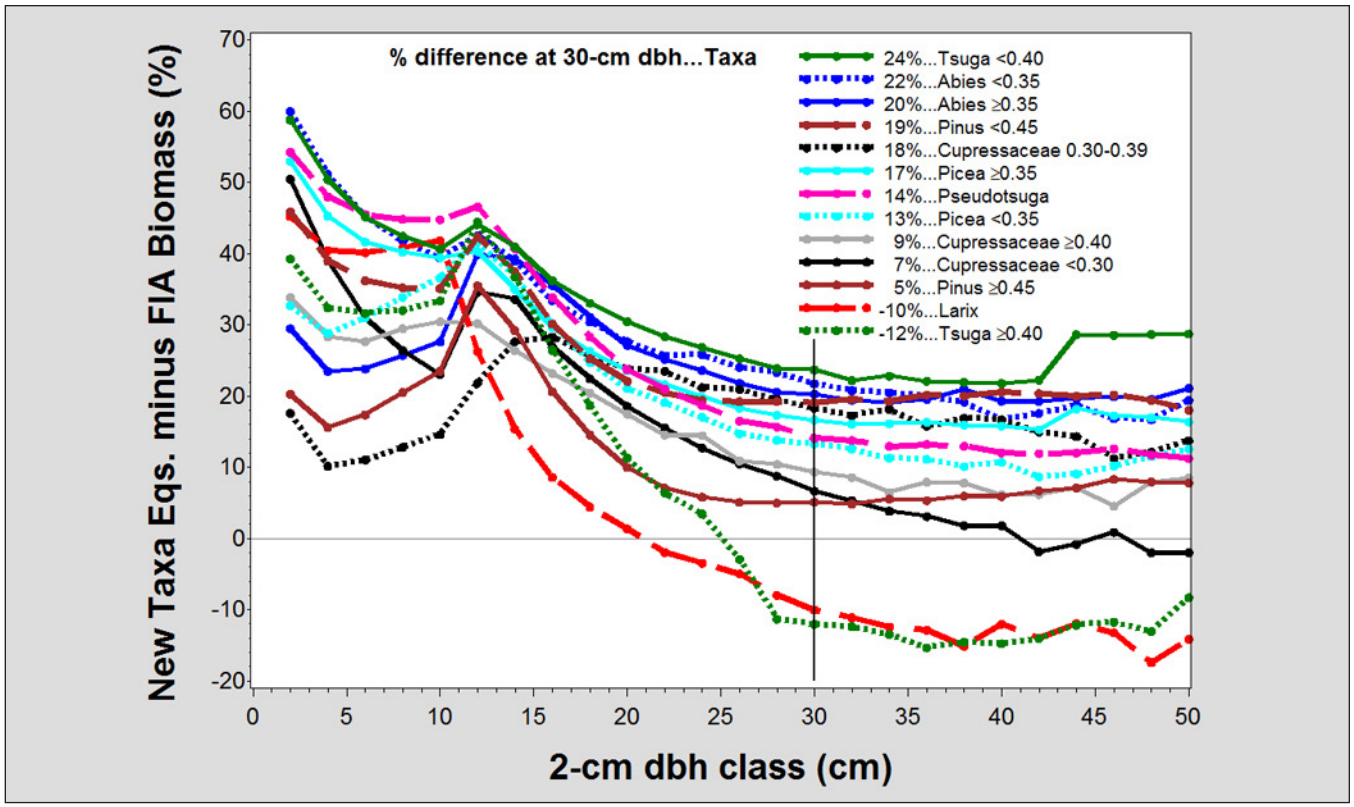


Figure 1.—Biomass equations for 13 conifer taxa compared to FIA data for 1,209,140 trees. Difference is equation prediction minus FIA biomass estimate, each first averaged within 2-cm diameter class. Legend order corresponds to curves at 30-cm d.b.h.

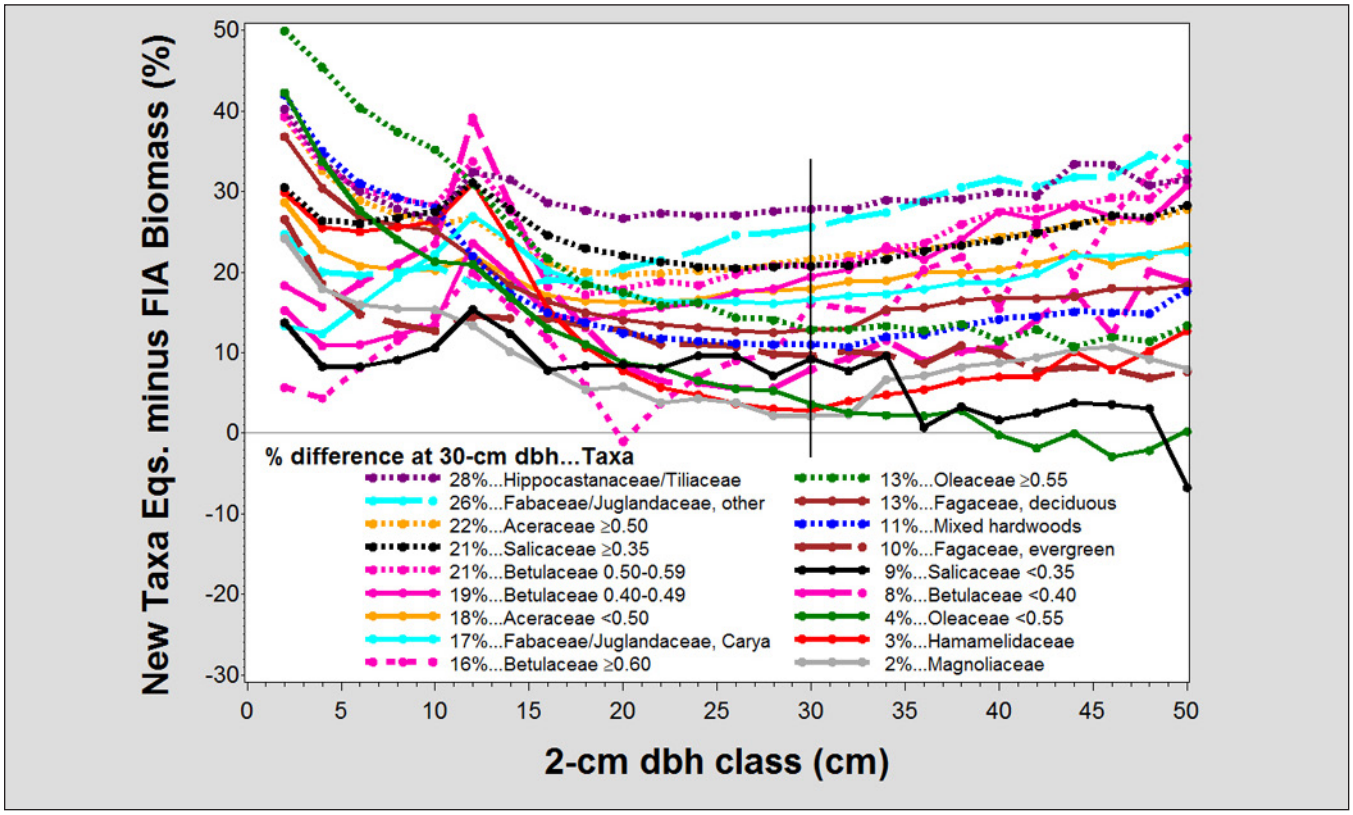


Figure 2.—Biomass equations for 18 hardwood taxa compared to FIA data for 1,192,774 trees. Difference is equation prediction minus FIA biomass estimate, each first averaged within 2-cm diameter class. Legend order corresponds to curves at 30-cm d.b.h.

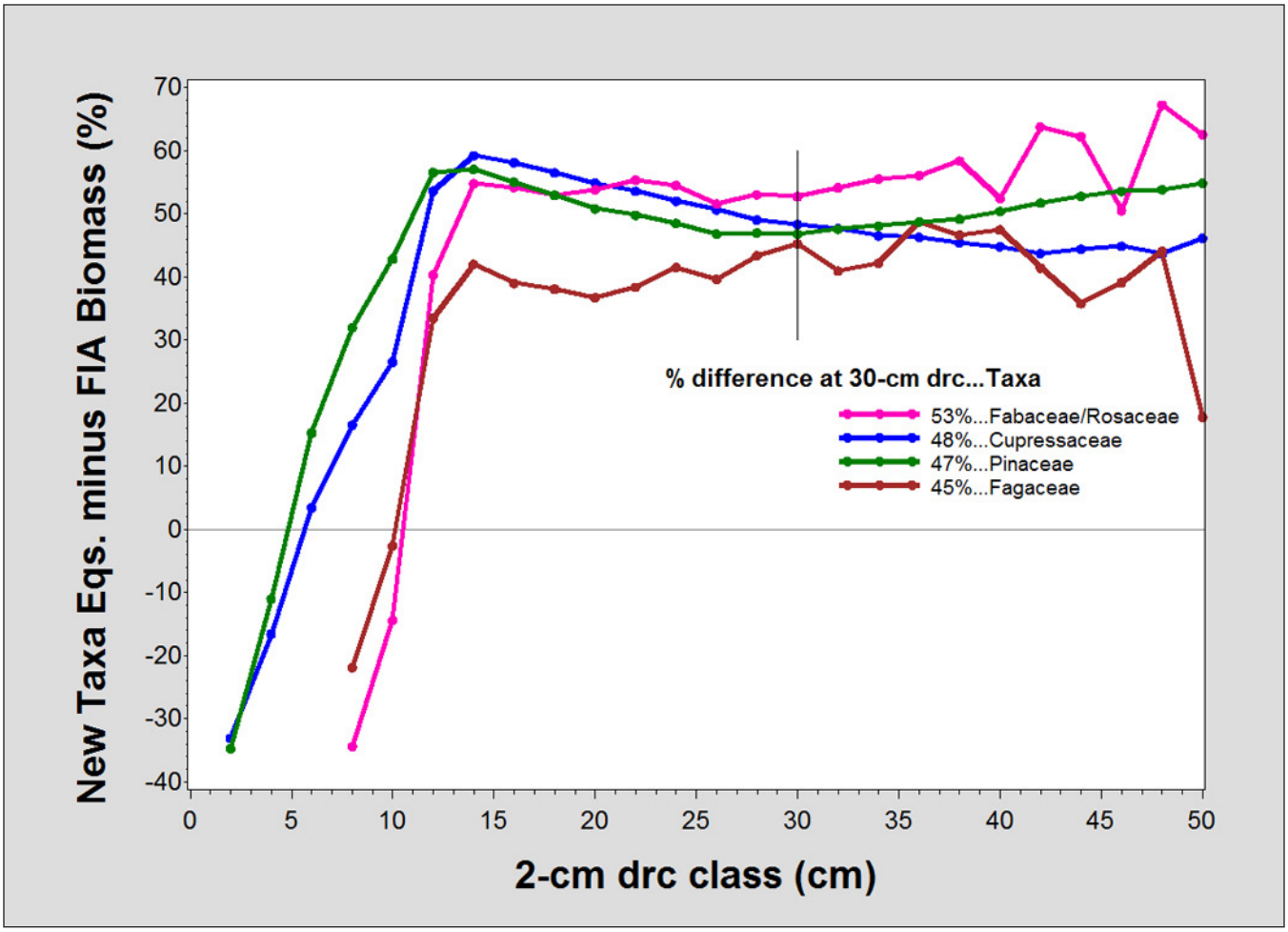


Figure 3.—Biomass equations for four woodland taxa compared to FIA data for 150,167 trees. Difference is equation prediction minus FIA biomass estimate, each first averaged within 2-cm diameter class. Legend order corresponds to curves at 30-cm d.r.c.

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LIDAR

APPLYING INVENTORY METHODS TO ESTIMATE ABOVEGROUND BIOMASS FROM SATELLITE LIGHT DETECTION AND RANGING (LiDAR) FOREST HEIGHT DATA

Sean P. Healey, Paul L. Patterson, Sassan Saatchi, Michael A. Lefsky, Andrew J. Lister, Elizabeth A. Freeman, and Gretchen G. Moisen[1]

Abstract.—Light Detection and Ranging (LiDAR) returns from the spaceborne Geoscience Laser Altimeter (GLAS) sensor may offer an alternative to solely field-based forest biomass sampling. Such an approach would rely upon model-based inference, which can account for the uncertainty associated with using modeled, instead of field-collected, measurements. Model-based methods have been thoroughly described in the statistical literature, and an increasing number of model-based forestry applications use tactically acquired airborne LiDAR. Adapting these methods to GLAS's irregular acquisition pattern requires a strategy for identifying a subset of GLAS "shots" that can be considered a simple random sample. We have developed a flexible method of dividing the landscape into equal-area polygons from which a GLAS shot can be chosen at random as a member of the sample. This process bears similarities to the approach used by the Forest Inventory and Analysis (FIA) Program as it moved toward its current hexagonal sample grid.

Although the ultimate application of this approach would be production of consistent biomass estimates across different countries, well-calibrated FIA estimates over the United States provide a convenient testing ground. Applied to California, this approach produced almost exactly the same estimate of biomass density (Mg/ha) as the FIA sample. The GLAS-based estimate had a considerably higher standard error than FIA's estimate, but it comes at a much lower cost and is based upon globally available GLAS measurements.

INTRODUCTION AND METHODS

Most official national and international forest carbon reporting mechanisms have traditionally relied upon information from field-based inventories. However, many countries do not have such inventories, and even among those that do, significant discrepancies exist in methods and definitions. A potential alternative to purely field-based sampling may lie in the 70-m circular waveform Light Detection and Ranging (LiDAR) returns from the spaceborne Geoscience Laser Altimeter System (GLAS) sensor. Such returns have been shown to be sensitive to biomass, and there may be a chance to use a smaller subset of co-located field plots to create modeled biomass "samples" over the areas sampled by GLAS.

In this paper, we describe a method for identifying a subset of GLAS shots which can be treated as a simple random sample for the purposes of a forest biomass inventory. This process is necessary because GLAS acquisition patterns are irregular and, in aggregate, cannot strictly be considered either random or systematic. We then demonstrate the use of such a

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sample over California with a model-based estimator similar to that used by Stähl et al. (2011) to estimate aboveground biomass. Model-based estimation allows us to predict, instead of measure, biomass at each sample point using relationships derived from a separate set of co-located ground and LiDAR measurements. Variance estimators used in this process take into account the uncertainty associated with the models used. For full methodological detail of this estimation process, consult Healey et al. (in press).

The sample design we describe is similar to that used by the Forest Inventory and Analysis (FIA) Program. Prior to a move toward a national sampling framework in the late 1990s, FIA plots were distributed and measured in slightly different ways in different regions of the country. The move to a nationally coherent sampling frame was accomplished by superimposing a hexagonal grid over the entire country, with the area of each grid cell equal to the nominal area represented by each FIA sample (Reams et al. 2005). In cells where one existing plot fell, that plot was kept. In those with more than one plot, only one was selected at random for retention. In those with no existing plots, a plot was established in a random location.

Establishment of this semi-systematic, equal-area sample frame allowed FIA to accommodate existing plot locations while drawing a sample which was spatially balanced across the country but was random with respect to forest conditions (Reams et al. 2005). The sample design we propose for GLAS follows a similar approach. One and only one GLAS shot is retained in each cell of an equal-area (but not equal-shape) tessellation of the area labeled as "forest" in a global land cover map. This tessellation is created following a fractal-based approach, using simple geometric rules to create equal-area clusters (Lister and Scott 2009). Since retroactively "adding" GLAS measurements (the last of which were collected in 2008) is not possible, tessellation cell size (and, inversely, sample number) is limited by the constraint that each equal-area cell must contain at least one GLAS shot.

Given the elimination of all GLAS shots except one in every tessellation cell under this approach, it is of practical interest to know the precision of resulting biomass estimates. The precision (i.e., standard error) of model-based estimates of biomass in California using the GLAS sample will be compared to design-based estimates derived from FIA's sample of more than 5,500 field measurements in the state.

RESULTS

In view of the constraint that there be at least one GLAS shot in each tessellation cell, the maximum number of cells in California is 182, or one per 48,000 ha. While the minimum number of GLAS shots in a single cell was one, the average was 560, from which a single shot was chosen at random. These randomly selected shots constitute the "S1" model-building sample (Fig. 1). The average distance between each point in the S1 population and its closest neighbor is 19.6 km (median = 13.5 km). The minimum overall distance (i.e., closest pair of neighbors) is 2.4 km.

Thirty-five co-located GLAS/FIA plots were available for use in determining the relationship between a GLAS derivative called Lorey's height (described as "basal area-weighted height") and biomass (i.e., the S2 sample; Fig. 2). The most parsimonious applicable model for this relationship was considered to be a model with a single quadratic term and no intercept (biomass = 0.3717 Lorey's height^2). A no-intercept model was used because of our assumption that forested plots with no biomass should return no Lorey's height. Significance tests indicated negligible gain from including a linear term in the model.

It should be noted that seven values (less than 4 percent) of the S1 sample exceeded the largest value in the model-building S2 data set shown in Figure 2 (specifically, these values were 45, 46, 48, 50, 52, 54, and 60 m). Ideally, the model-building data set should span the entire range of the values to be modeled. Given the small percentage of Lorey's heights in S1 not represented in S2, however, we assume that the

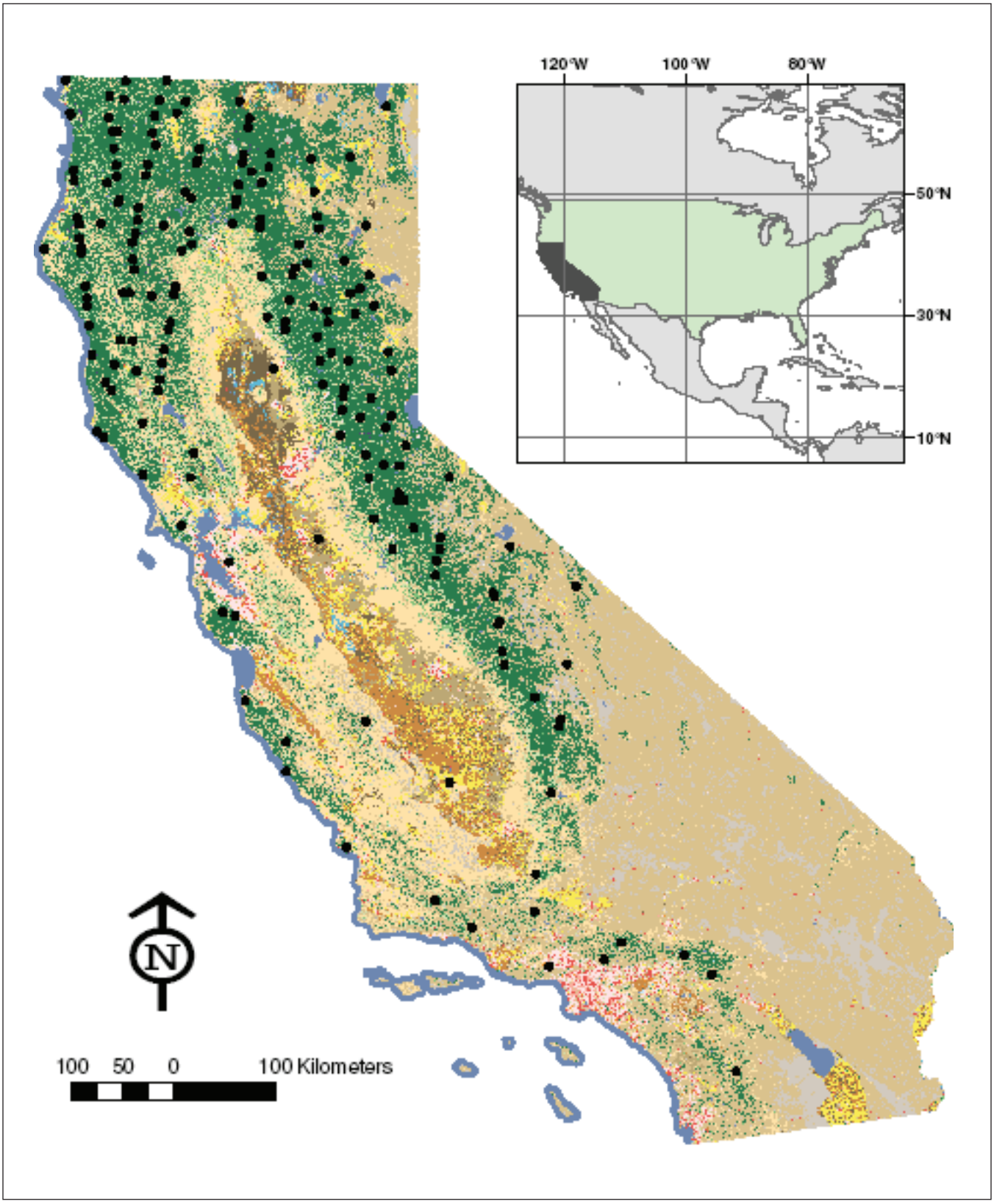


Figure 1.—The 182 GLAS shots selected for inclusion in the S1 sample of California forests. This sample has properties similar to the sample used in the U.S. NFI and is treated here as a simple random sample. A National Land Cover Database cover map is shown for context.

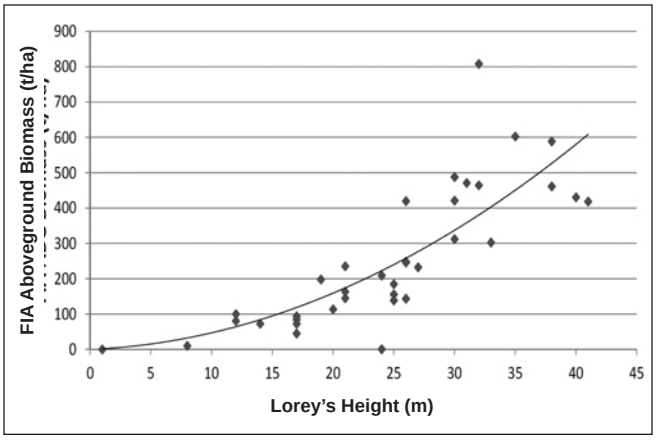


Figure 2.—Relationship between FIA-measured aboveground tree biomass and GLAS-based Lorey's height in California. The line is described by: y = 0.3717 x2.

model is valid for the entire population. We likewise assume no spatial autocorrelation among S1 samples. Our GLAS-based estimate of biomass density in California's forests was 211.11 Mg/ha, which was within standard error bounds (±2.88) of the FIA estimate of 208.95 Mg/ha (Miles 2011). The FIA estimate was derived through a 10-year ground sample of 5,261 forested plots. The standard error of the GLAS-based estimate was 20.70 Mg/ha (Fig. 3). The modeling variance was approximately 0.77 times the variance contributed by the sampling process.

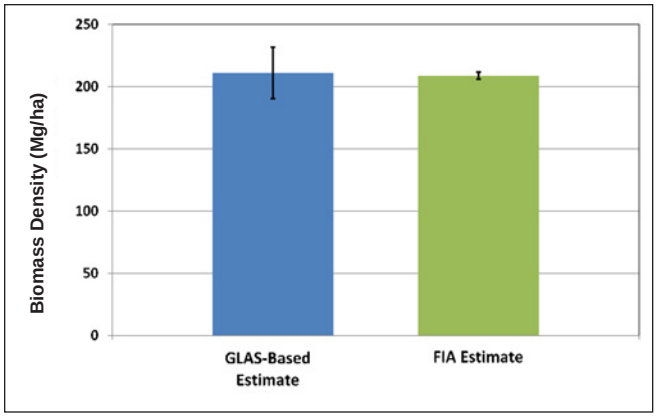


Figure 3.—Comparison between the FIA carbon density estimate for California's forests and the estimate made here using GLAS- and model-based estimation. The estimates are nearly identical, although FIA's estimate has significantly less uncertainty (bars indicate standard error).

DISCUSSION

Model-based estimation using the sample design we describe provides a transparent method for estimating biomass for particular spatial domains. This sample design, in which one arbitrarily located sample point is drawn from equal-area sample units distributed across the landscape, is similar to that used by FIA, and our estimate of biomass density in California closely matched FIA's design-based estimate. The standard error of our estimate (approximately 9.8 percent of the estimate) was substantially larger than that of the FIA estimate (1.4 percent) and that derived through model-based estimation by Andersen et al. (2011) using specifically acquired airborne LiDAR data (8 percent). However, the cost of the FIA estimate was approximately $10.5 million (based on a commonly used valuation of $2,000 per plot), and the LiDAR acquisition alone in Anderson et al.'s (2001) much smaller study area cost $60,000. Future use of GLAS data in the process described here represents an almost no-cost option for providing consistent, moderate-precision biomass estimates across the globe.

A primary advantage of the model-based inference used here is the capacity to apply models developed in areas of rich inventory data to GLAS shots, informing estimates in ecologically similar areas where field data are sparse. For example, Nelson et al. (2009) used relationships observed in a limited area of co-located biomass/GLAS observations to estimate biomass for all of Quebec, following a modified model-based approach. However, the validity of inference in model-based approaches depends upon how well the stipulated models accord with the population of interest (Gregoire 1998). The question of how well the model applies to the population of interest is a critical consideration in the application of our approach, whether the model was developed *in situ* or from a spatially remote but perhaps ecologically similar area. Since our model was created from an arbitrary subset of FIA's presumably unbiased ground sample, there is a compelling argument that the model is appropriate for the forests of California.

The degree to which this model may apply beyond California remains an open question. Saatchi et al. (2011) noted regional differences in the relationship between biomass and GLAS-based Lorey's height in their pan-tropical study. Data collected to support biomass estimation using the global GLAS data set would at least have to span major ecological systems. The consolidation of ground data needed to support a global GLAS-based biomass inventory would require significant international cooperation and, as illustrated by our results, would likely not improve the precision of biomass estimates available in countries with established national forest inventories (NFIs). Those inventories typically rely upon a denser sample than is available from GLAS and do not have to account for model variance, which in our example made up approximately 44 percent of the total variance.

However, a GLAS-based biomass inventory would represent an internationally coherent basis for comparison among countries, especially those without established NFIs. Even moderate-precision biomass estimates would be an improvement in many countries (Gibbs et al. 2007), and consistent sample design and estimation methods would remove an important source of uncertainty in international monitoring. GLAS data were acquired in spatial patterns difficult to associate with either a systematic or random process. The sample design presented in this paper allows identification of a subset of GLAS data which may be used as a simple random sample to estimate biomass, perhaps globally, with consistent measures of uncertainty under a model-based estimation framework.

CONCLUSIONS

- The methods presented here constitute a globally extensible approach for generating a simple random sample from the global GLAS data set. The properties of the sample collected by GLAS have hitherto not been strictly identifiable with any particular design.
- Model-based estimation, following Stähl et al. (2011), based upon GLAS data in California produced an estimate of biomass density (biomass/ha) almost identical to the estimate derived from the design-based NFI.
- Global application of model-based estimation using GLAS, while demanding significant consolidation of training data, would improve inter-comparability of international biomass estimates by imposing consistent methods and a globally coherent sample frame.

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THE UTILITY OF LiDAR FOR LARGE AREA FOREST INVENTORY APPLICATIONS

Nicholas S. Skowronski and Andrew J. Lister[1]

Abstract.—Multi-resource inventory data are used in conjunction with Light Detection and Ranging (LiDAR) data from the Pennsylvania Department of Natural Resource's PAMAP Program to assess the utility of extensive LiDAR acquisitions for large area forest assessments. Background, justification, and initial study designs are presented. The proposed study will involve three phases: 1) characterization of relationships between LiDAR cloud metrics and statistical summaries of tree information on forest inventory plots, 2) use of the inventory data to calibrate LiDAR-based forest biomass models, and 3) use of subsets of the LiDAR dataset as part of a ground-based forest inventory. Initial results of the first phase indicate moderate relationships between various combinations of ground inventory and LiDAR data.

INTRODUCTION

Large area forest assessments have been of interest for many years. Traditionally, these assessments have been conducted by ground-based inventories like those conducted by the U.S. Forest Service's Forest Inventory and Analysis (FIA) Program (Gillespie 1999). Since the early 1900s, FIA has conducted inventories of the nation's forest resource through a combination of periodic and annual field data collection campaigns. Data on tree and site factors in forested areas are collected, processed, and converted into summary information that is used by resource planners, land managers, scientists, and other interested parties.

The use of air- and space-borne sensors in forest assessments has increased over the last 40 years. In the last decade, the use of LiDAR (Light Detection and Ranging) technology in particular has increased dramatically. Cost considerations previously limited the use of LiDAR to relatively small—generally sub-state—areas. Now, entities such as state governments can afford to acquire LiDAR over large areas. For example, Pennsylvania's PAMAP Program funded state-level acquisition of LiDAR between 2006 and 2008 (PA DCNR 2012). The existence of co-occurring, large area LiDAR and forest inventory datasets creates opportunities for studies assessing the costs and benefits of using LiDAR in various ways for forest assessments.

The most common use of LiDAR in forest assessments involves the generation of pixel-based estimates of forest parameters such as volume, biomass, or tree abundance in relatively small study areas (e.g., Asner et al. 2011, Lefsky et al. 2003). However, recent interest in large area assessments of forest carbon stocks as part of United Nations climate change agreements, such as those contained in the United Nations Framework Convention on Climate Change's program for Reducing Deforestation and Degradation (REDD) (Gullison et al. 2007), has led to a need for investigations of cost-effective

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strategies for measuring and monitoring forest carbon in areas that do not have established, ground-based forest inventories. LiDAR is a particularly appealing option due to the nature of the information obtained, reflectance information generally shows strong relationships with forest canopy height and density, two attributes closely related to forest biomass and thus carbon content. LiDAR has the added benefit of targeted acquisitions that can be less susceptible to cloud cover which affects space-borne sensors like Landsat.

An option that is not often explored, however, is the practical use of LiDAR to aid in large area, ground plot-based forest inventories. Due to the immense data volumes and processing requirements, it can be impractical to collect and process LiDAR over large areas on a regular basis. However, advances in computing technology make this an option worth exploring. A promising approach is the use of subsets of the LiDAR information for stratification or, in another supporting role with ground plots, as the basis for the estimate generation.

The goal of the current study is to address the need for methods that use LiDAR to generate estimates of forest attributes, particularly tree carbon stocks, over large areas in an efficient way. Specific objectives of the study are to 1) characterize relationships between LiDAR cloud metrics and FIA data from various ecosystems around Pennsylvania, 2) assess the usefulness of FIA data for calibrating LiDAR-based forest biomass models, and 3) compare the costs and benefits of using LiDAR-based maps of forest attributes with estimates generated from several combinations of LiDAR and ground data in a design-based forest inventory framework. Results of these three analyses will not only improve our understanding of how FIA data can serve as training data for LiDAR-based biomass modeling, but also to help inform decisions about carbon inventory and monitoring strategies both in the United States and in other countries considering using LiDAR for this purpose.

STUDY AREA

The study area is the state of Pennsylvania. It is located between 74° 43′ and 80° 31′ west longitude, and 39° 43′ and 42° north latitude; the state contains approximately 44,819 square miles (116,083 km^2) of land area. Pennsylvania is nearly 60 percent forested and is composed of a variety of ecosystems including highly urbanized in the east, agricultural in the center, and large areas of contiguous forest in the mountainous regions in the north and west.

METHODS

Each FIA plot consists of four circular 48 ft (14.6 m) diameter subplots, with one subplot located in the center and three equidistant subplots distributed symmetrically around and located 120 ft (36.6 m) from the center subplot. The subplots occupy 0.17 acres (0.07 ha), and the subplot array can be subtended by a circle of 1.5 acres (0.6 ha) in area. On each plot, information for several site factors (including ownership, forest type, land use, slope, and others) are collected, as well as data on individual trees, including species, diameter at breast height, total height, and the relative canopy position of each tree (classified as dominant, codominant, overtopped, intermediate, and open grown). Tree data are collected in the field on portions of plots that are classified as “accessible forest,” which is defined in part as belonging to a group of trees at least 0.4 ha in extent and at least 37 m wide at its narrowest point, being capable of natural tree regeneration, and having a minimum stem count (stocking), dependent on species and tree size (USDA Forest Service 2011). All data are stored in a relational database.

Using information found in and tools associated with the relational database, total volume, total aboveground carbon, total basal area, average tree height, and average diameter-weighted height were computed for each combination of species, canopy position class, and forest type. About 1500 single condition plots—those that are 100 percent forested

land use—were used in the analysis. Some plots were omitted based on LiDAR data quality (outliers were removed with heights three standard deviations above the mean height).

The statewide LiDAR dataset was processed using the Toolbox for LiDAR data Filtering and Forest Studies (TiFFs) (Chen et al. 2007). The .LAS LiDAR files were provided in a preprocessed format with ground and canopy returns identified by the PAMAP vendor. One-foot (0.3-m) resolution Digital Elevation Models (DEMs) were generated using these predefined classifications. The LiDAR point cloud was then spatially intersected with each FIA plot location and clipped to spatial extent of each subplot. Data from each subplot were aggregated to the plot-level and standard LiDAR-derived statistical parameters (mean and quadratic mean, standard deviation, skew, kurtosis, and decile heights) and the LiDAR derived Canopy Height Profile (CHP) parameters (Skowronski et al. 2011) were generated using only first returns for each plot.

PROPOSED ANALYSES

To characterize relationships between LiDAR cloud metrics and FIA data, exploratory data analysis will be performed, including the generation of correlation and scatterplot matrices relating the independent variables (the LiDAR metrics) to various subsets of the FIA data, including subsets of the data by species, species group, forest type, geographic area, and canopy position class. The goal of these analyses will be to gain a better understanding of inter- and intra-variable group relationships, and to inform decisions for and interpret results of the second phase of the project: carbon model development. For this phase, all subsets linear regression will be performed to generate a suite of carbon models and associated fit statistics and error assessments, with the goal of obtaining predictive models that can be applied to large areas of Pennsylvania. Finally, based on results of the first two phases, a sample design study will be performed. FIA generates estimates of forest parameters using a post-stratification statistical design (Bechtold and Patterson 2005) using strata created from classified Landsat images. We plan to generate a stratum map using LiDAR canopy maps instead of Landsat and calculate various estimates of forest parameters. We also plan to subdivide the LiDAR dataset by generating "strips" of LiDAR over the FIA plot locations and over several randomly selected areas with no FIA plots, to generate estimates using a double sampling (two phase sample) design. Finally, we plan to implement the regression estimator using the appropriate model(s) from phase 2 of the study. We will then compare all of the resulting estimates in terms of relative efficiency, or the improvement in sampling error relative to that achieved by a simple random sample. Of particular interest will be an assessment of the relative costs and benefits of acquiring and processing the LiDAR information (versus standard methods using less costly combinations of plots and Landsat imagery) and the development of a decision framework for the use of LiDAR in large area inventory applications (Kohl et al. 2011).

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IMPROVING LIDAR BASED PREDICTION OF FOREST BIOMASS USING MODELS WITH SPATIALLY VARYING COEFFICIENTS

Chad Babcock, Andrew O. Finley, and John B. Bradford[1]

Abstract.—Many studies and production inventory systems have shown the utility of coupling covariates derived from Light Detection and Ranging (LiDAR) data with forest variables measured on geo-referenced inventory plots through regression models. The objectives of this study were to propose and assess the use of 1) a new technique for LiDAR variable extraction using Singular Value Decomposition to obtain uncorrelated covariates; and 2) a Bayesian hierarchical modeling framework that accommodates both residual spatial dependence and non-stationarity of model covariates through the introduction of spatial random effects. We explore these objectives using three forest inventory datasets that are part of the North American Carbon Program each comprising point-referenced measures of aboveground forest biomass and discrete LiDAR. For each dataset, we considered three LiDAR variable extraction methods and three regression model specifications. Models were assessed based on fit criteria and predictive performance using a leave-one-out cross-validation. Results showed that among the LiDAR variable extraction methods, no single set of covariates offered a consistent advantage across the datasets. The addition of spatial random effects to the regression model intercept only improved fit and predictive performance in the presence of substantial residual spatial dependence. Allowing all regression slope parameters to vary spatially, via the addition of spatial random effects, greatly improved model fit and predictive performance across all datasets. The proposed Bayesian modeling framework also provides access to pixel-level posterior predictive distributions that are useful for uncertainty assessment.

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ALTERNATIVE ESTIMATION TECHNIQUES FOR FIA DATA

AN EFFICIENT ESTIMATOR TO MONITOR RAPIDLY CHANGING FOREST CONDITIONS

Raymond L. Czaplewski, Michael T. Thompson, and Gretchen G. Moisen[1]

Abstract.—Extensive expanses of forest often change at a slow pace. In this common situation, FIA produces informative estimates of current status with the Moving Average (MA) method and post-stratification with a remotely sensed map of forest-nonforest cover. However, MA "smoothes out" estimates over time, which confounds analyses of temporal trends; and post-stratification limits gains from remote sensing. Time-series estimators, like the Kalman Filter (KF), better detect and analyze unexpected or rapid changes in dynamic forests. KF is a recursive multivariate model-based estimator that separates complex time-series of panel estimates and multi-sensor remotely sensed data into a sequence of smaller and more manageable components. Population-level results are disaggregated into expansion factors that assure additivity and simplify small area and small domain estimation. Other statistics gauge fit of alternative models to annual FIA panel data, which permits quantitative rankings among alternative cause-effect hypotheses.

INTRODUCTION

The 1998 Report by the Blue Ribbon Panel on Forest Inventory and Analysis (FIA) motivated the comprehensive redesign of the FIA program (Bechtold and Patterson 2005). FIA replaced decadal periodic surveys with annual panel surveys to produce more timely analyses for every State. However, a single annual panel uses only 10 to 20 percent of the field plots available to a periodic survey. To improve precision, FIA uses a simple Moving Average (MA) of five or more annual panels. While design-unbiased as an estimator of the average conditions among multiple panels, MA is biased for time-series of annual estimators (Bechtold and Patterson 2005). This bias is acceptably small whenever net change is relatively minor, but not when landscapes are affected by unusually rapid changes. Concerns with the MA for annual trend analyses are escalating. In 2012, the National FIA User Group recommended "renewed efforts to investigate alternatives to the simple moving average for improved trend detection and estimation, … including short term projections (5 to 10 years)." We describe an estimator designed to satisfy this and previous recommendations from the National FIA User Group.

MONITORING ANALYSES AND THE NATURE OF CHANGE

To some degree, every acre of every forest changes every year through predictable processes of stand dynamics, ambient disturbances, timber management, and socioeconomic forces. In a static landscape, changes in forest conditions and land use are nearly at equilibrium, and MA is an acceptable statistical estimator. However, other landscapes change more rapidly.

Unexpected change can be subtle, spatially ubiquitous, and undetected during early onset. An example is

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the growth decline of southern pines during the 1970s. Causes might have been changes in air pollution, climate, land use, and/or distribution of stand conditions (Gadbury and Schreuder 2004). Such changes are not well observed with remote sensing, although geospatial data on stressors (e.g., air pollution) contribute valuable circumstantial information. Sufficiently precise estimators require a large sample of FIA field plots, which implies analyses over large geographic areas (e.g., a multi-state ecoregion) and long time intervals (e.g., 5 to 20 years). Detailed analyses might include the small subsample of "Phase 3" Forest Health Monitoring plots (Bechtold and Patterson 2005). Cause-effect analyses might use model-based inference to compare alternative cause-effect hypotheses (Gadbury and Schreuder 2004).

Other changes are episodic disturbances, which are often apparent with the naked eye. An example is severe mortality of western pines caused by outbreaks of mountain pine beetles. Other examples include changes in the extent of wildfires, timber harvest and management treatments, conversion and reversion among agricultural fields and forestlands, and development within the wildland–urban interface. Though locally intense, they might affect only 1 to 5 percent of a forested landscape per year, and they are observed with a correspondingly small number of FIA plots. Annual remote sensing provides indicators that are well correlated with the extent, intensity and location of such changes. Remeasurements of FIA field plots at 5- to 10-year intervals monitor detailed tree-level consequences of stand-level changes.

Models of population processes are arguably essential for detailed monitoring. Model-based estimators increase precision with small sample sizes. A model can capture an analyst's hypotheses regarding expected behavior of a forest population. Residual differences between model predictions and panel estimates detect deviations from expectations. Different models represent alternative sets of cause-effect hypotheses, and analyses of residuals compare the fit of each alternative to FIA field data. Models forecast future conditions based on past processes.

Sensitivity of a monitoring program depends upon a sufficiently large sample size within each annual panel. Furthermore, numerous field plots are required for statistical methods that empirically compensate for systematic measurement errors with remotely sensed data. Hence, the target population must cover large geographic expanses, perhaps spanning several states. However, certain changes tend to "average out" as the extent of the population increases, and many monitoring questions involve small subpopulations. A partial solution is multivariate small area estimation, which uses diverse sets of full-coverage geospatial data (e.g., Landsat and MODIS) as predictors of field observations (e.g., Czaplewski 2010).

A MODEL-BASED TIME-SERIES ESTIMATOR

The sample-survey literature covers a diverse collection of estimators for individual pieces of a statistical monitoring system. However, the multivariate "Kalman filter" (KF) estimator (Bar-Shalom et al. 2001) can integrate all pieces into a single cohesive structure. The senior author is using a matrix language to develop software that implements the following.

KF is a time-series technique. It combines a design-based panel estimator with a model-based estimator for expected changes in population parameters (Czaplewski and Thompson 2009). KF is a sequential recursive method. It starts at time t=1 with the first panel of field data and FIA's design-based estimator. The resulting vector estimate of population parameters (i.e., "state-vector") serves as initial conditions in a model for changes in the population as posited by the analyst. This multivariate linear model

predicts the state-vector at time t=2, including a covariance matrix for random errors propagated from time t=1 plus estimated prediction errors between times t=1 and t=2. The second panel of field plots provides an independent design-based estimate of corresponding population parameters for t=2. KF uses the multivariate composite estimator to "optimally" combine these competing model-based and design-based estimates. The result is a single, more precise estimator at time t=2. This "best" estimate at time t=2 serves as initial conditions for the transition model that predicts the state vector at time t=3. This sequential recursive technique proceeds for the entire time-series.

Analyses of residual differences between model-based predictions and design-based panel estimates help improve the estimated covariance matrix for model prediction errors, thereby mitigating bias in the model-based portion of the KF estimator. The model represents analysts' understanding of population-level processes (Czaplewski and Thompson 2012) or a population-level aggregation of plot-level processes (see for example Healey et al., these proceedings). The model can forecast future conditions and the associated covariance matrix for random errors.

The state vector has partitions for each year. This autoregressive structure improves estimates for many time periods with each FIA panel. Its covariance matrix provides variance estimates for changes between 5- or 10-year intervals, which KF uses with corresponding design-based estimates from plot remeasurements to improve annual estimates of status and changes.

The state vector may have hundreds of variables, and digital "round-off" errors can degrade numerical results. However, the engineering literature abounds with solutions that use the square root of a covariance matrix (e.g., Bar-Shalom et al. 2001). Covariance matrices are typically rank-deficient, and feasible estimates require thoughtful pivots of state-space.

KF computes a vector of "optimal" weights that combines each model- and design-based vector estimate at each time-step. Restrictions on those weights can impose inequality constraints. For example, the estimated annual mortality rate of insect-infected live trees can exceed 100 percent if sampling errors in two independent annual panels are large. Inequality constraints force the estimated rate between 0 and 100 percent. Those same population-level weights may be stored in the FIA plot-level database as time-series of multivariate expansion factors, one for each state variable, at the condition and tree levels (Czaplewski 2010). This step assures additivity across statistical tables, facilitates certain types of small domain and small area estimation, and potentially reduces certain difficulties in analyses with mixed-condition plots.

Insufficient sample size causes sampling zeros, which can produce implausible estimates for "rare" variables. We collapse classification systems so that each category has at least 50 plots within each annual panel. Assuming no cross-classifications, annual sample size within Colorado's forests would support only seven forest type groups, seven ownership categories, and seven tree species groups. KF expansion factors permit more detailed estimates within the FIA database, but the statistical efficiencies of those detailed estimates are suboptimal.

Czaplewski (2010) developed KF structures for multiple sources of multivariate remotely sensed and other geospatial data. Unlike post-stratification, geospatial variables may be continuous or categorical, with or without cross-classification. KF uses full-coverage Landsat data or sample surveys with LIDAR or high-resolution aerial photography. This KF structure accommodates time-series of remotely sensed data, including annual change detection. Czaplewski (2010) illustrates compatible methods that use geospatial data for small-area estimates for special studies, which improves the compromise between large sample sizes and small analysis areas.

DISCUSSION AND CONCLUSIONS

FIA analysts and user community require defensible estimates of trends in forest resources. Estimates at one point in time, such as forest area or amount of standing live biomass, have limited value. Detailed assessments of insect epidemics, such as the mountain pine beetle in the West, require reliable estimates of annual tree mortality over long timespans. Monitoring broad-scale trends in tree growth helps better understand effects of climate change. Before making major capital investments, a forest products company must know trends in timber volume, and their causes, within a modestly sized geographic area. Trends in tree removals are a substantial component of economic assessments, such as the effect of recessions on the forest product sector. To serve these analysis requirements, FIA requires an easily understood statistical estimator that supports diverse analyses of time-series with panel data.

Although the MA estimator is easily understood, it can have substantial lag-bias. On the other hand, the purely design-based estimator for each independent panel is unbiased for annual monitoring. Unfortunately, the latter is limited by small sample sizes. Annual trends can be estimated only through differences among estimates from independent panels (e.g., independent estimates of lodgepole pine in Montana for 2010, 2011, and 2012). Sampling error can exceed net annual change, however, obscuring major changes in a rapidly changing population, or producing statistical estimates of change that misleadingly appear large for a truly static population. Furthermore, independent panels limit the ability to understand the causes of annual change. Remeasurements of individual FIA plots at 5- or 10-year intervals help better understand long-term changes at the plot and tree scales, but this protracted remeasurement interval obscures annual trends. Regardless, the design-based approach, by itself, restricts an analyst's ability to quantify and interpret trends at the annual time scale.

The multivariate Kalman filter is a relatively simple alternative in an annual monitoring program. It fully utilizes all available remotely sensed data. It stores results as condition- and tree-level expansion factors, which simplifies analyses. Its structure helps detect unexpected changes and rank competing sets of cause-effect hypotheses. This model-based approach is inherently multidisciplinary, however, and success requires teamwork among analysts, modelers, remote sensing technologists, computer scientists, and statisticians.

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THE FOURTH DIMENSION IN FIA

Francis A. Roesch[1]

Abstract.—In the past, the goal of forest inventory was to determine the extent of the timber resource. Predictions of how the resource was changing were made by comparing differences between successive inventories. The general view of the associated sample design included selection probabilities based on land area observed at a discrete point in time. That is, time was not considered part of the sample design because it was not considered an element of the sampled population. Over the last few decades, the general goal of Forest Inventory and Analysis (FIA) has been changing to monitoring the dynamic forest ecosystem. However, much of the literature discussing FIA's new annual monitoring system, its sample design, and estimators is still based on an areal probability paradigm. In Roesch (2008; Forest Science 54(4): 455-464), I pointed out why it is usually necessary to include the dimension of time when describing the sampled population and the sample design for FIA and similar forest inventory systems. Here, I further explore the inferential advantages of replacing the areal probability paradigm with a three-dimensional probability paradigm with an application.

INTRODUCTION

In the past, the primary goal of most national-scale forest inventories had been simply to determine the extent of the timber resource. Estimates of how the resource had changed, made by comparing differences between successive inventories, were merely an incidental benefit of these historic inventories. Over the last few decades, many national-scale forest inventories have morphed into full-fledged efforts to monitor many aspects of dynamic forest ecosystems. The U.S. Forest Service's Forest Inventory and Analysis Program (FIA) is no exception and is concerned with evaluating the dynamic state of the Nation's forest populations. Most inventories at this scale rely on a sampling scheme that has historically been described as a three-step process. In the first step, a set of random points is located in a two-dimensional space, specifically the land area of interest. The second step concerns the selection of a set of observation times while the third step chooses a cluster of trees in the vicinity of each sample point at each observation time. The first step, and only the first step, was viewed as random, leading to a sample design description in which the sample frame partitions the two-dimensional areal population. In Roesch (2008), I addressed the fact that in today's panelized sample designs, the determination of the set of observation times is also random, and the sampled population and the sampling frame are three-dimensional.

To make estimates for the target population, the sampled population must be identifiably associated with the target population. This association requires knowledge of the probability of selection for the realized set of observations on each tree (or element) in the sample over the course of the period of interest. Because there are potentially many sets of observation times realizable for each element in the population, I described the sample unit as a three-dimensional jigsaw puzzle piece resulting from partitioning the three-dimensional population volume. The description meets the requirements for a probability sample: the

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population is divided up into mutually exclusive, exhaustive sample units (the three-dimensional puzzle pieces) that in toto make up the sample frame. Each unit has a definite probability of selection and the total of these probabilities is equal to 1.

AN APPLICATION

Traditionally, many measures associated with forest trees have been reported within tree size classes, such as tree diameter classes. For instance, basal area or volume growth within 2-inch diameter classes for each year within a specific period may be of interest. The contribution of measurement error to total variance is usually large enough to preclude the measurement of the same trees more frequently than about every 5 years. Often the measurement interval and the period of interest are long enough for a large number of trees in the population to grow through multiple diameter classes creating a potentially intractable problem from the viewpoint of successively applied two-dimensional samples. I show below that estimation under the three-dimensional paradigm is both obvious and manageable.

In this application, I use FIA data to estimate annual basal area growth of survivor trees within specific size classes (Table 1) over a defined area (A) and temporal period. FIA conducts a continuous forest inventory using a rotating panel design (Bechtold and Patterson (2005) and Roesch (2007). The design consists of

Table 1.—Diameter classes corresponding to standard merchantability limits with accommodation for differences in hardwood and softwood saw log standards

Diameter Class	Lower Limit (Diameter ≥)	Upper Limit (Diameter <)
D1	0	5
D2	5	7
D3	7	9
D4	9	11
D5	11	∞

g mutually exclusive, spatially disjoint temporal panels. These panels are measured in sequence for g consecutive years, after which the sequence reinitiates. That is, if panel 1 is measured in year y, it will also be measured in years $y + g$, $y + 2g$, and so on. Panel 2 would then be measured in years $y + 1$, $y + 1 + g$, $y + 1 + 2g$, etc. Because FIA adheres to a two-dimensional view of this design, the program groups these data into evaluation groups of g years and then ignores temporal differences in observations within an evaluation group. The interested reader is referred to the "temporally indifferent method" in Patterson and Reams (2005). The temporally indifferent method is a smoothing function that has the tendency to obfuscate temporal trends and delay recognition of those trends. A judicious application of the three-dimensional view of this design can negate the necessity of the temporal indifference assumption and its associated problems.

To fully exploit the three-dimensional view, we must look at the data differently than it has been traditionally viewed. With respect to annual growth, we note that each plot is not only located in a particular place, but that it is also observed at particular times, and that the times of observation are possibly more important than the place of observation, once place is accounted for. Initially, we will focus on two observations for each plot. Assign to each observation of variable x labels for plot i and (adjusted) beginning date t_i^b and ending date t_i^e, separated by the (adjusted) time span of s_i years. Represent each of these observations as x_i^b and x_i^e, respectively. The dates and times are adjusted to approximate the time of observation relative to the proportion of growing season elapsed within a year. Although beyond the scope of this investigation, this could be done using data contributing to the USDA plant hardiness zone maps (USDA 2012). For simplicity, we make two assumptions, both of which can be refined by an appropriate model to suit a particular investigator or alternative application, as needed. The first is that we assume that the growing season spans from March 1 to November 30

everywhere within the area of interest. The second assumption is that growth for each plot is uniform throughout the growing season. We can then represent each observation date as the year of observation plus the proportion of the growing season that has elapsed (i.e., in the format *year.p*), and s_i is simply the difference between the two. Because we have no observations between x_i^b and x_i^e, we make the further assumption that basal area growth for each living tree is uniform between the two observations (e.g., across s_i). This assumption could also be refined by the application of the appropriate model, such as conditioning on x_i^b or on annual precipitation. We then allocate the proportion of basal area growth observed over s_i to the proportion of each year spanned by s_i, (thereby accounting for the marginal probability of the time dimension). This assumption of linear (basal area) growth is an approximation that should only be used for relatively short time intervals. Well-developed growth models would provide better estimates on individual trees, but can be unavailable for many of the species and condition classes encountered in a wide area forest monitoring effort. The assumption that basal area growth is uniform between observations allows us to estimate when the threshold for each diameter class limit was crossed and to allocate growth within diameter classes to the years the growth occurred in those diameter classes. This method is a major advantage over FIA's current estimation methods, because the latter do not provide a mechanism to accomplish this. This development leads immediately to two simple estimators for annual basal area growth (within diameter class), a probability proportional to size estimator (BAG_y^{DCPPS}):

$$BAG_y^{DCPPS} = \frac{1}{n_y}\sum_{i=1}^{n_y}\frac{bag_{i,y}}{p_{i,y}}, \qquad [1]$$

where:

n_y = the number of plots observing growth in year y,

$P_{i,y}$ = the product of portion of year y growing season observed by plot *i* and the portion of plot *i* area within the area of interest, and

$bag_{i,y}$ the basal area growth observed on plot *i* and assignable to year *y*;

and a ratio estimator (BAG_y^{DCRAT}):

$$BAG_y^{DCRAT} = \frac{\sum_{i=1}^{n_y} bag_{i,y}}{\sum_{i=1}^{n_y} p_{i,y}}. \qquad [2]$$

These estimators were used to obtain annual estimates from 2006 to 2010 of basal area growth of survivor trees per acre from FIA data for South Carolina. The results are compared to FIA's end of period estimator (EOP) and an improved diameter class estimator (DC) (Sheffield and Turner, 2010), both of which are based on the temporal indifference assumption.

RESULTS

Figure 1 gives the results for estimating the annual basal area growth of survivor trees by the diameter classes given in Table 1 from each of the four estimators. The figure shows the results for the PPS estimator (eq. 1) (top left), the ratio estimator (eq. 2) (top right), the pooled EOP estimator (bottom left), and the pooled diameter class (DC) estimator (bottom right). Note that under a non-stringent condition, the estimators resulting in the top two graphs are unbiased. A linear trend for the intervals covering the year of interest is sufficient for unbiasedness. Note also that these two estimators gave almost the same results, which are quite different from the estimators resulting in the bottom two graphs. For the EOP estimators to be unbiased, a flat line trend (i.e., linear with a slope of 0) over all years used in the estimators would have to exist. With a 5-year cycle, a flat line trend must have been true for the 10 years before any annual EOP estimate of growth. From the top graphs, we see that a flat line trend is definitely not indicated for three of the five diameter classes. Between 2006 and 2010, the pooled DC (Sheffield) estimator gave results that were at times closer to the results for the estimators in the top two graphs than the FIA EOP estimator, in the bottom left graph, although the trend through those years is not discernible in either of the EOP estimators.

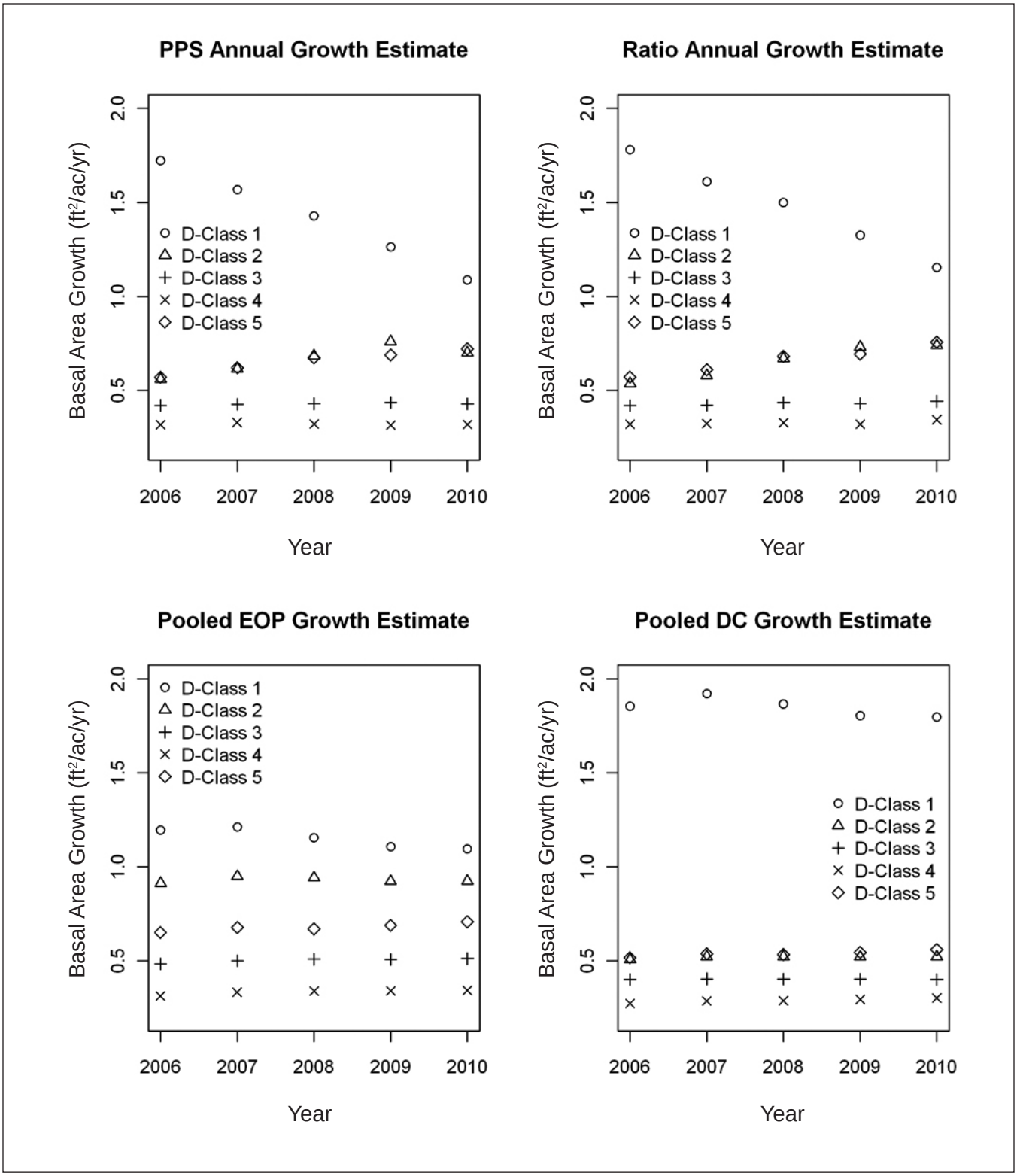


Figure 1.—Annual basal area growth estimates by the diameter classes given in Table 1 from each of the four estimators, clockwise from the top left: the probability proportional to size (PPS) estimator, the ratio estimator, the pooled diameter class (Sheffield) estimator, and the pooled EOP (FIA-temporally indifferent) estimator.

CONCLUSIONS

The field of statistics gives us many estimation tools to bolster analyses. All four estimators discussed here somehow use "outside information" to make annual estimates. In the estimators resulting in the top two graphs of Figure 1, the "outside information" has a clear relationship to the estimates of interest, because the observations span the estimates to which the data contribute. It is clear in the formulation of the EOP estimators and in Figure 2, that much of the outside information used in those estimators does not span the time estimated. In the results for 2010, for instance, Figure 2 shows that 80 percent of the information used in the EOP estimators is from "outside" of, and prior to, 2010. This prior information is incorporated under a model that assumes that the mean of the "outside" information is the same as the mean for 2010. It is not very helpful to start a search for trend by first assuming that there is not any trend. The description of continuous forest inventories as a sample of a three-dimensional population is uniquely informative. It arose from the recognition of the importance of the time of observation on the outcome of the sample and it is useful for putting temporally ordered observations into perspective while formulating intuitively appealing model-unbiased estimators of growth and trend.

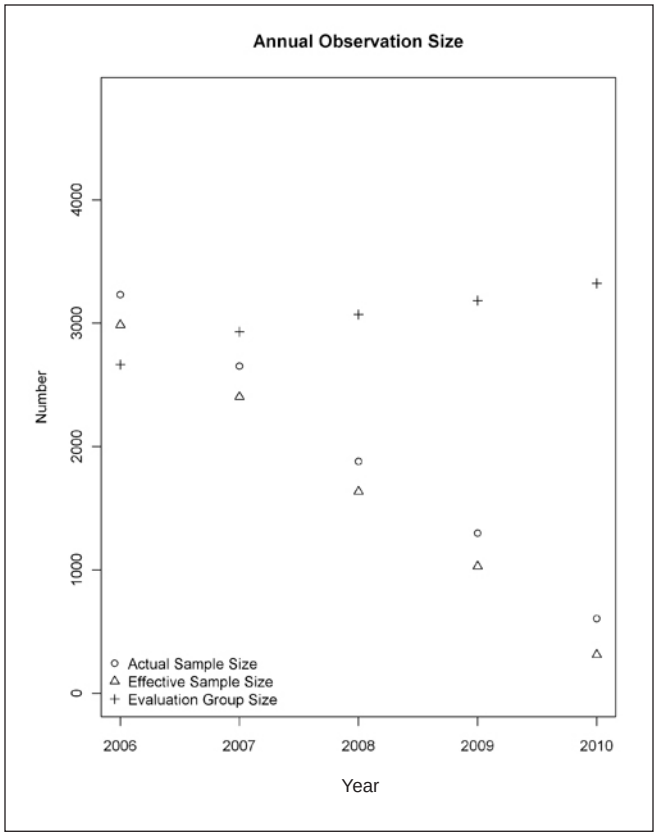


Figure 2.—The observation sizes of annual growth estimates for each year. The actual sample size is the number of plots with growth intervals spanning at least part of the year. The effective sample size is the sum of plot-year proportions covered by the plots making up the actual sample size. The evaluation group size is the number of plots used in the FIA EOP estimator (temporally indifferent) and the Sheffield DC EOP estimator. The majority of the plots used in the two pooled estimators (FIA and Sheffield) do not observe any part of the growth interval for that year.

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IMPROVING FIA TREND ANALYSIS THROUGH MODEL-BASED ESTIMATION USING LANDSAT DISTURBANCE MAPS AND THE FOREST VEGETATION SIMULATOR

Sean P. Healey, Gretchen G. Moisen, and Paul L. Patterson[1]

Abstract.—The Forest Inventory and Analysis (FIA) Program's panel system, in which 10-20 percent of the sample is measured in any given year, is designed to increase the currency of FIA reporting and its sensitivity to factors operating at relatively fine temporal scales. Now that much of the country has completed at least one measurement cycle over all panels, there is an immediate need for estimation strategies which make the best use of this sampling schedule. A primary obstacle is that only a fraction of plots can be considered current in any particular year. This leaves the analyst with a choice of ignoring annual trends or creating estimates one panel at a time and suffering precision losses which may render apparent year-to-year differences uninterpretable.

One option for increasing the temporal specificity of estimates is to update plot conditions for every year in a time series using the Forest Vegetation Simulator (FVS) and to use model-based estimation to create annual estimates using "observations" from every plot. The variance estimators used in such an approach would incorporate both sample and model uncertainty, the latter of which could be assessed at remeasured FIA plots. Disturbance maps created from time series of Landsat (or similar sensor) satellite imagery could be used to identify and appropriately alter FVS simulations for those plots which have been disturbed. Use of disturbance maps would allow sensitivity to year-to-year variation in the disturbance rate. FIA has recent experience in all of the components of the proposed approach including FVS, Landsat disturbance mapping, and model-based estimation. Further study to integrate these components into a production estimation system is warranted.

THE CHALLENGE OF FIA ANNUAL ESTIMATION

The Forest Service's FIA (Forest Inventory and Analysis) Program does not survey each of its plots every year. The sample is divided into random subsamples called panels, and each panel is remeasured once every 5 to 10 years (Patterson and Reams 2005). Measuring a fraction of the plots in a particular sample unit (e.g., a state) every year provides some sensitivity to forest changes as they occur throughout a measurement cycle. However, since the plot data for any cycle are collected uniformly over a 5-10 year period, one is left with the dilemma of using all plots to estimate conditions over a long and undifferentiated period, or making panel-wise estimates that provide high temporal specificity but low precision due to a low sample size. Once all plots have been surveyed, one can calculate a new moving average estimate every year (Roesch et al. 2002), but the period for such estimation is still an undifferentiated 5- or 10-year span, which can obscure the effects of discrete large-scale events such as fires, droughts, or insect outbreaks.

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Research is ongoing regarding the possibility of enhancing FIA trend analysis through use of the Kalman filter, a sequential application of composite estimators (Czaplewski and Thompson 2009), and mixed estimators (Van Deusen 2008). Building on concepts developed during the formative years of FIA's annual inventory (eg., Czaplewski 1999, McRoberts and Hansen 1999), this paper suggests an approach for identifying within-cycle trends by growing all plots (regardless of panel) forward in time with the Forest Vegetation Simulator (FVS) growth model (Crookston and Dixon 2005) so that there is an observed or modeled value for each plot in every year. As discussed below, this option would take advantage of a number of tools with which FIA has recent experience, including FVS, forest change detection using Landsat imagery, and model-based estimation.

USE OF FVS AND LANDSAT TO UPDATE PLOT VALUES

The FVS is maintained by the Forest Service's Forest Management Service Center and is delivered with executable code which automatically converts FIA data into an FVS-ready format. It is a distance-independent growth model that can project a wide range of stand characteristics over a 100-year time frame while simulating an equally wide range of disturbance/management scenarios. FVS is widely used by the Forest Service for forest planning in conjunction with FIA and other stand monitoring data. Because of its importance in the management community, FVS benefits from ongoing active calibration.

While FVS projections typically function at 5- or 10-year intervals, stand changes can also be produced in 1-year increments. In the approach we propose, each plot would be updated with FVS from the time of its last measurement to each subsequent point in time until it is re-measured (Fig. 1). Scenarios of undisturbed growth in FVS should provide a reasonable model for updating the majority of plots (i.e., growing forward all trees in the tree list, plus any changes due to mortality and recruitment functions), particularly since the maximum length of projection would be only 9 years and as few as 4 years in some states. However, a method of identifying disturbed (including managed) plots would be needed for two reasons: FVS projections for such plots using undisturbed dynamics could introduce significant error; and, more importantly, the value and point of producing within-cycle trend estimates would be greatly diminished if the monitoring system were insensitive to disturbance.

The Forest Service and FIA have extensive experience using the Landsat series of satellites to characterize the timing, type, and magnitude of forest disturbance (Nelson et al. 2009). Much of this experience has been gained through FIA's association with the NASA-funded North American Forest Dynamics project (NAFD). The NAFD project is currently producing a national wall-to-wall map of disturbance timing and type, and the Forest Carbon Management Framework (ForCaMF) project is currently producing disturbance timing, type, and magnitude maps for the entire National Forest System (approximately 75 million hectares). Furthermore, a follow-on to the Monitoring Trends in Burn Severity (MTBS) project called the Landscape Change Monitoring System is in development, targeting operational national-scale disturbance mapping. Results of these or other efforts could be used to direct disturbed plots into specialized scenarios to increase model accuracy and to introduce intra-cycle sensitivity to disturbance.

MODEL-BASED ESTIMATION

Model-based inference depends upon fundamentally different assumptions than the design-based methods used by most field-based inventories, including FIA's. (For a detailed description of the difference between model- and design-based inference, see Gregoire 1998.) Unlike design-based estimation, model-based methods treat observations as realizations of a random process (model). Model-based methods are appropriate for forest inventory situations where there is one

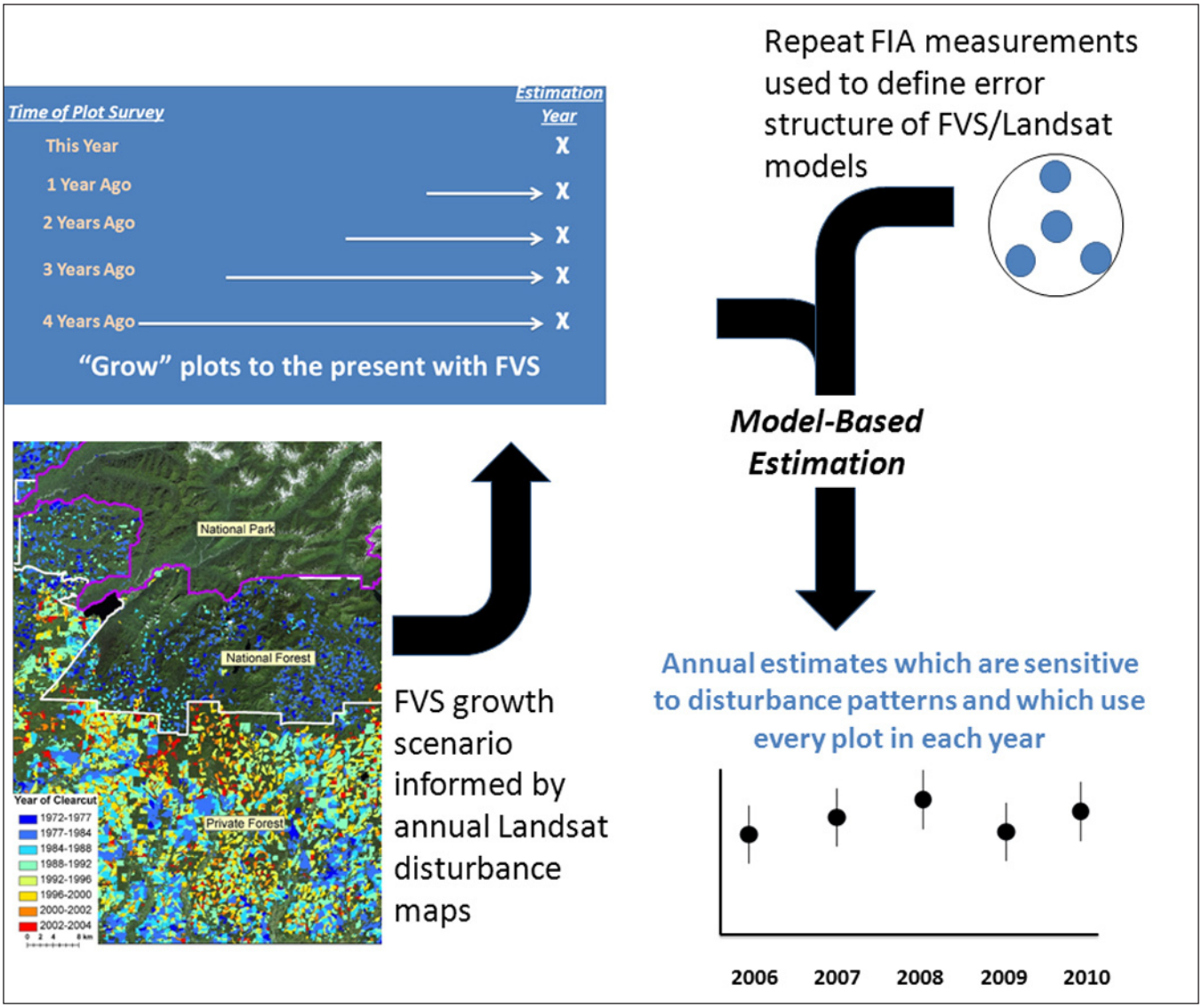


Figure 1.— Schematic of the estimation approach.

sample of plots where both the variable of interest and one or more predictors are known, and there is another, generally larger, sample in which only the predictors are known. Models built over the first sample are applied to the second sample, which is used to make a population estimate. Variance estimators incorporate elements of both sample uncertainty and model uncertainty. The authors have used this approach with FIA biomass measurements and predictor data from spaceborne lidar to predict biomass in California (Healey et al., in press).

In the idea we present, the entire FIA grid (all panels) constitutes the second type of sample; the current tree list is not known (or is known only for the most recent panel), but a tree list from some point in the past is known. This predictor tree list is used with FVS to model the forest condition to be estimated at each point in time (Fig. 1). Ongoing validation activities associated with the ForCaMF project mentioned above are comparing FVS predictions for incremental tree list changes with plot remeasurement occurring at intervals from 2 to 12 years. This work could be the basis for a larger validation effort, functioning as the first type of sample mentioned above by supplying model error rates to be used in variance estimates (Fig. 1). Model-based estimation should allow FVS-modeled updates which allow each plot to be used in estimating the forest condition of interest in every year.

ANTICIPATED BENEFITS

In general, using modeled observations in model-based estimation will tend to increase variance estimates relative to observations based on field measurements. However, in this case, use of model-based estimates would increase the sample number for any given year by a factor of 5 or 10. Tests are needed to determine the interaction of these two factors as they impact precision of annual estimates. One significant advantage of this approach is that repeated "observations" for each plot (through FVS models) will allow direct estimation of annual change (e.g., change in biomass per hectare). Currently, since each year's panel is independent of the previous year's, change must be inferred from differences in sequential estimates of a variable's "state." Addressing change directly, as illustrated in Figure 2, may lead to a better ability to compare inventory estimates to ancillary drivers such as housing starts or drought patterns. It would also allow more timely identification and reporting of forest change than would be possible from trend-based alternatives, some of which require several years of continued data collection before changes are confirmed.

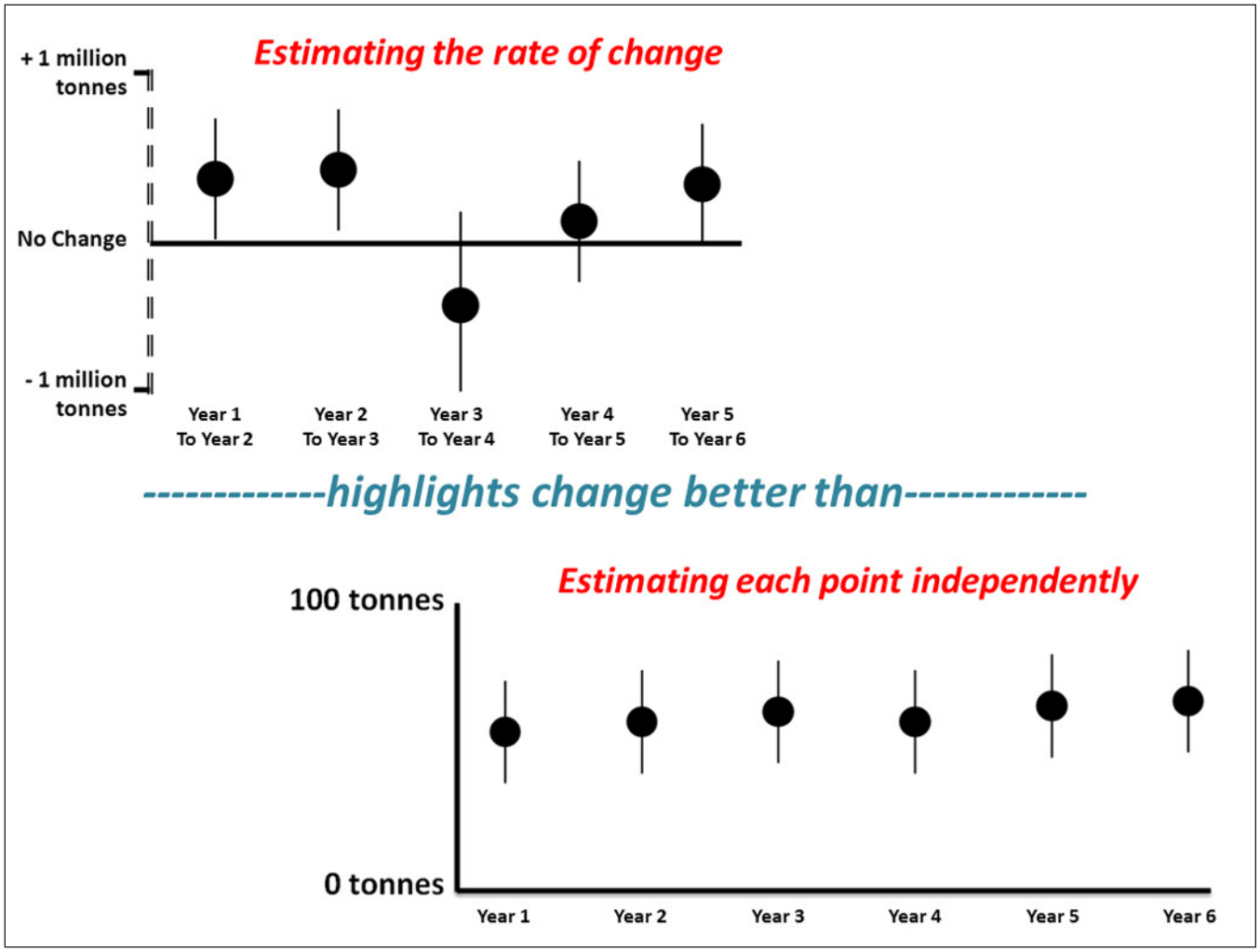


Figure 2.—Hypothetical illustration of possible benefits of estimating change directly. Estimating the difference between a forest attribute at two points in time allows ecosystem change to be assessed more directly than comparison of sequential state estimates. The incremental observations shown would only be possible because the Forest Vegetation Simulator (FVS) provides modeled observations of each plot annually.

CONCLUSIONS

1. Model-based estimation of FVS-derived intra-panel change may provide greater temporal specificity than other estimation methods.
2. Ongoing FIA work with FVS, Landsat disturbance mapping, and model-based estimation form a foundation from which future research may proceed.

ACKNOWLEDGMENTS

Thanks are due to Sara Goeking and Mark Nelson for substantive reviews.

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ADVANCEMENTS IN LiDAR-BASED REGISTRATION OF FIA FIELD PLOTS

Demetrios Gatziolis[1]

Abstract.—Meaningful integration of National Forest Inventory field plot information with spectral imagery acquired from satellite or airborne platforms requires precise plot registration. Global positioning system-based plot registration procedures, such as the one employed by the Forest Inventory and Analysis (FIA) Program, yield plot coordinates that, although adequate for some purposes, often contain substantial error. Conversely, the registration of Light Detection and Ranging (LiDAR) data is accurate and precise. Considering the proliferation of high density LiDAR data, there is potential to substantially improve plot registration. Earlier attempts were not successful because they relied solely on the relative location of mapped tree stems and local maxima in vegetation surfaces generated from the LiDAR data. In this study, registration is achieved by examining the correlation between plot canopy surfaces generated by using the FIA field data and modeled tree crowns and the corresponding vegetation surface derived from the LiDAR data. With the LiDAR vegetation surface remaining stationary, the modeled surface is jittered in two dimensions at regular intervals, and the correlation is computed for each moving instance. Assuming that it satisfies a set of consistency criteria, the moving instance for which correlation is maximized yields the plot coordinates. Gains in computational efficiency are realized via parallelization. Results from eastern Oregon show that precise—better than 2 m—registration is achieved for 80 percent of the investigated FIA plots.

INTRODUCTION

Meaningful integration of remotely sensed and forest inventory field plot data requires precise plot registration. Where this requirement is not met, the energy returned to the remote sensing instrument corresponds poorly to the trees on the plot. Spatial discrepancies between remotely sensed data and plot locations compromise the strength and validity of modeling and diminish the utility of the data. It has been shown that the effects of registration issues become more pronounced with smaller field plot sizes (Fluwelling 2009, Frazer et al. 2011), and shorter spatial continuity in the inventory parameter of interest (Gobakken and Næsset 2009, Goodchild et al. 1993).

Most National Forest Inventory (NFI) programs, such as the Forest Inventory and Analysis (FIA) Program of the U.S. Forest Service, have collected field plot location primarily to facilitate future navigation to permanent plots. Historically, plot coordinates were obtained via several methods, including manual transfer from orthophotos and digital raster graphics, and, since the mid-1990s by using global positioning system (GPS) technology. Repeated visits to permanent plots generated multiple coordinates for each plot. Rather than accepting the latest as the most accurate, the Pacific Northwest FIA Program (PNW-FIA) designed and implemented a procedure, known as plot grid management (PGM), which evaluates all coordinates for each plot and selects the one "most accurate." Anecdotal evidence suggests that PGM and continuous advancements in GPS technology have improved coordinate accuracy but precision issues remain. PNW-FIA's past efforts to improve plot

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coordinates by using high resolution airborne imagery from the National Agricultural Imagery Program (NAIP) and manual interpretation were limited by the NAIP imagery's poor registration, obliqueness, and inadequate contrast.

Unlike NAIP and most satellite imagery, data acquired with Light Detection and Ranging (LiDAR) technology have negligible registration errors, are unaffected by sun angle and shadows, and when collected at high density provide detailed, three-dimensional (3D) characterizations of tree crowns and terrain. Gatziolis (2009) used a variant of the world-view algorithm to register fixed-radius, FIA-like plots in the temperate rainforest of Oregon. He linked 3D point patterns obtained by processing the LiDAR return cloud and corresponding to the locations of identified individual tree tops to point patterns generated from field plot data. Of 45 plots in the study area only 3 (11 percent) were registered with submeter precision, although for 18 more (40 percent) registration precision ranged between 1 and 5 m. A similar approach (Dorigo et al. 2010) was evaluated in Austria using lower density LiDAR data and variable radius inventory plots. It, too, relied on matching tree tops derived from plot data to tops identified on a LiDAR-derived vegetation height surface. The plot location was determined iteratively as the one that minimized the weighted sum of height differences between matched trees. It was reported that 67 percent of plot centers were registered within 4 m from of location identified by an image analyst.

While these approaches improved the registration for most plots, registration was precise (<2 m) for very few. By matching only tree tops, potentially valuable information on the shape and spatial arrangement of individual crowns and canopy openings is not utilized. Investigations that incorporate crown shape and spatial distribution into plot registration techniques are therefore warranted, especially when considering the recent proliferation of publicly available, high density LiDAR data acquisitions that can support these techniques. One such effort is explored and evaluated in this study. To enhance potential application, technique development focused on full automation, computational efficiency, quantitative criteria that determine plot registration success or failure, accommodation of standard and clustered plot designs, and dynamic adjustment to local vegetation structure conditions.

STUDY AREA AND METHODS

The Malheur National Forest in eastern Oregon is dominated by open, mostly coniferous forests and gentle terrain. Discrete return, high density LiDAR data of approximately nine returns per square meter were acquired over the entire Forest in 2007 and 2008. A 0.91-m ground digital elevation model (DEM) was provided by the data vendor. A highest-return Canopy Height Model (CHM) was derived by subtracting DEM values from the elevation value of each return, as a 0.5-meter raster. Individual tree crowns were delineated via the valley-following algorithm on a smoothed version of the CHM and the location of each tree top was recorded (Fig. 1).

For each subplot of the 82 FIA plots within the study area field-visited within 2 years of the LiDAR acquisition date, 3D models were developed using field assessed tree location relative to subplot center, height, and species. Each subplot model was constructed using species-specific crown shapes ranging from conical to ellipsoidal or weighted combinations of the two, and modeled estimates of crown radius and length (Donnelly 1997, Shaw 2009). The ensuing 3D subplot representation was then rasterized to form a 0.5-m Subplot Height Model (SHM); crown portions outside the subplot boundary were excluded (Fig. 2). The retrieval of subplot center coordinates was based on the correlation between the stationary CHM and instances of the corresponding SHM moving at one-cell increments within a 40 by 40 m window centered at the initial coordinates retrieved from the production FIA database.

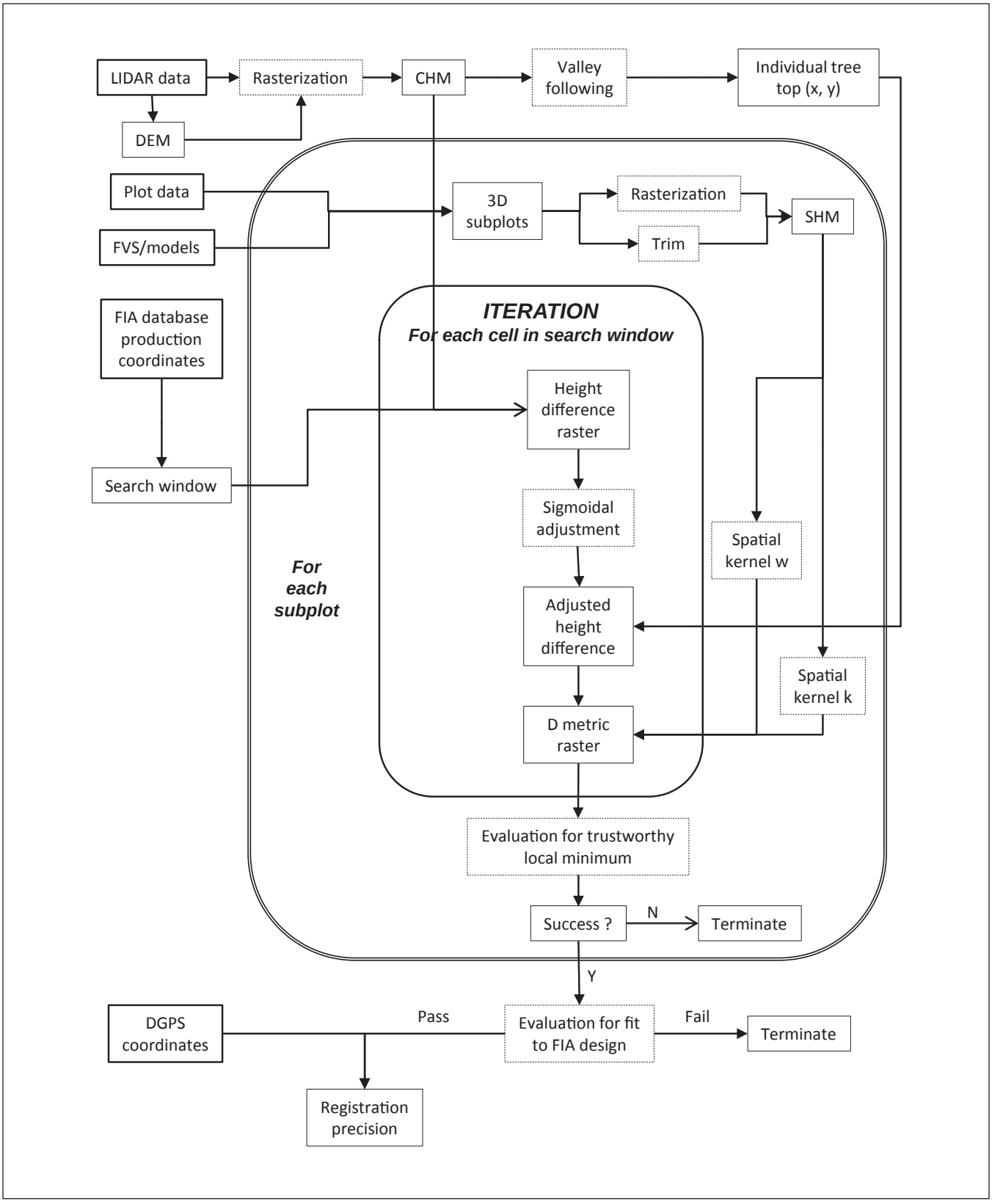
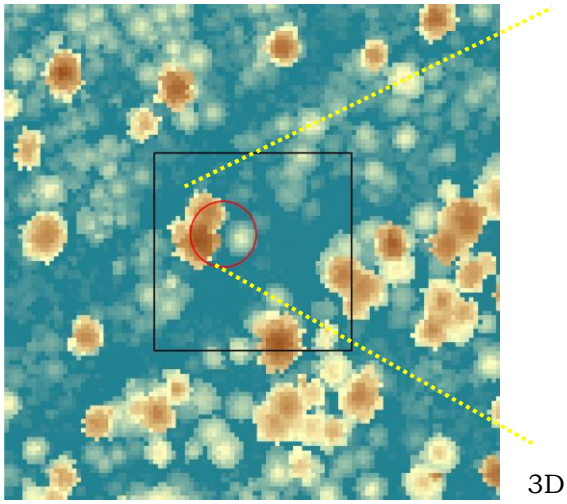
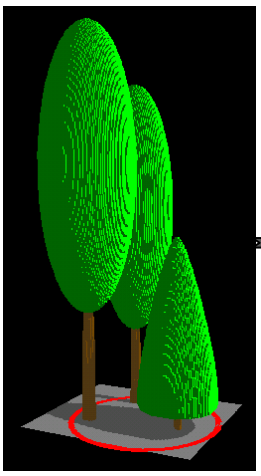


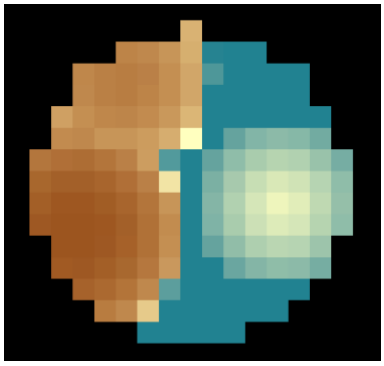
Figure 1.—Flow chart of the registration process. See text for acronym definitions.



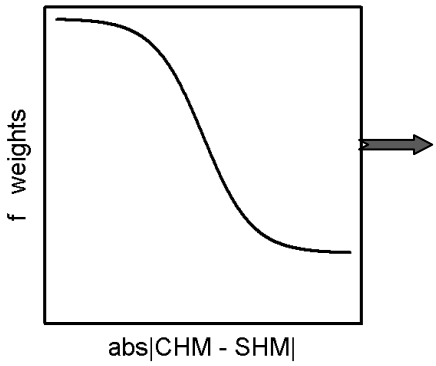
LIDAR CHM and search rectangle



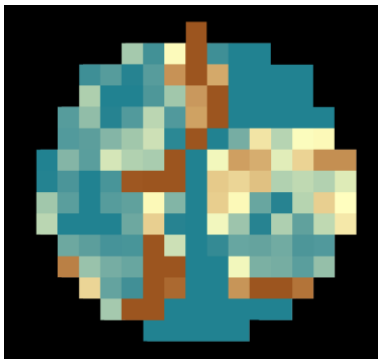
3D subplot model via field and FVS data

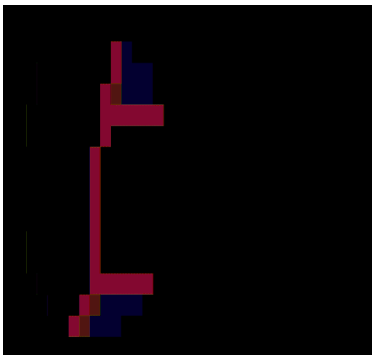


SHM

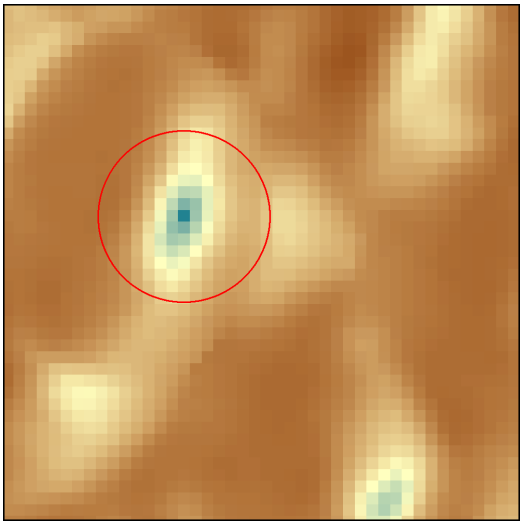


Sigmoidal height-difference adjustment and resulting raster





Weights by kernel *k*



D metric raster for a 40 x 40 m search window exhibiting a pronounced local minimum coincident with the center of an FIA subplot

Figure 2.—Illustration of the LiDAR data-based registration for an FIA plot. Darker raster tones indicate higher values or weights. See text for acronym definitions.

The correlation metric D

$$D = \sum_{i}^{N} f_i w_i k_i \left| CHM_i - SHM_i \right| \qquad [1]$$

across the search area was computed as the sum of absolute height differences between CHM and each SHM instance scaled by a nonspatial function *f* and two spatial kernels *k* and *w*. Note that N in Equation (1) denotes the number of cells in a subplot. Function *f* has sigmoidal form. The slope of the sigmoid is inversely related to crown height variability (steeper for uniform canopies). Kernel *k* is computed once for each SHM as the distance between cells with openings (defined as those with SHM <2 m), and vegetation cells (Fig. 1). Kernel *w* assigns low weight to all cells in SHM instances corresponding to crowns in the CHM with their top outside the boundary of the subplot instance. Kernel *w* neutralizes the effect of trees not tallied in the subplot but having a crown portion within it. If the two-dimensional representation of metric *D* exhibits a single local minimum that is at least one standard deviation from its mean across the search area, the coordinates of the cell center at the minimum are considered a trusted subplot match. The plot coordinates are computed from subplot matches, if any, provided that subplot arrangement approximates the FIA clustered design. Scripts were coded in C with parallelization support provided by the OpenMP library. Plot coordinates derived via matching were compared to those obtained by post-processed differential GPS (DGPS) with internally calibrated precision of 1.05 m.

RESULTS AND DISCUSSION

The root mean square discrepancy between production and DGPS coordinates was 8.86 m. At this (mis)registration level, the mean areal overlap between the actual and assumed subplot areas is only 28 percent. Sixty-six of the plots, over 80 percent, were registered within 2 m from the DGPS data. For more than half of those plots, all four subplots were registered. For six plots, the distance to DGPS references was between 2 and 5 m with all but one of them having just one subplot registered (Table 1).

Table 1.—Plot registration results

Distance to DGPS Coordinates (m)	Number of Plots (percent)	Mean of Per-plot Registered Subplots
<2	66 (80.5)	2.89
2-5	6 (7.3)	1.33
Unable to register	10 (12.2)	0.40

The process failed for 10 plots (12 percent) primarily because no trustworthy match could be found for any of the subplots, although in two cases matches were found but were rejected as incompatible with the FIA design. There were no false positive registrations.

The results indicate that the four subplots in the FIA design compensate for the limited areal extent of the individual subplot. The few crowns in most FIA subplots do not usually represent a unique tree arrangement within the search area but the cluster of four subplots allows the often many individual subplot matches to be filtered down to a single trusted matching solution for the plot. Because the majority of registration failures were associated with estimates of crown radius or shape substantially different from those observed in the LiDAR return cloud, assessing crown attributes via regional models might be a better choice than using generalized, national models. The weighting functions in Equation (1) quantify heterogeneity in the canopy and of openings that is apparent and prevalent in the study area. In such conditions, precisely registered plots can be used to assess the *f*, *w*, and *k* parameters and then used them to register other plots in the region. Parameter optimization will likely yield a pronounced local minimum in the distribution of metric *D* that can be automatically detected by using as threshold a moment in the distribution of *D*, such as the one standard deviation suggested. In the event that the crown and opening arrangement in one or more of the subplots is uncommon, plot registration can be achieved within search areas much larger than the one used in this study. However, where canopies exhibit uniformity and gaps are rare, as is typical in the Oregon temperate rainforest, consistent registration appears improbable. In such conditions, differences in canopy height

and shape across the search area are comparable in magnitude to, if not smaller than, the discrepancies between real and modeled subplot crowns, and thus they rarely yield a unique and trusted matching solution. In open forests, canopy variability dominates imprecision in the modeled tree crowns, thereby allowing plot to be precisely registered.

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HOT-DECK MATCHING OF ANNUAL INVENTORY PLOTS TO ENHANCE TRENDS AND PROJECTIONS

Paul C. Van Deusen[1]

Abstract.—Annual forest inventory plots awaiting remeasurement can be matched with plots that can serve as pseudo remeasurements using various hot-deck matching schemes. It will be shown that some matching approaches allow for short-term projections that reflect a business as usual (BAU) scenario and require few assumptions. These methods also allow for creating scenarios that reflect increasing frequency of particular events relative to what occurs in the BAU scenario. Scenarios are generated where increasing future harvest levels are controlled to demonstrate this capability. The moving average, as applied by U.S. Forest Service Forest Inventory and Analysis (FIA), is typically linked to an evaluation group. It is noted that this linkage is unnecessary and limits the value and flexibility of the method. The combination of short-term projections with an n-year moving average is suggested to provide trend estimates that encompass the current year and a few years into the future. These methods are not difficult to implement and they expand the utility of FIA data. As the number of FIA plots with multiple remeasurements increases, estimation methods should be enhanced to take advantage of the increasing value of the database. The methods are demonstrated with several operational size applications to FIA data.

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POSTERS

A COMPARISON OF FIA PLOT DATA DERIVED FROM IMAGE PIXELS AND IMAGE OBJECTS

Charles E. Werstak, Jr.[1]

Abstract.—The use of Forest Inventory and Analysis (FIA) plot data for producing continuous and thematic maps of forest attributes (e.g., forest type, canopy cover, volume, and biomass) at the regional level from satellite imagery can be challenging due to differences in scale. Specifically, classification errors that may result from assumptions made between what the field data represent and what the corresponding spectral information of the image pixels depict. This investigation aimed at determining whether image objects derived from Landsat TM imagery can be used as an alternative to a 3 by 3 neighborhood of pixels for characterizing forested FIA plots. Results showed strong positive correlations between the different scales of base map units across all of the image derivatives. Further examination of the data using the Wilcoxon signed rank test for paired samples indicated that in most cases, finer level image objects were a better representation of the 3 by 3 neighborhood of pixels than coarser ones and some image derivatives performed better than others. The same tests were applied to a subset of plots dominated by quaking aspen (*Populus tremuloides* Michx.) with similar results. Information gained may provide further insight into object based segmentation and classification methods using FIA plot data, satellite imagery, and ancillary geospatial data.

INTRODUCTION

Several studies have compared image pixel-based classification to image object-based segmentation and classification for mapping different vegetation attributes from remote sensing imagery, many of which have shown that using image object-based segmentation combined with decision tree image classification methods often achieve higher accuracies (Chubey et al. 2006, Gao and Mas 2008, Hay et al. 2005, Karl and Maurer 2010, Kim et al. 2010, Yasumasa et al. 2011).

Quaking aspen (*Populus tremuloides* Michx.) was selected as the species of interest because it is a critical species that supports wildlife and livestock, watershed function, the forest products industry, landscape diversity, and recreation in the Interior West (Bartos and Campbell 1998). Studies have indicated that changes in fire regimes, an increase in herbivore presence in young aspen stands, and recent drought episodes are the main factors for increased mortality rates in aspen (Deblander et al. 2010).

This objective of this investigation was to determine whether different scales of image objects derived from Landsat TM imagery can be used as an alternative to a 3 by 3 neighborhood of pixels for characterizing canopy cover of forested Forest Inventory and Analysis (FIA) plots and aspen dominated FIA plots.

FIA PLOT DATA

Multi-condition forested plots having 10 or greater percent canopy cover of live trees were queried from the FIA database for Utah, inventory years 2000-2009, resulting in 3,224 plots. Basal area per acre

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was computed by species and summed to the plot level. The Interior West core optional variable crown cover percent (CRCOVPCT_RMRS) was used in conjunction with basal area per acre, to calculate tree cover and tree cover by species (absolute cover) for the plots (USDA Forest Service 2011). Ultimately, these values were used to calculate the percent canopy cover by species (relative cover) for the plots.

PREDICTOR DATA

Three different Landsat TM scenes acquired over Utah during the summer of 2009 were used in the analysis (Table 1). The scenes were converted to Top-Of-Atmosphere (TOA) reflectance using standard Landsat-specific methods. The following vegetation indices and image transformations were calculated for each scene:

1. Enhanced vegetation index (EVI)
2. Normalized difference vegetation index (NDVI)
3. Normalized difference moisture index (NDMI)
4. Modified soil adjusted vegetation index (MSAVI2)
5. Tasseled cap transformation (TCAP)
6. Principal components analysis (PCA)

Layer stacks were created for each scene using the following derivatives: Landsat TM reflectance bands 1:6, NDVI, PCA first principal component, and TCAP bands 1:3. Due to anomalies with the blue bands resulting from the TOA conversion, EVI was calculated on the Landsat Standard Terrain Correction (Level 1T) product.

NEIGHBORHOOD PIXELS AND IMAGE OBJECTS

A 3 by 3 neighborhood of pixels was generated for each forested FIA plot location to correspond to the FIA plot design. To create the 3 by 3 neighborhoods around the 3,224 FIA plots, point feature classes of the X and Y plots (plot center of subplot one) were converted to 30 m thematic raster images, and then 3 by 3 neighborhood filters were applied. As a Landsat pixel is 30 m by 30 m or 900 m^2, a 3 by 3 neighborhood consisting of nine pixels is 8,100 m^2 or a little greater than 2 acres. The area of one FIA subplot is 168.11 m^2, therefore the area of four FIA subplots is 1809.56 m^2. The outermost circumference of four FIA subplots is 6052.08 m^2 or just under 1.5 acres, which is almost 75 percent of the 3 by 3 neighborhood pixel area (Fig. 1A).

Several different scales of image objects were generated from the Landsat TM layer stacks using Trimble eCognition software (Definiens 2009). Using National Agriculture Image Program (NAIP) 1 m color-infrared imagery acquired in 2011 as a backdrop, the different scales of image objects were visually evaluated to determine which scale(s) best delineated forest stands (Figs. 1B, 1C, and 1D). Ultimately, two different scales of image objects (scale parameter 25 or “coarse”, and scale parameter 15 or “fine”) were identified for use in this analysis. Table 1 is a summary of the image object acreages for each TM scene.

Table 1.—Acreage summaries for image objects corresponding to forested FIA plots. Image object size is a function of the scale parameter.

TM Scene (Path/Row)	Number of FIA Plots	eCognition Scale Parameter	Average Size (Acres)	Minimum Size (Acres)	Maximum Size (Acres)
37/32	691	25	161.36	10.23	717.00
37/32	691	15	62.14	2.45	232.40
38/31	153	25	158.28	21.57	695.21
38/31	153	15	60.54	9.56	175.02
38/33	466	25	161.86	12.90	607.58
38/33	466	15	61.66	5.56	248.42

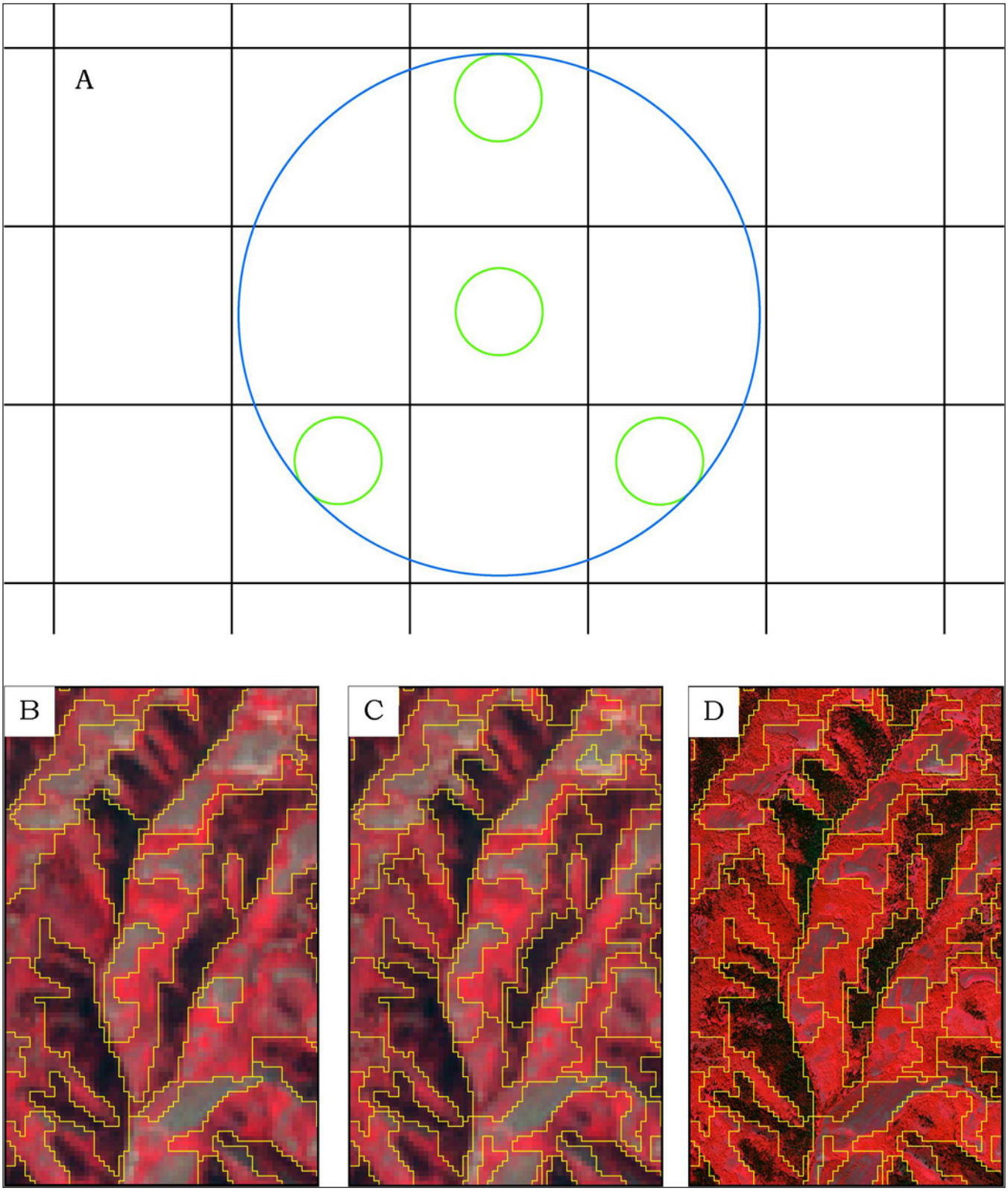


Figure 1.—An example of the FIA plot design over a grid of Landsat TM pixels (A) followed by examples of the two different scales of image objects used in the analysis overlaid on Landsat TM (RGB 4, 3, 2) and 2011 1 m NAIP (RGB 4, 3, 2) (D). Scale factor 25 (B) is coarse, scale factor 15 (C) is fine, and scale factor 15 (D) is fine.

MAP UNIT COMPARISONS

Zonal statistics were calculated for the predictor data using the two different scales of image objects and the 3 by 3 neighborhood pixel areas for each Landsat TM scene. Simple linear correlation was used to examine the relationships between the zonal means of the 3 by 3 neighborhood pixel areas and the corresponding image objects for the forested FIA plots for all of the predictor layers. The scatterplots (Fig. 2A) showed strong positive correlations between the different scales of base map units across all of the image derivatives with the finer scaled image objects consistently having higher Pearson's r values (Table 2). This was expected due to eCognition's homogeneity criterion, which is a combination of spectral homogeneity and shape homogeneity, used to produce image objects. Essentially, the upper heterogeneity threshold is determined by the maximum standard deviation derived from the weighted input image layers and controlled by the scale parameter—the lower the scale parameter, the lower the threshold, the smaller the image objects (Definiens 2009).

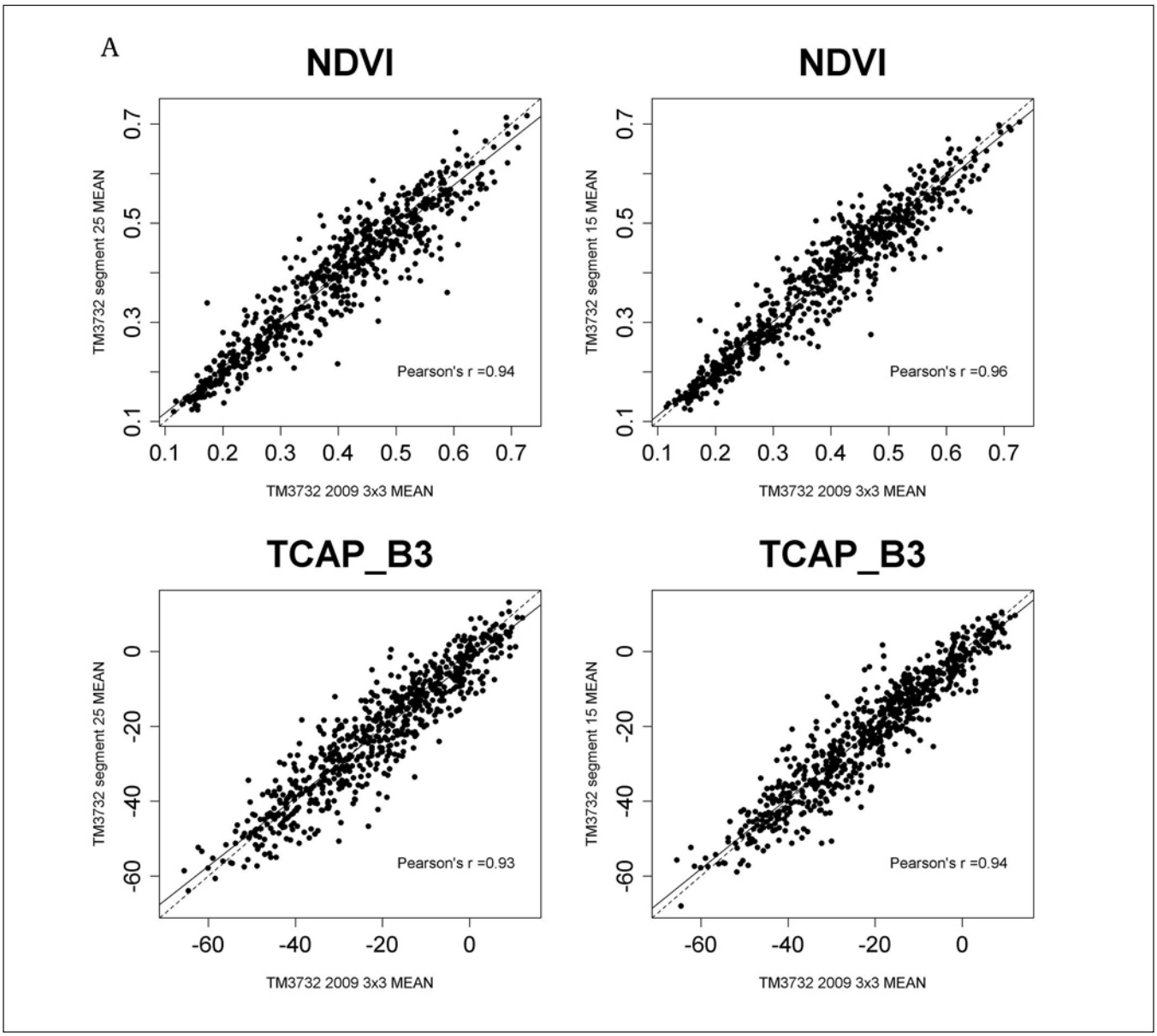


Figure 2A.—An example of scatterplots (NDVI and TCAP Band 3—Wetness) for forested FIA plots showing strong positive correlations between the 3 by 3 pixel area values and the image object values.

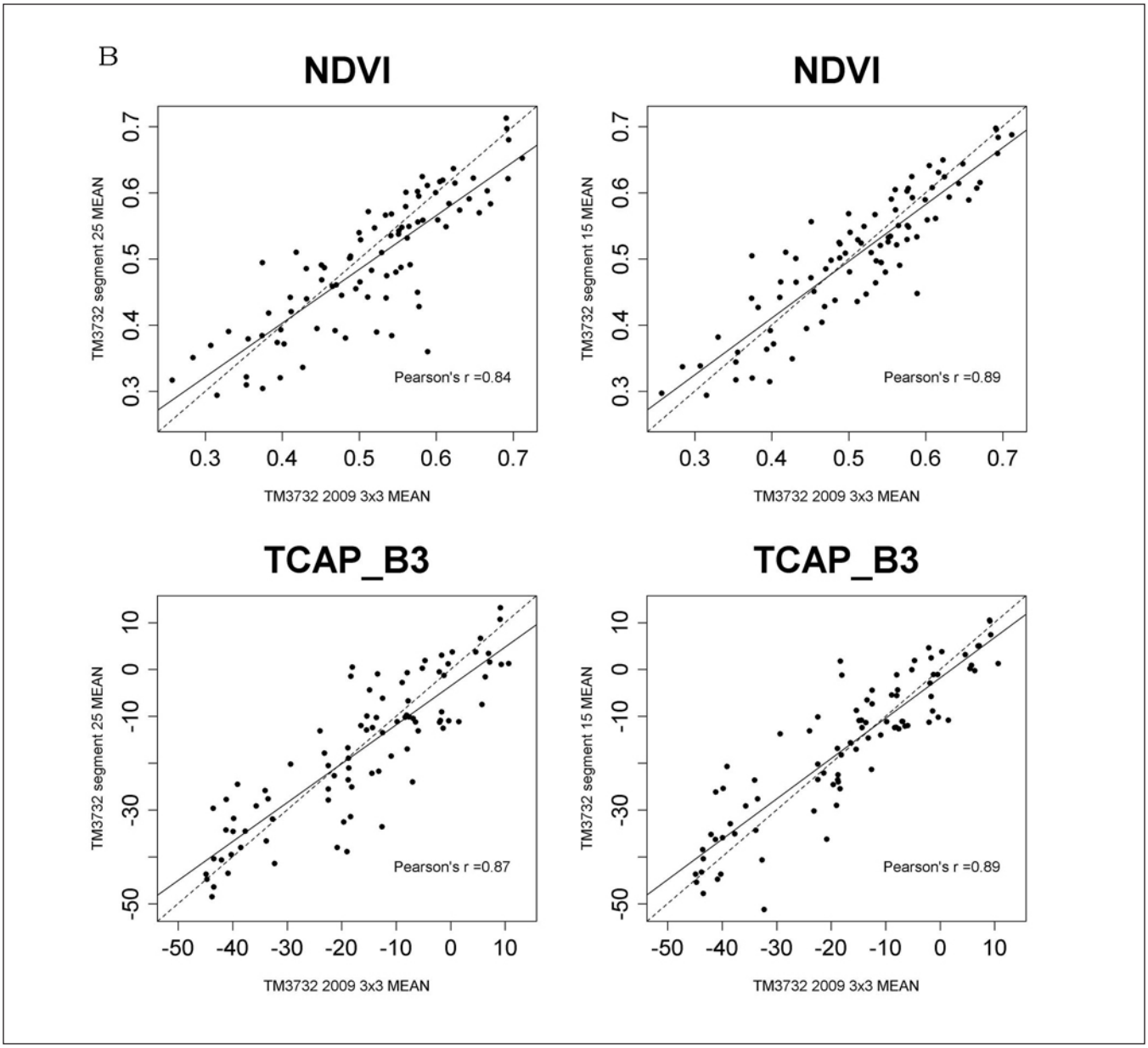


Figure 2B.—An example of scatterplots (NDVI and TCAP Band 3—Wetness) for aspen plots with a relative cover >50 percent showing strong positive correlations between the 3 by 3 pixel area values and the image object values.

Table 2.—Results of the 3 by 3 neighborhood pixels compared to image objects for forested FIA plots. P values less than α = 0.05 are bold.

TM Scene (Path/Row)	N	Image Derivative	Pearson's r		Wilcoxon Signed Rank Test	
			Scale 25	Scale 15	Scale 25	Scale 15
37/32	691	EVI	0.9	0.94	0.1551	0.7078
		MSAVI2	0.95	0.96	**0.0001**	**0.0311**
		NDMI	0.91	0.93	**0.0041**	**0.0199**
		NDVI	0.94	0.96	**0.0006**	0.0665
		PCA(1)	0.95	0.97	**0.0290**	0.0505
		TCAP(1)	0.95	0.97	**0.0445**	0.0567
		TCAP(2)	0.93	0.95	**0.0171**	0.3549
		TCAP(3)	0.93	0.94	**0.0059**	**0.0203**
38/31	153	EVI	0.91	0. 95	0.0953	**0.0097**
		MSAVI2	0.94	0.96	0.8931	0.2189
		NDMI	0.92	0.95	0.5368	0.9075
		NDVI	0.94	0.96	0.9594	0.1984
		PCA(1)	0.93	0.96	0.4797	0.7150
		TCAP(1)	0.93	0.95	0.5119	0.7993
		TCAP(2)	0.92	0.96	0.3960	**0.0373**
		TCAP(3)	0.93	0.95	0.6072	0.8845
38/33	466	EVI	0.93	0.95	0.5420	0.4122
		MSAVI2	0.96	0.97	0.1684	0.3393
		NDMI	0.94	0.95	**0.0048**	**0.0228**
		NDVI	0.96	0.97	0.2911	0.4211
		PCA(1)	0.97	0.98	0.2528	0.9638
		TCAP(1)	0.97	0.98	0.4766	0.7257
		TCAP(2)	0.95	0.96	0.4616	0.3658
		TCAP(3)	0.94	0.96	**0.0009**	**0.0204**

FIA plots with a relative cover greater than 50 percent of quaking aspen were filtered from the whole sample and simple linear correlations applied. The scatterplots again showed strong positive correlations (Fig. 2B) and the finer scaled objects consistently had higher Pearson's r values (Table 3).

To get a further understanding of the relationships between the pixel-based and object-based values, a Wilcoxon signed rank test for paired samples was used to test for differences between the 3 by 3 pixel neighborhood and a) the coarser image object values, and b) the finer image object values. Results (Table 2) of the test when applied to the forested FIA plots showed that:

1. Sometimes finer scale objects more closely represented the 3 by 3 pixel area values.
2. Often the 3 by 3 pixel area values were the same as the image object values.
3. Sometimes the 3 by 3 pixel area values were different than the image object values.
4. Rarely the coarser scale objects more closely represented the 3 by 3 pixel areas.

MSAVI2, NDMI, and TCAP(3) from TM scene 3732 and NDMI and TCAP(3) from TM scene 3833 had very low p values for the 3 by 3 pixel areas when compared to both scales of image objects, meaning that neither scale of image objects are the same as the 3 by 3 pixel areas for those particular image derivatives. Applying a Wilcoxon signed rank test for paired samples to the subset of quaking aspen plots (Table 3) had comparable results to that of the forested FIA test where similar derivatives were significantly different from the 3 by 3 pixel values at both scales.

1. Often finer scale objects more closely represented the 3 by 3 pixel area values;

Table 3.—Results of the 3 by 3 neighborhood pixels compared to image objects for aspen plots with a relative cover ≥50 percent. P values less than α = 0.05 are bold.

TM Scene (Path/Row)	N	Image Derivative	Pearson's r		Wilcoxon Signed Rank Test	
			Scale 25	Scale 15	Scale 25	Scale 15
37/32	88	EVI	0.83	0.92	**0.0040**	0.0745
		MSAVI2	0.83	0.89	**0.0098**	0.2078
		NDMI	0.85	0.89	0.3207	0.8183
		NDVI	0.84	0.89	**0.0118**	0.2123
		PCA(1)	0.85	0.89	0.4202	0.1062
		TCAP(1)	0.85	0.89	0.2479	**0.0461**
		TCAP(2)	0.83	0.9	**0.0042**	0.1035
		TCAP(3)	0.87	0.89	0.5114	0.7704
38/31	34	EVI	0.91	0.92	0.9596	0.1906
		MSAVI2	0.91	0.94	**0.0249**	0.1629
		NDMI	0.91	0.94	**0.0328**	0.2556
		NDVI	0.91	0.94	**0.0299**	0.1682
		PCA(1)	0.9	0.95	0.1430	**0.0036**
		TCAP(1)	0.9	0.95	0.1629	**0.0038**
		TCAP(2)	0.92	0.95	0.3880	0.8527
		TCAP(3)	0.91	0.94	**0.0445**	0.2280
38/33	43	EVI	0.89	0.93	**0.0066**	**0.0010**
		MSAVI2	0.96	0.97	**0.0006**	**0.0002**
		NDMI	0.9	0.93	**0.0005**	**0.0006**
		NDVI	0.94	0.96	**0.0006**	**0.0001**
		PCA(1)	0.99	0.99	0.9762	0.9381
		TCAP(1)	0.99	0.99	0.7154	0.6712
		TCAP(2)	0.93	0.96	**0.0013**	**0.0007**
		TCAP(3)	0.9	0.93	**0.0019**	**0.0048**

2. Sometimes the 3 by 3 pixel area values were the same as the image object values;
3. Sometimes the 3 by 3 pixel area values were different than the image object values and
4. Rarely the coarser scale objects more closely represented the 3 by 3 pixel areas.

EVI, MSAVI2, NDMI, NDVI, TCAP(2), and TCAP(3) from TM scene 3833 all had very low p values for the 3 by 3 pixel areas when compared to both scales of image objects meaning that neither scale of image objects are the same as the 3 by 3 pixel areas for those particular image derivatives.

The very low p values from both the forested FIA plots and quaking aspen plots may be attributed to complex forest stand characteristics (structure and composition) coupled with the local variance structure of the imagery and therein, the resulting image objects. In other words, the differences in the local variance structure related to the forest stand structure and composition with respect to the scale of the image objects generated for these scenes and for those particular derivatives.

Additionally, the results of the Wilcoxon signed rank test for paired samples when applied to the subset of quaking aspen plots seems to infer that an even finer scale of image objects may be needed to delineate and characterize specific forest types more effectively.

FUTURE WORK

Additional analyses is needed to further understand the relationships between forested FIA plots and image objects for use in producing continuous and thematic maps of forest attributes at the regional level. Finer scales of image objects may help to better delineate

smaller homogeneous forest stands, mixed forest stands where the proportions of a particular species (e.g., quaking aspen) are less than what is typically considered "dominant" (>50 percent relative cover), and forest structure.

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IS LODGEPOLE PINE MORTALITY DUE TO MOUNTAIN PINE BEETLE LINKED TO THE NORTH AMERICAN MONSOON?

Sara A. Goeking and Greg C. Liknes[1]

Abstract.—Regional precipitation patterns may have influenced the spatial variability of tree mortality during the recent mountain pine beetle (*Dendroctonus ponderosa*) (MPB) outbreak in the western United States. Data from the Forest Inventory and Analysis (FIA) Program show that the outbreak was especially severe in the state of Colorado where over 10 million lodgepole pines (*Pinus contorta* Dougl. Ex Loud.) succumbed to MPB between 2002 and 2009. Aerial detection maps of MPB–related mortality show that the infestation was initially widespread and evenly distributed throughout the range of lodgepole pine in Colorado, but gradually became more severe in the northern portion of the state. Because southern Colorado receives relatively high summer precipitation due to the effects of the North American monsoon (NAM), the spatial pattern of MPB-related mortality suggests that infestation severity was lower in areas with the higher summer precipitation. This study investigated the link between lodgepole pine mortality due to MPB and seasonal precipitation patterns associated with the NAM in Colorado. Data regarding insect-related tree mortality and damage data were summarized from FIA data collected between 2002 and 2009, and gridded precipitation data were acquired from the North American Regional Reanalysis Project. Results indicated that while absolute NAM-related precipitation was not an important predictor of infestation severity, the deviation of a five-year average of summer and fall precipitation relative to climatic means was important.

INTRODUCTION

An outbreak of mountain pine beetle (Dendroctonus ponderosae) (MPB) has killed millions of trees across the western United States and Canada in the past decade. In Colorado alone, over 10 million lodgepole pines (Pinus contorta Dougl. Ex Loud.) died due to MPB infestation between 2002 and 2007 (Thompson 2009). Thompson et al. (2010) noted a spatial pattern in the distribution of insect-related mortality of lodgepole pine in Colorado. The relatively minor infestation severity in the southern part of the state mirrors the distribution of summer precipitation related to the North American monsoon (NAM). During the months of July, August, and September, the NAM alters regional wind patterns and introduces tropical moisture to northwestern Mexico and parts of the southwestern United States, including southern Colorado (Higgins et al. 1997). As a consequence, these areas experience relatively high seasonal precipitation until wind patterns return to a more dry and westerly flow in autumn. Based on this geographical phenomenon, it seems possible that MPB infestation severity is inversely related to seasonal precipitation associated with the NAM.

The purpose of this study was to identify a subset of stand-level and precipitation variables that have the strongest influence on infestation severity. Hicke and Jenkins (2008) identified several tree-level and stand-level variables that affect the susceptibility of lodgepole pine to MPB. However, the influence of

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monsoonal precipitation patterns on the severity of MPB infestations in the southwestern United States has not yet been explored. Based on the apparent geographically inverse linkage between NAM-related precipitation and lodgepole pine mortality due to mountain pine beetle, we expected that cumulative precipitation for the months of July, August, and September would be among the best predictors of infestation severity.

METHODS

Stand-level data were queried from the national Forest Inventory and Analysis (FIA) database. Between 2002 and 2009, a total of 497 FIA plots with at least one tallied lodgepole pine were measured in Colorado. This analysis included 248 Colorado plots that contained a minimum of 20 tallied lodgepole pines that were either live or recent mortality trees at the time of survey; 185 plots included at least one tree with insect-related damage or mortality on the plot. Infestation severity was calculated as the percentage of tallied lodgepole pines that were recorded either as mortality trees with insects listed as the mortality agent, or as live trees with severe insect damage. Infestation severity was negative log-transformed for normality.

Independent variables included both stand-level variables, which were queried from the FIA database, and precipitation data (see Table 1). Because field

Table 1.—Variables considered as potential predictors of insect-caused lodgepole pine damage and mortality. Data sources are the National Forest Inventory database (FIADB) and North American Regional Reanalysis (NARR) Program. Intervals used to calculate 3-year and 5-year means end in the year equal to the median mortality year.

Variable	Type	Source
-Log(Percent [damage + mortality])	Continuous	FIADB (calculated)
Measurement year	Class	FIADB
Median mortality year	Class	FIADB (calculated)
Elevation	Continuous	FIADB
Stand age	Continuous	FIADB
Live basal area	Continuous	FIADB
Number of all trees	Count	FIADB (calculated)
Number of lodgepole pines	Count	FIADB (calculated)
Mean diameter at breast height (d.b.h.)	Continuous	FIADB (calculated)
Standard deviation of d.b.h.	Continuous	FIADB (calculated)
Mean tree height	Continuous	FIADB (calculated)
Winter (Jan/Feb/Mar) climatic mean, 1981-2010	Continuous	NARR (calculated)
Spring (Apr/May/Jun) climatic mean, 1981-2010	Continuous	NARR (calculated)
Summer (Jul/Aug/Sep) climatic mean, 1981-2010	Continuous	NARR (calculated)
Fall (Oct/Nov/Dec) climatic mean, 1981-2010	Continuous	NARR (calculated)
Winter (Jan/Feb/Mar) 3-yr mean	Continuous	NARR (calculated)
Spring (Apr/May/Jun) 3-yr mean	Continuous	NARR (calculated)
Summer (Jul/Aug/Sep) 3-yr mean	Continuous	NARR (calculated)
Fall (Oct/Nov/Dec) 3-yr mean	Continuous	NARR (calculated)
Winter (Jan/Feb/Mar) 5-yr mean	Continuous	NARR (calculated)
Spring (Apr/May/Jun) 5-yr mean	Continuous	NARR (calculated)
Summer (Jul/Aug/Sep) 5-yr mean	Continuous	NARR (calculated)
Fall (Oct/Nov/Dec) 5-yr mean	Continuous	NARR (calculated)
Winter (Jan/Feb/Mar) 3-yr anomaly	Continuous	NARR (calculated)
Spring (Apr/May/Jun) 3-yr anomaly	Continuous	NARR (calculated)
Summer (Jul/Aug/Sep) 3-yr anomaly	Continuous	NARR (calculated)
Fall (Oct/Nov/Dec) 3-yr anomaly	Continuous	NARR (calculated)
Winter (Jan/Feb/Mar) 5-yr anomaly	Continuous	NARR (calculated)
Spring (Apr/May/Jun) 5-yr anomaly	Continuous	NARR (calculated)
Summer (Jul/Aug/Sep) 5-yr anomaly	Continuous	NARR (calculated)
Fall (Oct/Nov/Dec) 5-yr anomaly	Continuous	NARR (calculated)

crews in the Interior West region of the FIA assign an estimated mortality year to each mortality tree, we used the median mortality year for all mortality trees on the plot, rather than measurement year, as the year of most severe impact. For insect-damaged live trees, which are defined as those already infested and unlikely to survive, the mortality year was estimated as the year following the measurement year and then incorporated into the median mortality year calculation. Median mortality years ranged from 1999 to 2009.

Precipitation data were acquired from the North American Regional Reanalysis (NARR) Project (Mesinger et al. 2006). The initial dataset consisted of gridded monthly precipitation at a resolution of 32 km for the period 1993-2009. Seasonal precipitation for each year was calculated as the sum of precipitation during 3 months, where summer consisted of July, August, and September to coincide with the NAM (see Table 1). Climatic mean precipitation was calculated for each calendar month based on the 30-year period 1981-2010, and these monthly climatic means were summed in 3-month intervals to obtain seasonal climatic means. Seasonal 3-year and 5-year interannual precipitation means were also calculated for each plot, where the average associated with each plot was based on the period ending in the median year of lodgepole pine mortality for that plot. To calculate 3-year and 5-year seasonal precipitation anomalies, which are defined here as the simple difference between short-term precipitation and long-term climatic conditions, the 30-year climatic means were subtracted from the 3-year and 5-year interannual means. Therefore positive anomalies indicate relatively wet periods, while negative values indicate dry periods.

Analysis was done using two iterations of PROC GLMSELECT (SAS Institute Inc. 2009). The first iteration did not include any interaction terms, while the second included interactions between stand-level and precipitation variables as well as among precipitation variables. Selection of variables was stepwise, with significance levels of 0.15 for both entering and staying in the model. Final model selection was based on minimization of the Akaike information criterion (AIC). Based on our expectation that seasonal precipitation related to the NAM has an inverse relationship with infestation severity, we expected that climatic mean summer precipitation would be a component of the final model. Because stepwise variable selection methods may overestimate the importance of independent variables (Harrell 2001), correlations were assessed between infestation severity and each of the five variables identified from the stepwise regression to reinforce the interpretation of each variable's importance.

RESULTS

The model with the minimum AIC value included the following variables, in order of entry into the model: 5-year fall precipitation anomaly, mean diameter at breast height (d.b.h.), live basal area, 5-year summer precipitation anomaly, and stand age (Table 2). During the second run of the GLMSELECT procedure, some

Table 2.—Variables included in the model with the minimum Akaike information criterion (AIC), where minimum significance level for entering and staying in the model was 0.15. R values are Pearson correlation coefficients of each variable against the log-transformed response.

Step	Variable	AIC	ΔAIC	F Value	Pr > F	r
0	Intercept only	285.0214	48.34	0.00	1.0000	N/A
1	Fall (Oct/Nov/Dec) 5-yr anomaly	254.3260	17.64	35.38	<0.0001	0.4025
2	Mean diameter at breast height (d.b.h.)	245.2348	8.55	11.25	0.0010	0.2274
3	Live basal area	239.2317	2.55	8.00	0.0052	-0.2298
4	Summer (Jul/Aug/Sep) 5-yr anomaly	237.6833	1.00	3.49	0.0635	0.3705
5	Stand age	236.6843	0.00	2.93	0.0889	-0.0655

interaction terms were selected as important variables in the final model. These included interactions between mean d.b.h. and both summer and fall 5-year precipitation anomalies. However, because this model's AIC value was comparable to that of the initial model, and the selected interaction terms included a nearly identical subset of climatic and stand-level predictor variables as the initial model, results are presented only for the first and simpler model.

Based on values for Pearson's correlation coefficient (Table 2), infestation severity was more strongly correlated with the precipitation variables in the final model than with the any of the stand-level attributes. The 5-year summer and fall precipitation anomalies were negatively correlated with infestation severity. These negative correlations signify that 5-year periods of relative drought during summer and fall are most strongly associated with high infestation severity. Although stand age emerged as an important predictor variable in the AIC-based variable selection, its low correlation with infestation severity suggests it is not important.

DISCUSSION

Of the five predictor variables in the final model, two represented seasonal precipitation anomalies and three were based on stand attributes. The three stand-level attributes (mean d.b.h., basal area, and stand age) are known to affect infestation severity of lodgepole pine by mountain pine beetle (Hicke and Jenkins 2008, Raffa et al. 2008). Several aspects of the two precipitation variables are notable. First, both variables represent anomalies from long-term climatic conditions, indicating that anomalies are more important than absolute precipitation metrics as predictors of infestation severity. Because absolute summer precipitation did not meet the criteria for inclusion in the final model, there is no evidence that the absolute quantity of precipitation associated with the NAM has an impact on infestation severity. However, interannual variability in seasonal precipitation, including precipitation associated with the complex meteorological dynamics of the NAM, may impact infestation severity. Second, the two precipitation variables included in the final model indicate that seasonal anomalies during summer and fall are more important than those during winter and spring. Finally, while the 5-year summer and fall anomalies were important, no 3-year anomalies appeared in the model. Assuming that the inverse relationship between seasonal precipitation anomalies and infestation severity is caused by increased stress during long-term drought, the temporal realm of influence of precipitation anomalies on infestation severity appears to last longer than 3 years.

Other analyses of weather and climate data may yield further insights about the factors affecting infestation severity. Future research should investigate whether the relationship between infestation severity and seasonal precipitation anomalies holds elsewhere, and if so, whether the 5-year timescale is similarly important. While precipitation is thought to affect the susceptibility of trees to insect attacks, temperature data may also be useful for modeling insect populations and infestation severity. Analyses of temperature data, such as monthly and daily maxima, minima, and anomalies, may further illuminate the complex relationships among climate, weather, MPB population dynamics, and lodgepole pine stands.

ACKNOWLEDGMENTS

Shih-Yu Wang of Utah State University provided helpful review comments about climate data sources and analysis methods, and Mike Thompson of the Interior West FIA Program provided valuable insights regarding use of FIA data to monitor trends in lodgepole pine mortality related to MPB. The authors acknowledge the National Oceanic and Atmospheric Administration's National Climatic Data Center for making NARR precipitation data available for free download. NARR data were processed and exported to GIS-compatible format using OpenGrADS climate data analysis freeware.

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TRENDS IN STANDING BIOMASS IN INTERIOR WEST FORESTS: REASSESSING BASELINE DATA FROM PERIODIC INVENTORIES

Sara A. Goeking[1]

Abstract.—Trends in U.S. forest biomass and carbon are assessed using Forest Inventory and Analysis (FIA) data relative to baseline assessments from the 1990s. The integrity of baseline data varies by state and depends largely on the comparability of periodic versus annual forest inventory data. In most states in the Interior West FIA region, the periodic inventory's sample design, plot configuration, estimation procedures, and definitions were different from those for the annual inventory, which are nationally consistent. Direct comparisons of periodic versus annual inventory data are therefore tenuous and may reflect changing protocols rather than actual changes, yet they comprise the best available method of assessing recent trends in some states. This study attempts to clarify trends in aboveground tree biomass in the Interior West region by comparing estimates at matched plots that were sampled during both periodic and annual inventories. To illustrate the ramifications of ignoring changes in inventory protocols, mean trends at paired plots were compared to those demonstrated by unpaired comparisons of entire periodic and annual inventories. In some states, the results produced by the two methods are contradictory. This demonstrates the importance of reassessing the use of estimates based on periodic forest inventories as reference conditions.

INTRODUCTION

The Forest Inventory and Analysis (FIA) program provides data for monitoring forest biomass at state, regional, and national scales. At a national scale, the U.S. Greenhouse Gas Inventory monitors trends in forest biomass and carbon based on FIA data (Heath et al. 2011). However, in the Interior West FIA region, the sample designs used in the historical forest inventories of the 1980s and 1990s, including those used for Resource Planning Act assessments (Smith et al. 2009), were neither internally consistent nor spatially balanced (Fig. 1). In 2000, the national FIA program implemented the spatially and temporally balanced sample design referred to as the annual inventory. Implementation in Interior West states occurred between 2000 and 2009, and due to a 10-year cycle length, most states have not yet completed a full annual inventory cycle. This constrains temporal monitoring to periodic inventory data coupled with a single measurement from the annual inventory.

The forest inventories conducted in the state of Idaho between 1980 and 2002 exemplify the quandary presented by comparing periodic and annual forest inventory data (see Witt et al. 2012). Idaho's most recent periodic inventories relied partially on aerial photograph interpretation to assess changes since the 1981 Idaho woodland inventory, and if no change was observed, then the 1981 data were merged with the 1990s inventory dataset. Each inventory also targeted specific ownership groups. For example, Idaho periodic inventories prior to 1992 did not include national forest lands. In contrast, periodic inventories conducted from 1993 to 2002 consisted almost solely of national forest lands. Each national forest was responsible for conducting its own periodic inventory, so inventory methods, sample grids, and the actual

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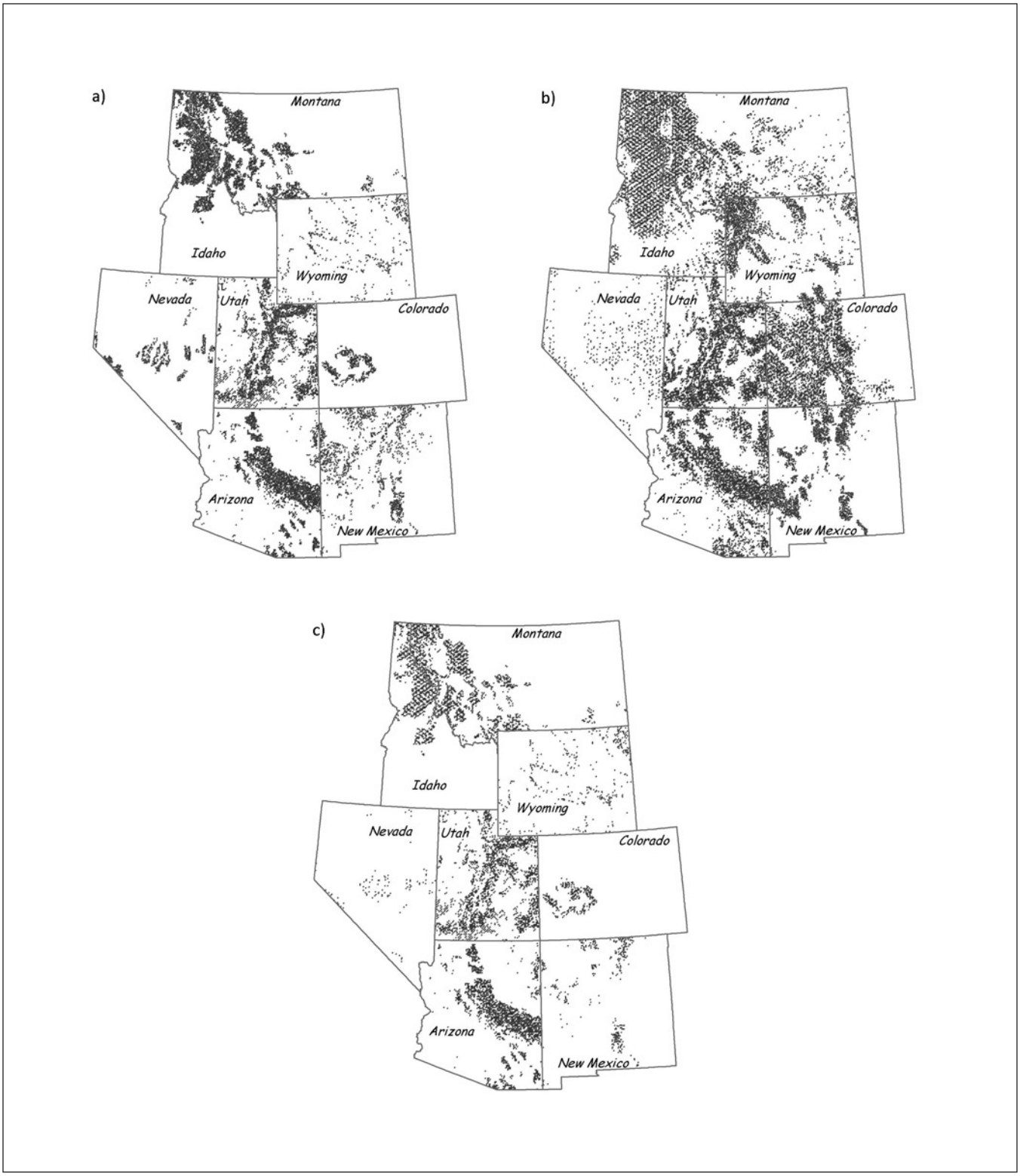


Figure 1.—Maps showing the spatial distribution of a) time 1, b) time 2, and c) time 1/time 2 matched plots in the Interior West FIA region.

inventory year(s) varied among forests, and vast areas within some national forests were completely omitted from the periodic inventory's sample grid. Due to these spatial and temporal inconsistencies in Idaho's periodic inventory, direct comparisons between periodic and annual inventory estimates are somewhat incongruous at both the statewide and the ownership group levels.

Despite their incompatibilities, comparisons of periodic versus annual inventories are the primary method of assessing recent trends in forest resources in the Interior West region. Due to the phased implementation of the annual inventory as well as the 10-year cycle length, annual-to-annual remeasurement data are only available for a small percentage of plots. The purposes of this study were: 1) to assess trends in mean aboveground tree biomass per plot by comparing only plots that were measured during the two most recent forest inventories (i.e., paired measurements); and 2) to identify cases where these trends contradict those demonstrated by comparisons of unpaired plot measurements.

METHODS

The study area consisted of eight Interior West states: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. Each state was evaluated separately due to temporal inconsistencies in the timing of both periodic inventories and the initiation of the annual inventory. For most states, time 1 consisted of the most recent periodic inventory while time 2 represents the annual inventory (Table 1). In New Mexico and Wyoming, the annual inventory was not

Table 1.—Measurement years of the periodic and annual inventories included in this study, by state, in the Interior West FIA region. For each state, only the most recent periodic inventory cycle was included. Total plots measured (n) and the number of paired plots between the two inventories is indicated. Asterisks indicate annual inventory cycles where the first measurement year indicates initiation of the annual inventory.

State	Cycle	n	Measurement Years	Plot Design
ARIZONA	2	1,966	1995-1999	4-subplot fixed-radius
	3*	3,291	2001-2009	4-subplot fixed-radius
	Paired plots	1,600		
COLORADO	1	388	1997	4-subplot fixed-radius
	2*	3,315	2002-2009	4-subplot fixed-radius
	Paired plots	270		
IDAHO	1	1,215	1998-2002	4-subplot fixed-radius
	2*	2,319	2004-2009	4-subplot fixed-radius
	Paired plots	664		
MONTANA	1	2,368	1993-1999	variable radius
	2*	3,217	2003-2009	4-subplot fixed-radius
	Paired plots	1,522		
NEVADA	1	588	1994-1997	variable radius
	2*	465	2004-2005	4-subplot fixed-radius
	Paired plots	101		
NEW MEXICO	1	1,287	1985-1987	variable radius
	2	1,741	1996-2000	mixed
	Paired plots	343		
UTAH	1	2,686	1991-1995	variable radius
	2*	3,526	2000-2009	4-subplot fixed-radius
	Paired plots	1,838		
WYOMING	1	501	1983	variable radius
	2	1,981	1998-2002	4-subplot fixed-radius
	Paired plots	398		

implemented until 2008 and 2009, respectively, but periodic inventories were conducted in both states in the late 1990s through early 2000s. Due to a paucity of annual inventory data in these two states, the time 2 measurements consisted of the most recent periodic inventories and an earlier periodic inventory was treated as time 1. Figure 1 portrays the spatial distribution of all time 1 plots, all time 2 plots, and the paired time 1 and time 2 plots.

The tree-level variable DRYBIOT (total gross biomass ovendry weight per tree in pounds) was queried for all live and standing dead trees from the national forest inventory database (Miles et al. 2001); trees measured under obsolete protocols (e.g., down dead trees) or with diameter at breast height (d.b.h.) of less than 5.0 inches were omitted. For periodic plots where data collection protocols did not include condition mapping, individual tree biomass was multiplied by a tree-level expansion factor and a unit adjustment to obtain total plot biomass in oven-dry tons per acre. For plots where conditions may have been delineated (i.e., annual inventory plots and periodic fixed-radius plots), this expansion was performed at the condition level first, and then condition-level biomass was aggregated to the plot level. Plot-level biomass was aggregated separately for live and dead trees.

The periodic and annual inventory datasets were then merged to identify plots that were measured during both inventories. Plots were assumed to be colocated, or measured more than once, if they had the same combination of state, county, and plot identifiers. Interior West FIA protocols stipulate that annual inventory plots should be colocated with periodic plots with the same state, county, and plot identifiers. At a small proportion of these plots, the periodic plot center could not be located so it was assumed that even plots that were not colocated sampled the same or a similar condition as the original measurement. Comparisons based on this subset of "matched" periodic-to-annual plots allowed for paired comparisons.

Trends were assessed by comparing mean tree biomass per plot, first using comparisons of all plots in each inventory and then using only paired plots that were measured during both time 1 and time 2 inventories. Cases where the paired-plot trends conflicted with unpaired comparisons were identified.

RESULTS

In every state analyzed in this study, comparisons of paired plots that were measured during both inventories yielded different trends than those identified from comparisons of all plots (Fig. 2). In six states (Arizona, Colorado, Idaho, Montana, Nevada, and Utah), comparisons of all periodic and annual inventory plot data demonstrated declines in both mean live tree biomass and mean total (live plus dead) tree biomass per plot. However, comparisons of paired plots showed very little change in live tree biomass and increases in total tree biomass. Therefore, the two comparisons produced conflicting trends not only in magnitude but also in direction of change. Changes in dead tree biomass were similar among the two comparisons.

The two states that did not fit the pattern previously described were New Mexico and Wyoming, where unpaired comparisons showed increases in total, live, and dead tree biomass while paired comparisons demonstrated very little change in any tree biomass component. This is likely due to the fact that the time 2 measurement consisted of a second periodic inventory. As previously mentioned, periodic inventories typically targeted specific ownership groups. The time 1 periodic inventories in both states were completed in the early to mid-1980s and sampled a disproportionate amount of private and non-national forest public lands. The time 2 periodic inventories in both states were conducted in the late 1990s and sampled a relatively large amount of national forest lands. Therefore, the apparent increases in biomass, based on unpaired analyses, were primarily due to differences in sampling. Comparison of paired plots in both states showed very little change between the 1980s and late 1990s.

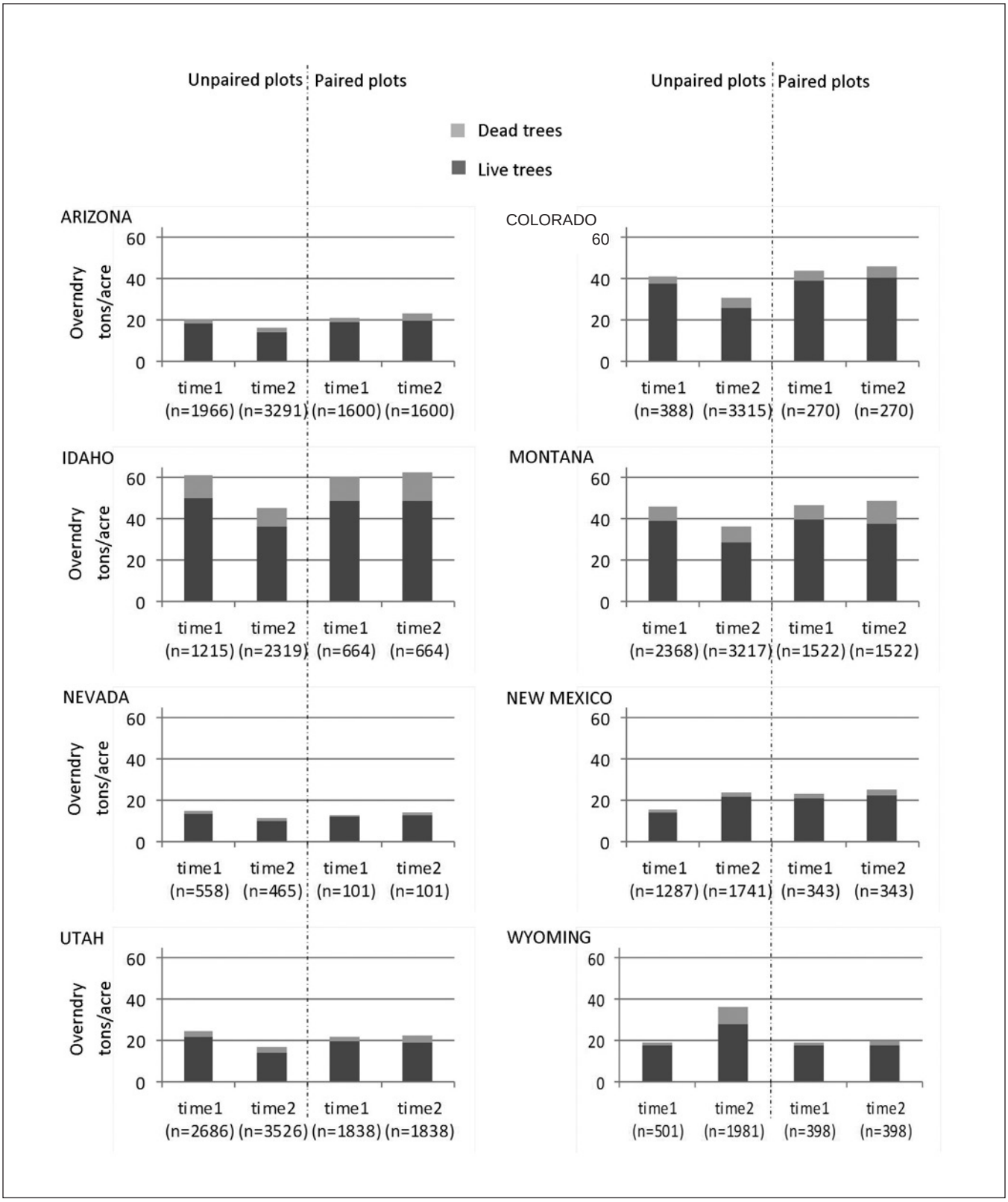


Figure 2.—Graphs showing mean aboveground biomass of live (dark gray) and dead (light gray) trees by state, in tons per acre.

Figure 3 shows the change in live, dead, and total aboveground mean biomass per plot from time 1 to time 2, by ecoregion subsection. Specific trends in live and dead biomass varied geographically, where areas of greatest decrease in live biomass presumably represent the occurrence of wildfires and/or disturbances such as insects that affect specific forest types.

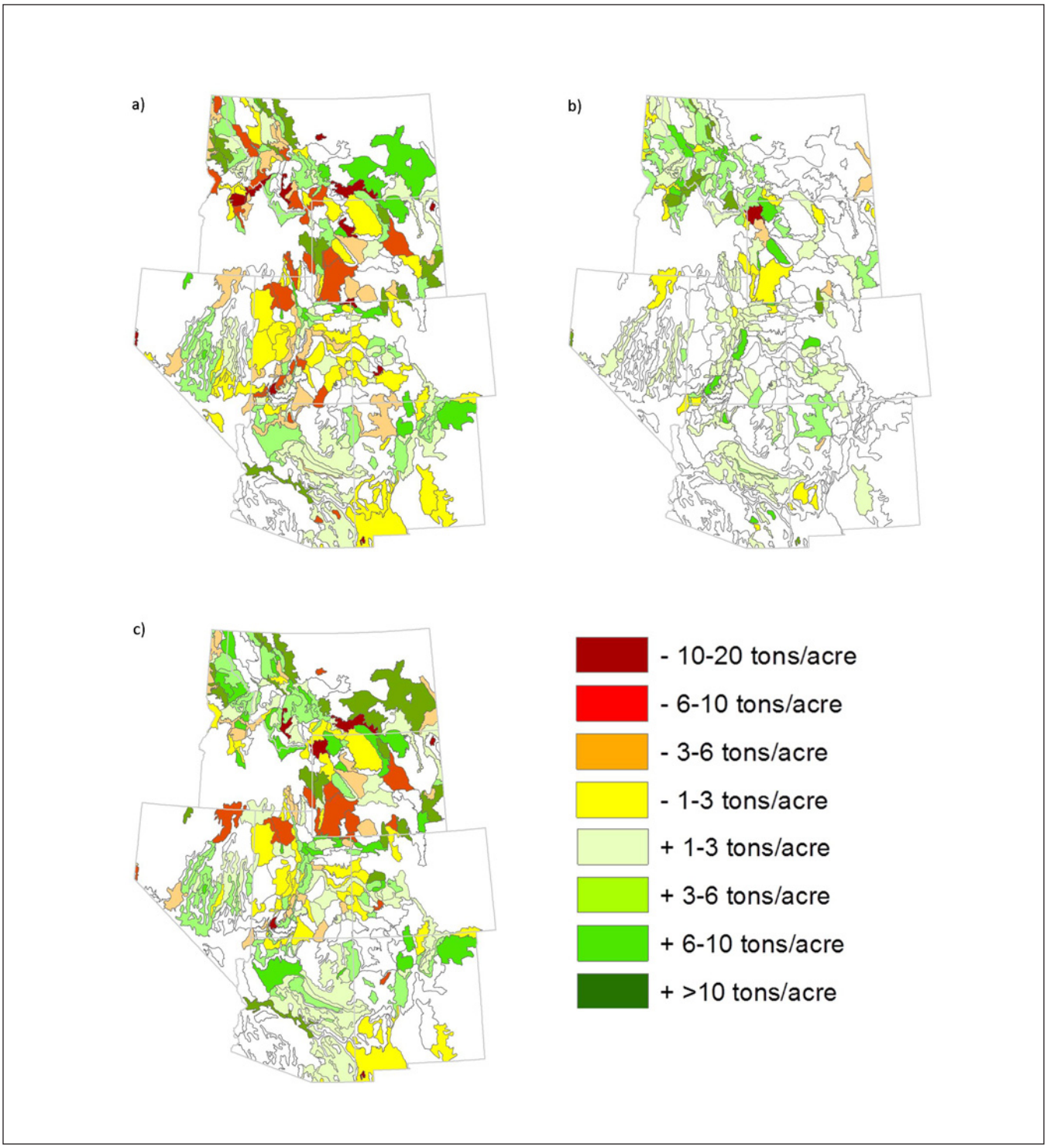


Figure 3.—Maps showing the magnitude of a) live, b) dead, and c) total aboveground tree biomass change at paired plots between time 1 and time 2, in tons per acre, averaged by ecoregion subsections. Blank subsections indicate either absence of paired plots or change less than 1 ton per acre.

DISCUSSION

Comparing periodic and annual inventory data is problematic due to numerous differences in definitions and protocols between the two inventories. Direct comparisons may produce apparent trends that differ from those found when comparing only paired plots, as demonstrated using aboveground tree biomass data from eight Interior West states. The unpaired comparisons for all states except New Mexico and Wyoming showed superficial decreases in standing tree biomass. This is likely due to the fact that most periodic inventories targeted specific ownership groups, which may correspond to oversampling of highly productive versus relatively unproductive forest lands. In contrast, the spatial configuration of the annual inventory represents ownership groups and productivity levels proportional to their existence across the landscape. As might be expected, results of the paired-plot comparisons often conflicted with those from the unpaired comparisons. In this case, using paired plot data versus spatially disparate samples represents the difference between trees in some states acting as a forest carbon source versus sink.

One caveat of this analysis is that conclusions about forest trends may characterize areas that were heavily sampled during the periodic inventory, and may not represent actual trends on a statewide basis. In other words, if areas were oversampled previously, the sample design of the annual inventory constrains them from continuing to be oversampled; yet using paired measurements cannot compensate for areas that were under-represented previously. Therefore, this analysis could not account for the fact that large areas were omitted from some periodic inventories, nor could it account for different plot configurations (i.e., variable-radius versus mapped-plot designs). Using paired-plot comparisons to infer statewide trends cannot account for small-scale disturbances that may have affected trends in under-sampled areas. Instead, it assumes that temporally variable processes operating at those plots (e.g., precipitation, temperature, and disturbances such as fire or insects) exhibit trends that are spatially representative of the state as a whole.

In terms of the absolute quantity of mean biomass per plot, the spatially balanced design of the annual inventory qualifies it as the most representative metric of the state as a whole. This means that the unpaired time 2 estimate (Fig. 2) is likely more accurate than the paired time 2 estimate. The two quantities differ in most states, suggesting that the paired plots used for trend assessment are not representative of actual mean conditions statewide. Note that this interpretation of absolute mean biomass per plot does not hold true in New Mexico and Wyoming because time 2 data in those states were collected during periodic inventories that targeted a narrow range of ownership groups and regions (see Fig. 1).

Finally, the sometimes conflicting trends produced by comparing paired plots versus entire statewide inventories confirm the need to account for discrepancies between the periodic and annual inventory estimates. Because many Interior West states are still in their first annual forest inventory cycle, additional plots can be incorporated into paired-plot comparisons as additional panels are completed and new annual plots are colocated with existing periodic plot locations. In some states, statistical modeling efforts may produce a more representative pre-2000 baseline of forest metrics, and thus enable more reliable trend assessment.

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POSTER ABSTRACTS

TAMARACK IN MINNESOTA: INVESTIGATING MORTALITY FROM EASTERN LARCH BEETLE USING FIA DATA

Susan J. Crocker, Jana Albers, Fraser R. McKee, Brian Aukema, and Greg C. Liknes[1]

Abstract.—Prior to European settlement, tamarack dominated the bogs, peatlands, and uplands of Minnesota's North Woods. Still a major component of Minnesota's forests, the extent and volume of tamarack has since waned. Mortality of tamarack has increased over the past decade. The majority of this mortality has been attributed to the activity of the eastern larch beetle (*Dendroctonus simplex* LeConte, Coleoptera, Scolytidae; ELB), a pest native to North America. Outbreaks of ELB have been documented in Minnesota since 1938. Largely separated by decades, the current outbreak of ELB has been ongoing since 2000. ELB frequently colonizes trees weakened by defoliators, however, within the current outbreak, it appears to be acting as the primary cause of mortality. While conditions that predispose stands to ELB attack are not well understood, physiological stress is often associated with infestation (Seybold et al. 2002). Factors related to the current outbreak are undetermined. However, drought, which has been a fixture in 9 of the past 10 years, could be playing an important role. Using data from the Forest Inventory Analysis program of the U.S. Forest Service, we analyzed trends in tamarack area and mortality over time. Additionally, tamarack mortality was aggregated by climate division to examine the relationship between mortality and drought. Future work will attempt to quantify the relative contribution of predisposing factors to tree mortality.

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AGENT-SPECIFIC TREE MORTALITY RATES IN THE EASTERN UNITED STATES FROM FIA DATA

Alan V. Di Vittorio and Jeffrey Q. Chambers[1]

Abstract.—Forest tree mortality plays an important role in the global carbon budget through so-called "background" mortality rates and larger, less frequent mortality events. The actual mortality turnover rates of forest biomass are not well understood and can vary with forest type, stand characteristics, and environmental conditions. Different agents, such as fire, insects, disease, and weather, operate on different time scales with effects varying across different ecosystems. This variability makes it difficult, but important, to determine patterns of agent-specific mortality for model projections of forest carbon balance. However, many regional and global ecosystem models assume a single, nonfire mortality rate for all forests, which introduces bias to projections of forest carbon balance. Using the U.S. Forest Service Forest Inventory Analysis database (FIADB), we estimate annual average mortality rates, on a per-tree basis, for eastern U.S. forests between 2000 and 2010 (except for 1974-1984 Louisiana estimates). We present spatially explicit estimates of total mortality and of agent-specific mortality due to animals, disease, insects, fire, harvest, weather, vegetation, and unknown agent. These estimates include all trees greater than or equal to 1 inch in diameter in remeasured forest- or timberland plots, and exclude plots with annual average harvest rates greater than 3.5 percent. Estimated annual average mortality rates vary from 0.2 percent to 7.5 percent across the eastern United States. Removing fire and harvest effects limits this range to 0.2 percent to 4.9 percent. The unweighted regional average is 3.3 percent for total annual average mortality (30 states), and removing fire and harvest effects lowers this average to 2.4 percent. Unknown agents dominate the northern state estimates and vegetation encroachment dominates southern state estimates. Weather mortality estimates can be up to 98 percent, but are generally on the order of disease and fire estimates. These estimates indicate that uniform mortality rates in ecosystem models would be improved by spatially explicit values.

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REMOTE SENSING DATA AS A MONITORING TOOL: TRENDS IN WILDFIRE ACTIVITY FOR THE PAST QUARTER CENTURY AND THE RELATIONSHIP TO OTHER BIOPHYSICAL AND ENVIRONMENTAL VARIABLES.

Mark Finco, Brad Quayle, Kevin A. Megown, C. Kenneth Brewer, and Jennifer Lecker[1]

Abstract.—The Monitoring Trends in Burn Severity (MTBS, www.mtbs.gov) project is mapping extent, size, and severity of all large wildland fires greater than 1000 acres in the west and 500 acres in the east over the conterminous United States (CONUS), Alaska, and Hawaii. In 2012 the project reached a milestone, completing the mapping for all fires between 1984 and 2010. The MTBS project produces geospatial and tabular data using a consistent protocol for fire trend analysis at a range of spatial, temporal, and thematic scales.

Our poster presents some of the more important trends observed by intersecting the MTBS geospatial data with data layers related to other biophysical and environmental landscape characteristics. Many of these trends were stated in the initial chartering of the MTBS project by the Wildland Fire Leadership Council, including understanding the trends in burn severity by vegetation type, how burned area and severity differ by administrative ownership, and whether there is any trend in the proximity of fires to the wildland-urban interface.

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DETAILED MAPS OF TROPICAL FOREST TYPES ARE WITHIN REACH: FOREST TREE COMMUNITIES FOR TRINIDAD AND TOBAGO MAPPED WITH MULTISEASON LANDSAT AND GOOGLE EARTH

Eileen H. Helmer, Thomas S. Ruzycki, Jay Benner, Shannon M. Voggesser, Barbara P. Scobie, Courtenay Park, David W. Fanning, and Seepersad Ramnarine[1]

Abstract.—Tropical forest managers need detailed maps of forest types for REDD+, but spectral similarity among forest types, cloud and scan-line gaps, and scarce vegetation ground plots complicate producing such maps from satellite imagery. How can these challenges be overcome? We describe a case study of mapping tropical forests to floristic classes for Trinidad and Tobago with gap-filled Landsat imagery by judicious combination of field and remote sensing work (Helmer et al. 2012). Recent and forthcoming developments are making such mapping with Landsat imagery far more accessible to nonspecialists. We highlight some key steps to mapping tropical forest habitats with cloudy Landsat and related insights from this study.

In the study area, class characteristics like "deciduousness" allowed discrimination of floristic classes. We also discovered that the extensive training data needed for mapping tropical forest types with "noisy" gap-filled imagery can be collected by learning to identify tree communities in 1) imagery with fine spatial resolution of ≤1 m; 2) multi-season fine resolution imagery (usually only viewable on Google Earth™); or 3) Landsat imagery from different dates, particularly imagery from drought years, even if decades old. Further, we show that gap-filled, synthetic multi-season Landsat imagery significantly improves class-level accuracy for several seasonal forest associations (by 14 to 21 percent for deciduous, 7 to 36 percent for semi-evergreen, and 3 to11 percent for seasonal evergreen associations, and by 5 to 8 percent for secondary forest and woody agriculture). Moreover, in some cases the seasonal spectral patterns in multiseason Landsat imagery have much more spatial detail than available ancillary maps of environmental variables, making them more useful when mapping tropical forest tree communities with Landsat. These detailed mapping efforts can lead to new views of tropical forest landscapes. Here we learned that the xerophytic rain forest of Tobago is closely associated with ultramaphic geology, helping to explain its unique physiognomy.

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Helmer, E.H.; Ruzycki, T.S.; Benner, J.; Voggesser, S.M.; Scobie, B.P.; Park, C.; Fanning, D.W.; Ramnarine, S. 2012. **Detailed maps of tropical forest types are within reach: forest tree communities for Trinidad and Tobago mapped with multiseason Landsat and multiseason fine-resolution imagery.** Forest Ecology and Management. 279: 147-166.

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DOTS AND PLOTS

Dennis M. Jacobs and Joseph M. McCollum[1]

Abstract.—Fixed-radius circles provide fixed-area plots for sampling. An array of dots within circles provides secondary sampling points within fixed-area plot circles. The hexagonal grid offers an elegant equidistant array of points that will deliver a balanced association between the circular area and number of points. A chosen target is 100 points within the circular plot and no less than 100, to approximate the mental process that one dot is about 1 percent. Equidistant integer spacing provides a minimal 109 hexagonal points with one dot on the plot center, but the visual weight is not well balanced along the circle perimeter. However, the centers of 102 hexagons can be strategically placed inside the circle by using the inscribed and circumscribed radii of hexagons, and will provide equal weighting between the dot spacing and each dot's representative area. Dividing the area of the circle by 102 gives the area of each small hexagon. We can then determine the non-integer spacing for the equidistant dot grid, which has no point at the center of the circular area, but with the first ring of three dots balanced around the plot center placed upon the vertex of the three central hexagons. By the use of Cartesian coordinates and the Pythagorean Theorem, we present the numerical balance of the points bounding the circle perimeter. Solutions of 104 and 100 dots may be obtained by balancing upon the bisector of two hexagon centers.

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PROGRESSION OF THE INVENTORY AND MONITORING OF NONFOREST LANDS WITH TREES

Dacia M. Meneguzzo, Greg C. Liknes, and Charles H. Perry[1]

Abstract.—Since its inception more than 80 years ago, the Forest Inventory and Analysis (FIA) Program has evolved from a timber-based inventory to an enhanced inventory that includes all forest land. However, FIA's definition of forest land requires areas of tree cover to be 120 feet wide and 1 acre in size. As a result, small scattered patches and linear plantings of trees are excluded from the inventory yet they are of ecological and economic importance. In the Great Plains region, it is these types of nonforest lands with trees that make up much of the total tree cover. In Nebraska, for example, past inventory reports have contained information only about the extent of nonforest tree cover but it has not been included consistently and explicit spatial information is lacking. Moving to an all-tree inventory would be ideal but ground-based data collection is cost prohibitive. Advances in remote sensing offer a promising solution to this problem. Our poster presents a timeline of past methodologies and area estimates of nonforest lands with trees as well as a new methodology for an image-based inventory of all tree cover using freely available, digital aerial photography from the National Agriculture Imagery Program (NAIP). Furthermore, the repeat availablity of NAIP imagery will make it possible to continuously monitor tree cover in the Great Plains.

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FOREST ATLAS OF THE UNITED STATES

Charles H. Perry, Linda R. Smith, Mary A. Carr, Randy Vreeke, and others[1]

Abstract.—The United States has a tremendous forest resource—more than 750 million acres of native and planted forests managed by public and private landowners for forest products, recreation, wilderness, wildlife habitat, and many other purposes. Over the past 150 years, basic surveys of United States forests have evolved into a rigorous inventory program that is used to share information about the value of these forests and the challenges that confront them. More recent technological and methodological advancements make it possible to create spatial products (maps) from the inventory data and other spatial data, such as digital elevation models and satellite imagery. The Forest Atlas of the United States uses these maps to highlight the value of our nation's forest in a graphic and novel manner. In the Forest Atlas of the United States, we explore these questions and many more: Where do forests grow? What else lives in forests? What shapes forests? What benefits do forests provide? What is in the future for our forests? This project represents a strategic partnership between several parts of the Forest Service, integrating FIA inventory data with remote sensing and GIS applications. Our poster provides a sample of the content that will be included in the forthcoming atlas and highlight the use of maps, graphics, accessible text, and images to communicate forest monitoring information with the public.

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ASSESSING CHANGES IN VEGETATION COMPOSITION AND STRUCTURE: WHAT CAN WE LEARN FROM 500 PLOTS?

Bethany K. Schulz and W. Keith Moser[1]

Abstract.—Using remeasurement data from more than 500 plots measured by the Northern Research Station's Forest Inventory and Analysis Program, we assess changes in vegetation indicator estimates, including species richness, vegetation composition, and structure. We highlight changes in the frequency of introduced species at the plot, subplot, and quadrat levels. Most introduced species are increasing in constancy, with a few exceptions.

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LOGGING RESIDUE UTILIZATION IN THE STATE OF IDAHO 2008 AND 2011

Eric A. Simmons, Erik C. Berg, Todd A. Morgan, Charles B. Gale, Stanley J. Zarnoch, and Steven W. Hayes[1]

Abstract.—The purpose of this study was to respond to land managers' need for better information on growing-stock removals, utilization of trees, and logging residues as a result of harvesting timber.

A two-stage sampling design was used to select felled trees for measurement within active Idaho logging sites in 2008 and 2011. Fifty percent of the harvested trees were ≤12 inches diameter at breast height (d.b.h.) and accounted for 18 percent of the total growing-stock volume removed and 19 percent of the mill-delivered (utilized) volume. Trees in this range produced 20 percent of the logging residue. About 49 percent of the harvested trees were between 12.1 and 27 inches d.b.h. and accounted for 80 percent of the total growing-stock volume removed and 80 percent of the mill-delivered volume. Trees in this range produced 78 percent of the logging residue. Removal factors quantifying impacts on growing stock revealed that harvesting efforts removed 1,011 cubic feet of timber volume from growing stock for every thousand cubic feet delivered to the mill, with just 24 cubic feet left in the forest as logging residue.

Weight estimates in green tons for the tops and limbs were added to the bole residues to obtain a total tree residue factor to be used as a biomass estimation tool. This tool can provide forest planners and managers the ability to predict potential feasibility of utilizing residues, and to gauge the impact on air quality or fire behavior if the residues burned.

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MINING HISTORICAL FIA REPORTS TO DEVELOP ESTIMATES OF FOREST LAND THROUGH TIME IN THE NORTH CENTRAL REGION OF THE UNITED STATES

Paul A. Sowers[1]

Abstract.—The Forest Inventory and Analysis (FIA) Program began collecting inventory data in the early 1930s. While contemporary data (from approximately the last decade) is actively managed in a relational database system and readily accessible with a variety of software tools, older data was previously available only in printed reports for many parts of the United States. For 11 states in the North Central United States, printed reports spanning the 1940s to the 1980s were scanned and made available on demand as a series of CD-ROMs. These scanned reports have now been manually converted to data files and assembled as county-level, GIS compatible datasets.

Data from the first annual FIA inventory were acquired using FIA's online EVALIDator tool and combined with the historical data. A series of county-level choropleth maps are presented showing forest land area change across the 11 state region. The maps are portrayed in a matrix depicting the pairwise changes across the different inventory combinations.

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MAPPING ASPEN IN THE INTERIOR WEST

Charles E. Werstak, Jr.[1]

Abstract.—Quaking aspen (*Populus tremuloides* Michx.) is a critical species that supports wildlife and livestock, watershed function, the forest products industry, landscape diversity, and recreation opportunities in the Interior West (Bartos and Campbell 1998). Studies have indicated that changes in fire regimes, an increase in herbivore presence in young aspen stands, and recent drought episodes have been the main factors for increased mortality rates in aspen stands (Deblander et al. 2010). Forest Inventory and Analysis (FIA) plot data are a consistent source of ground-based information that if used appropriately, can be extremely valuable for mapping and modeling forest attributes such as forest type and canopy cover. GEO-object based image analysis, or GEOBIA, is a relatively new subdiscipline of geographic information systems (GIS) focused on developing automated techniques for partitioning remotely sensed imagery into image objects and accessing them for use in a variety of mapping applications (Hay and Castilla 2008). Spatial data mining is an automatic or semi-automatic exploration to identify patterns in data that have a geographic component (Shekhar et. al. 2005). Random Forests™ is an ensemble classifier that uses multiple decision trees to predict target variables from input variables (Breiman and Cutler 2003). To help understand the current status and extent of quaking aspen across the Interior West, efficient and repeatable mapping and modeling techniques need to be further established. This investigation aims at exploring viable methods for creating canopy cover maps of quaking aspen for several different locations across Utah. FIA plot data for inventory years 2000-2009 that correspond to image objects derived from Landsat TM imagery will be analyzed along with other ancillary geospatial data using spatial data mining and Random Forests™. Information gained from this investigation may provide further insight into object based segmentation and classification techniques using FIA plot data, satellite imagery, and ancillary geospatial data.

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SUSTAINABILITY OF OAKS IN WEST VIRGINIA

Richard H. Widmann[1]

Abstract.—There is growing concern for the sustainability of the oak resource in West Virginia. A look at the U.S. Forest Service's Forest Inventory and Analysis data over the 12 million acres of timberland in West Virginia shows that oak volume has continued to increase, but all of this increase has been due to growth on large-diameter trees. High mortality in the lower diameter classes and low recruitment has resulted in oaks being underrepresented in the lower diameter class. Oak species now represent 46 percent of trees more than 20 inches in diameter, but only 7 percent of the trees less than 9.0 inches in diameter. In 2- and 4-inch diameter classes, oaks represent 5 and 6 percent of trees in these classes, respectively. Because of this disparity, volumes of oak will likely decrease across the State as large trees are harvested or die and recruitment into large-diameter classes decreases. Loss of this keystone species will affect wildlife populations and wood-using industries that now depend on oak.

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DOES STANDING WATER OR SNOW PACK BIAS ASSESSMENTS OF TREE REGENERATION WITHIN LARGE-SCALE FOREST INVENTORIES?

Christopher W. Woodall, James A. Westfall, Brian F. Walters, Daniel J. Johnson, and Kai Zhu[1]

Abstract.—A critical component of large-scale assessments of forest ecosystem sustainability and function is that of tree regeneration. As forest inventory measurements may occur year round at high latitudes, winter snow banks and subsequent spring floods may impede measurement of tree seedlings (<1 inch diameter at breast height [d.b.h.]), especially at high latitudes/elevations. Using FIA's measurements of seedlings across eastern states, potential biases of tree seedling measurements as affected by snow depth and water obstruction was assessed. It was found that there is a general trend of a decrease in average annual seedling density across time as stand density increases across the eastern United States—a trend that is potentially exacerbated within plots where there is substantial snow/water obstruction (>10 cm) to seedling measurement. Assessments of seedling surveys should not be biased if sufficient temporal and spatial scales are used relying on the unbiased spatial and temporal allocation of field plot measurement to eliminate potential bias. However, seedling assessments may be biased if they occur at the plot-level with snow/water present on the plot with the greatest potential bias found on plots with no obstruction at time one but with substantial snow/water obstructions at time two.

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RATES OF COARSE WOODY DEBRIS BIOMASS LOSS AND CARBON DEBT IMPLICATIONS IN EASTERN U.S. FORESTS

Christopher W. Woodall, Matthew B. Russell, Anthony W. D'Amato, Shawn Fraver, and Brian F. Walters[1]

Abstract.—Emerging questions from bioenergy policy debates have highlighted knowledge gaps regarding the carbon and biomass dynamics of individual pieces of coarse woody debris (CWD) across the diverse forest ecosystems of the United States. Using a subset of CWD pieces remeasured across eastern U.S. forests, the rate of biomass loss was estimated over time using decay class transition models coupled with volume and wood density loss trajectories. Results indicate that biomass loss is related to the genera of the species considered, its size, and location within the broad climatic regions of the eastern United States. This biomass loss may be broadly summarized as CWD "half-life's" across the eastern U.S. FIA's inventory of CWD may provide carbon debt policy discussions with objective assessments of CWD biomass/carbon loss.

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FRAMEWORK FOR ASSESSING CLIMATE CHANGE RISKS TO FOREST CARBON STOCKS

Christopher W. Woodall, Grant M. Domke, Karin L. Riley, Christopher M. Oswalt, Susan J. Crocker, and Gary W. Yohe[1]

Abstract.—Efforts to negotiate the role of forest carbon stocks in global efforts to mitigate potential climate change effects has highlighted the need to quantify risks to forest carbon stocks such as massive disturbance events. As risk may be conceptualized around the magnitude of an event and its associated probability, this study examined potential changes to forest carbon stocks following major disturbance (e.g., hurricane) and proposed a framework for assessing the probability of climate change risks to these stocks. Results suggest that a valid framework for conceptualizing risk may be centered on the various forest carbon pools (e.g., forest floor and belowground), the variability of the associated stocks across large scales, and the magnitude of the stocks themselves. Furthermore, given the diversity of the forest pools involved, the nature of massive disturbances themselves (e.g., insects versus wildfires) can have divergent effects of forest carbon stocks resulting in major research unknowns.

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BIOMASS AND CARBON ATTRIBUTES OF DOWN WOODY MATERIALS ACROSS FORESTS OF THE UNITED STATES

Christopher W. Woodall, Brian F. Walters, Grant M. Domke, Chris Toney, Andrew N. Gray, Sonja N. Oswalt, and James E. Smith[1]

Abstract.—In past decades, down woody material (DWM) has emerged as central to wildlife habitat, a controlling factor of forest nutrient cycles, facilitator of tree regeneration, a carbon store, and fire hazard. Using the first ever national empirical inventory of DWM across forests of the United States, the biomass and carbon attributes of DWM were assessed. Results indicated that DWM are ubiquitous in forests; however, they are only found in large amounts in certain specific ecosystems subject to unique climatic or disturbance attributes (e.g., slow decay or recent tree mortality). It is suggested that the national empirical inventory of DWM carbon stocks replace the simulated stocks used in past national greenhouse gas inventories.

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Morin, Randall S.; Liknes, Greg C., comps. 2012. **Moving from Status to Trends: Forest Inventory and Analysis (FIA) Symposium 2012; 2012 December 4-6; Baltimore, MD.** Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]. 478 p.

These proceedings report invited presentations and contributions to the 2012 biennial Forest Inventory and Analysis (FIA) Symposium, which was hosted by the Research and Development branch of the U.S. Forest Service. As the only comprehensive and continuous census of the forests in the United States, FIA provides strategic information needed to evaluate sustainability of current forest management practices across all ownerships. Papers and abstracts included in the publication have been sorted into topic areas that match the sessions presented during the meeting. Symposium papers cover high priority and timely issue-based topics including climate change, wildlife, fire, bioenergy, geo-spatial extensions, monitoring over time, integrating remote sensing and GIS applications, statistical and related quantitative solutions to emerging needs, and many others.

KEY WORDS: statistics, estimation, sampling, modeling, remote sensing, forest health, data integrity, environmental monitoring, cover estimation, international forest monitoring

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