Effects of Land Use/Cover Change and Harvests on Forest Carbon Dynamics in Northern States of the United States from Remote Sensing and Inventory Data: 1992–2001

Daolan Zheng, Linda S. Heath, Mark J. Ducey, and James E. Smith

Abstract: We examined spatial patterns of changes in forest area and nonsoil carbon (C) dynamics affected by land use/cover change (LUC) and harvests in 24 northern states of the United States using an integrated methodology combining remote sensing and ground inventory data between 1992 and 2001. We used the Retrofit Change Product from the Multi-Resolution Land Characteristics Consortium to quantify LUC. We then calculated C dynamics using C densities for major forest types based on US Forest Service Forest Inventory and Analysis data by forest area for different statuses (i.e., afforestation, deforestation, and forest remaining forest) and incorporated county-level harvest data. Across the region, 16,740 km^2 of forestland changed to nonforest, whereas 9,120 km^2 of nonforest became forestland, a net loss of 7,620 km^2 of forestland during the period or -0.13%/year. The region as a whole functioned as a C sink of 627 Tg (1 teragram = 10^{12} g) or 70 Tg of C/year. Regional C sequestration calculated using forest type identification at the state level was 5% higher than that from the county-level identification. Integrated annual effects of LUC and harvest on reducing C stocks at the state level varied substantially, ranging from 0.4% in North Dakota to 5.1% in Delaware with an average of 3.2% across the region (3.4% in the 13 northeastern states and 2.6% in the 11 northcentral states), compared with what it would be without these effects. We also found that within the region the annual LUC rate was significantly correlated with population density at the state level ($P < 0.001$). For. Sci. 57(6):525–534.

Keywords: carbon density, carbon sequestration, forest change statuses, integrated effect

Climate change and land use affect each other. Both are expected to have major impacts on the ecological, social, economic, and political aspects of human society (Dale 1997). Therefore, a better understanding of how land use/cover change (LUC) and harvests affect forest ecosystem carbon (C) dynamics and exchanges of C fluxes with the atmosphere is necessary to improve our ability to effectively manage forest ecosystems to offset possible future global warming.

Since the 1990 Intergovernmental Panel on Climate Change assessment, there has been considerable research on the role of terrestrial ecosystems, particularly forests, in the global C cycle (Dixon et al. 1994). Forests dominate the dynamics of the terrestrial C cycle because they contain 73% of the C in world soils (Post et al. 1982), and 77% of the C in plants (Intergovernmental Panel on Climate Change 2002). Canadell et al. (2007) suggested that the C sink on land in recent years is larger than the sink by ocean. Although area of forestland in the conterminous United States has declined in comparison with that in the period before European settlement, it still accounts for about one-third of the total US continental area (Birdsey and Schreuder 1992, Heath and Birdsey 1993). Although the changes in C associated with land cover change do not define the total net flux of C between land and atmosphere, they are one portion of flux that can be directly linked to human activity (Houghton et al. 1999). This is the portion that is addressed by the United Nations Framework Convention on Climate Change and by the Kyoto Protocol.

Both natural and human disturbances can alter the structure, composition, and configuration of forest ecosystems and affect forest productivity and C dynamics. These disturbances play an important role in the global C cycle and climate change and need to be accurately and efficiently monitored and quantified at various scales, especially over large scales. The rapid advance of remote sensing (RS) techniques in recent decades has made RS a reliable, practical, and effective way for studying terrestrial ecosystems at large scales (Tucker et al. 1984, Running et al. 1994, Hansen et al. 2000, Homer et al. 2004, Zheng et al. 2008) because continuously observed RS data allow users to pursue spatial pattern analyses, high frequent revisitation of remotely sensed information with relatively consistent methodology over large areas allows users to conduct temporal analyses at intervals when data are available, and RS data observed at various sensor resolutions provide alternatives for ecological analyses at multiple scales.

Satellite-derived products alone, however, may not provide all of the information needed to resolve ecological issues without support of field-based inventory data. Field data can be used to validate RS observations and for ecosystem model development and validation. For example,

Daolan Zheng, University of New Hampshire, Natural Resources, 215 James Hall, Durham, NH 03824—Phone: (603) 868-7696; Fax: (603) 868-7604; daolan.zheng@unh.edu. Linda S. Heath, US Forest Service, Northern Research Station—lheath@fs.fed.us. Mark J. Ducey, University of New Hampshire—mjducey@unh.edu. James E. Smith, US Forest Service, Northern Research Station—jsmith11@fs.fed.us.

Acknowledgments: Funding support for this study was primarily provided by the US Forest Service, through Grant 05-DG-11242343-074 and partly by a Research Joint Venture Agreement (Grant 110165) between the University of New Hampshire and US Forest Service Northern Research Station Work Unit NRS-5. Additional support was provided by a grant from the National Science Foundation, "Collaborative Research: The Northeastern Carbon Sink: Enhanced Growth, Regrowth, or Both?" to M.J.D.

Manuscript received August 10, 2009, accepted May 24, 2010

forest-area changes detected from RS data need to be converted to C using density data developed from field observations. A previous study has demonstrated that forest C density varies significantly with forest type (Smith et al. 2006). In this study C dynamics were calculated by state, based on forest types identified at the county level, and the results were compared with C dynamics based on forest types identified at the state level. Furthermore, harvest data are needed to illustrate utilization rates (how much C is left in the forest after harvest). As a result, combining RS observations with ground inventory data can improve the quality and accuracy in ecosystem modeling and forest monitoring and management (Running et al. 1989, Prince and Goward 1995, Woodcock et al. 2001, Cohen et al. 2002, Zheng et al. 2004).

Forest disturbances can be caused by natural and human factors such as wind, insect, fire, LUC, and harvests. In this study, we focused on LUC and harvests and their effects on regional nonsoil forest C dynamics. We used remotely sensed information to identify different forest LUC statuses (i.e., afforestation [nonforest becoming forest], deforestation [forest becoming nonforest], and forestland remaining forestland) from 1992 to 2001 combined with forest C density and county-level harvest data from the US Forest Service Forest Inventory and Analysis (FIA) program to improve our understanding of forest C dynamics in 24 northern states. Timber harvest is an important component in calculating forest C stocks and dynamics in the United States (Mills and Kincaid 1992, Haynes 2003, Smith and Heath 2004). Specific objectives of this study include 1) quantifying forest area changes for different land cover change status in the northern region of the continental United States at the county level (tallied to the state level as necessary), 2) identifying the effect of each land cover change status on regional forest C dynamics as well as the spatial pattern of integrated effects (LUC and harvests), 3) revealing the relationship between deforestation rate and population density at the state level, and 4) demonstrating the difference between county-based forest C estimates and state-based estimates at the state level.

Materials and Methods

Study Area

The area is composed of 24 states. Eleven of the 24 states belong to the Northcentral subregion and the remaining 13 states are within the Northeastern subregion (Figure 1). The

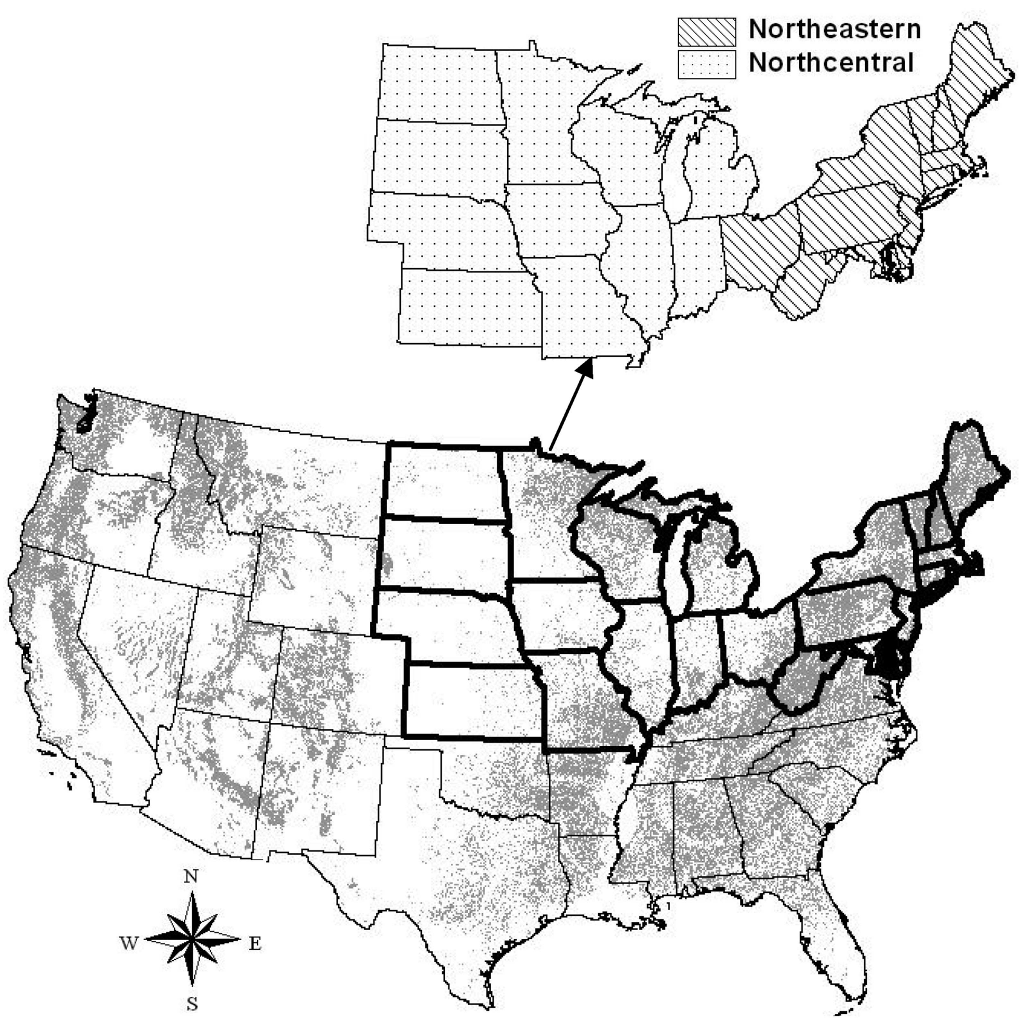

Figure 1. Illustration of study area (forests in gray) with two subregions: Northeastern and Northcentral.

entire area contains about 2.5 million km^2, with 27% forested in 2001 according to the National Land Cover Databases (NLCD) Retrofit Change map and populated with 126 million people at the 2000 census (Perry and Mackun 2001).

In general, much of the northern forest had been logged for timber products or cleared for agricultural use by the end of the 19th century except the northern areas of Maine and the Great Lakes States (Heath and Birdsey 1993). Beginning in the mid-19th century and accelerating in the 20th century, marginal agricultural land has reverted to forest, producing a large proportion of forests in the 35- to 75-year age classes (Heath and Birdsey 1993). These forest lands of mixed species are projected to sustain a period of net annual growth that will begin to decline around the decade 2030 (Haynes et al. 2007), partly due to projected decreased forestland area. Although growth in the region is expected to be greater than harvest in the near-term, and C stocks continue to accrue (Haynes et al. 2007), harvesting reduces regional forest C stocks. Accounting for harvesting removals could refine our estimation of regional C dynamics. C continues to be stored in harvested wood products, as well as in landfills when products are discarded. Wood harvested and burned for energy as a substitute for fossil fuels also provides C benefits; however, in this study we focus on C in the forest.

Retrofit Change Product

We used the Retrofit Land Cover Change Product provided by the Multi-Resolution Land Characteristics Consortium (2009). The product was generated from the 1992 and 2001 NLCD, derived from 30-m Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) satellite data (Vogelmann et al. 2001, Homer et al. 2004). Although one of the guiding principles of the NLCD 2001 map design was to maintain as much as compatibility with NLCD 1992 as possible, there were enough differences in the classifications to confound any direct comparison of the two data sets. Thus, the US Geologic Survey NLCD design team initiated research to devise a credible way to detect land use change from the products. A multistage processing method, including aggregating Anderson Level II to broader classification categories at Level I (Anderson et al. 1976), used both NLCD products to generate the NLCD 1992/2001 Retrofit Land Cover Change Product. This is probably the best data set currently available at a moderate resolution for national land cover change detection using relatively consistent classification methodology. This change product may contain more uncertainties than the misclassification errors in either the 1992 or 2001 map, although overall mapping accuracy in the 2001 map was increased to 85.3% at Anderson Level I from 80% in the 1992 map (Wickham et al. 2010). One advantage of using a wall-to-wall product such as the Retrofit change product is that it covers the entire land base over the period, even though it has misclassification errors. The FIA survey, on the other hand, did not cover the entire land base in the same way over the time period under study. The periodic FIA surveys focused on productive forest available for timber harvest, whereas the annualized survey design includes measurement and field visits to all plots that are probably forested.

The change product contains eight aggregated classes: 1) open water, 2) urban, 3) barren, 4) forest, 5) grass/shrub, 6) agriculture, 7) wetland, and 8) ice/snow (excluded in this study). Other change classes are generated from these eight classes to indicate changes of land cover from one type to another during the period. For example, class 12 indicates that the land was changed from water (1) in 1992 to urban (2) in 2001 and so on. We downloaded the NLCD Retrofit Land Cover Change Product and extracted the data for our study area. We aggregated forest-related change detections between 1992 and 2001 into three general land cover-change statuses: afforestation (change from nonforest to forest, including change classes of 14, 24, 34, 54, 64, and 74), deforestation (change from forest to nonforest, including classes of 41, 42, 43, 45, 46, and 47), and forest remaining forest (class of 4). Forest areas were calculated at both county and state levels for comparison.

C Density Calculations

C pools included in this study were nonsoil forest C, that is, live tree, understory, standing dead tree, down dead wood, and forest floor. The pool of C in harvested wood products removed from the forest was included in the sense that it was subtracted from the C stock on the forest remaining forest areas, but we assumed that this harvested C was immediately emitted to the atmosphere. This is a simplifying assumption, as changes in forest C do not necessarily equate to immediate impacts on atmospheric C because harvested C passes through wood-in-use sinks before returning to the atmosphere. Our study focuses on forest ecosystem C. Forest C densities for different forest-related change statuses were calculated using the C estimates from Smith et al. (2006), which are the default estimates for the 1605b US Voluntary Reporting of Greenhouse Gases Program (US Department of Energy 2009). Use of gross forest change statuses rather than net land cover transition data is important because deforestation causes a much more rapid loss in C stocks, whereas afforestation causes a gradual accumulation in C stocks for many decades (Woodbury et al. 2006). Thus, separating the land status may improve C estimates related to land cover changes.

Forest C dynamics were based on the C density tables provided in Smith et al. (2006), which are categorized by region and major forest type group and are not available for all forest types. Selection of the most representative C density table for each county was based on the most abundant forest type by area within each county according to FIA data. Calculations used the selected C density data and forest area dynamics for each county and state. However, all results were reported at the state level for comparison. Because there was a 9-year interval for the data we used, we assumed the average age of new forest was 5 years, but a total of 9 years of growth occurred for the areas of forest remaining forest. To calculate C loss from deforestation, we used a conversion factor of 0.8. This factor was based on the assumption that 80% of the nonsoil forest C would be lost during conversion to nonforest (Smith and Heath 2008).

Harvest Data

Unlike deforestation that changes the land use category from forest to nonforest, harvests are activities that occur in the category of forest remaining forest and remove nonsoil forest C from the ecosystems. Thus, including harvest data can improve our estimation of overall forest C dynamics across large scales. County-level harvest C removals were calculated using remeasured annualized plot data from the FIADB 3.0 forest inventory data (US Department of Agriculture 2008). Annual volumes of removals through harvest on forestland were calculated according to methods defined for the database (US Department of Agriculture 2009) for each county for all years from 1992 through 2001 and are expressed in C units. These usually resolved to 2 or 3 specific years during the interval, depending on the dates of inventories for the respective states. Annual rates of harvest assigned for each of the years 1992 through 2001 are based on the next, or more recent, year of harvest removals as evaluated in the FIADB. C estimates in these volumes of merchantable wood as well as expansion of C to include bark and tops of trees are based on methods described in Smith et al. (2006). County-level harvest data were summarized to state as necessary.

Data Analyses

We excluded the class of ice/snow contained in the original Retrofit Change Product because it does not exist in the region. County-level calculations were tallied to state and regional levels. To demonstrate the effect of a specific forest status on regional changes in forest area and C from 1992 to 2001, we calculated a percent change in terms of the 1992 map (Equation 1). In Equation 1, Δ $\text{Area}_{\text{status}}$ represents the area change during the period for a given status (i.e., afforestation, deforestation, or reforestation). The variable representing area could be substituted with C, depending on the analyses. Definitions of C calculations for different LUC statuses are available in Table 1.

$$Percent\ change = (\Delta Area_{status}/ForestArea_{no\ effect}) \times 100 \qquad (1)$$

We further linked the deforestation rate to 2000 population density from Esri (Tele Atlas North America, Inc. 2005) to

Table 1. Area changes and C dynamics caused by different forest land cover change status during the 9-year period (1992–2001) by state summarized from county-level calculations in the Northern region of the United States using the NLCD Retrofit Change Product.

State	Area change by status			C change by status					Integrated annual rate[e]
	Aff.	Def.	Ref.	Aff.[a]	Def.[b]	Ref.[c]	Harvest	Net[d]	
	.........(km^2).........			.................(1,000 tonnes).................					
Connecticut	4	169	7,296	4	1,758	15,254	2,633	10,867	−2.5
Delaware	24	94	1,259	26	935	2,620	1,324	387	−5.1
Illinois	295	655	21,992	324	5,940	23,154	7,103	10,435	−3.9
Indiana	231	326	21,244	257	3,091	20,597	9,375	8,388	−4.1
Iowa	192	355	9,895	215	2,772	12,370	2,418	7,395	−3.2
Kansas	251	120	7,636	273	824	10,172	897	8,724	−1.4
Maine	940	2,686	57,912	1,414	21,879	98,958	42,181	36,312	−4.3
Maryland	103	349	9,683	133	3,812	18,441	8,299	6,463	−4.4
Massachusetts	38	391	11,043	49	4,247	18,062	5,209	8,655	−3.8
Michigan	2,069	1,504	51,582	2,365	11,859	80,972	24,941	46,537	−3.3
Minnesota	1,526	1,059	58,246	1,800	7,006	84,314	19,541	59,567	−2.5
Missouri	593	2,038	65,992	652	15,489	69,936	10,055	45,044	−2.9
Nebraska	26	87	3,987	31	350	5,559	651	4,589	−1.7
New Hampshire	79	246	18,665	118	2,746	29,143	12,485	14,030	−3.8
New Jersey	44	206	7,368	57	1,811	12,908	3,647	7,507	−3.3
New York	236	1,277	66,284	348	11,937	107,824	22,669	73,566	−2.7
North Dakota	19	0	3,142	20	0	4,539	171	4,388	−0.4
Ohio	518	1,103	32,946	626	9,640	67,027	16,430	41,583	−3.1
Pennsylvania	533	1,262	70,125	662	11,760	132,734	30,192	91,444	−2.6
Rhode Island	2	57	1,298	2	551	2,725	550	1,626	−3.2
South Dakota	79	267	6,850	100	1,257	11,410	143	10,110	−1.1
Vermont	47	159	17,792	70	1,780	27,489	8,557	17,222	−3
West Virginia	160	659	50,585	188	6,125	99,457	26,000	67,520	−2.7
Wisconsin	918	1,399	54,689	1,060	9,682	84,926	31,588	44,716	−3.6
Total	8,927	16,468	657,511	10,794	137,251	1,040,591	287,059	627,075	−3.2

Aff., afforestation; Def., deforestation; Ref., forest remaining forest.

[a] C gains through afforestation were estimated using C accumulation tables for afforestation (Smith et al. 2006), assuming the average age of 5 years during the 9-year period.

[b] C losses through deforestation were estimated using average forest nonsoil C density by county from the latest FIA data, assuming that 20% of the C remained after forest became nonforest.

[c] C sequestration by forest remaining forest was estimated using C accumulation rate for reforestation (Smith et al. 2006) determined by mean total live tree biomass of the most common forest type in a given county.

[d] Net change in C during the 9-year period = $(C_{Ref} + C_{Aff} - C_{Def} - C_{Harvest})$.

[e] Integrated effect from both LUC and harvest on C dynamics at annual rate (%): $[(C_{Harvest} - C_{Aff} + C_{Def}) \times -1/(C_{Ref} - C_{Aff} + C_{Def} + C_{Harvest})] \times 100/9$.

examine the relationship between the two factors. In doing so, we calculated the deforestation rate in relation to total land area for each of the 24 states instead of total forest area shown in Equation 1 because the population density was obtained based on the total land area as well. Because an initial examination of the data suggested a non-normal error structure with outliers, we focused on testing for a relationship using a nonparametric approach (Spearman rank correlation test) rather than fitting a regression using conventional methods. Finally, we compared the changes in area and C dynamic between county- and state-based estimation to illustrate the differences at state level. Both C dynamics estimated using county-level and state-level forest type identifications were compared to the net FIA based estimates (Smith and Heath 2004) at the state level for the same period to determine whether the finer resolution improved the results.

Results and Discussion

Area Dynamics

Approximately 16,740 km^2 of regional forestland changed to nonforest types, whereas 9,120 km^2 of nonforest types reverted to forest, resulting in a net loss of 7,630 km^2 forest lands (or -1.1%) during the 9-year period. This represents an annual rate of 847 km^2 net forest loss or -0.13% per year (Table 2). Spatial variation in area change from the LUC effect ranged from a 5.3% loss in Delaware over the 9-year period to 1.7% gain in Kansas within the region. All states in the Northeastern subregion had forest losses during the period, with most experiencing medium (-0.3 to 0.15%) and high ($<-0.3\%$) annual mean LUC rates. No high-level LUC rate was found in the Northcentral subregion. All states in the Northcentral subregion experienced either medium (-0.15% to -0.3%) or low (0 to -0.15%) LUC rates or even gained forest areas during the period (Figure 2a).

In term of absolute values of forest area change during the period, the four states that lost the most forest area were Maine (1,750 km^2), Missouri (1,470 km^2), New York (1,040 km^2), and Pennsylvania (740 km^2). The four states that gained the most forest area were Michigan (570 km^2), Minnesota (470 km^2), Kansas (140 km^2), and North Dakota (30 km^2). Approximately 2.6% of total regional land experienced land cover change at least once. Of that change, 40% was forest related (forest to nonforest or nonforest to forest).

Water, urban, barren, and wetland were the land cover types that gained area from 1992 to 2001, whereas forest, agricultural land, and grass/shrub lost area (Figure 3). Taking the region as a whole, the greatest change occurred between forest and agricultural land, accounting for 50% of all forest-related changes that resulted in approximately 2,000 km^2 forest gain from agricultural land during the period (Table 2). We also found that within the region, LUC effects were significantly and positively correlated with population density at the state level (Spearman $\rho = -0.68$, $P = 0.0008$) (Figure 4). The relationship would be approximately linear and fairly precise were it not for two distinct outliers. New Jersey was one outlier, showing high population density but a relatively low LUC rate. New Jersey is the nation's most densely populated state (433 persons/km^2) (Figure 4), but its population is distributed unevenly and significant forest and agricultural areas occur in portions with low population density. Furthermore, 38% of forestland in New Jersey is publicly owned, the highest percentage of forestland in public ownership of any state east of the Mississippi (Widmann 2005), and therefore likely to be unavailable for major land cover change. Maine was the other outlier, with a relatively low population density (15 persons/km^2) and a much higher LUC rate than would be expected at that density. Part of the reason for the high rate of LUC is probably misclassification errors in the Retrofit change product. For example, in the state of Maine, 51% of all LUC during the period was attributed to the changes from forest to grass/shrub and wetland, the two cover types with relatively low mapping accuracies (Hollister et al. 2004).

Caution is advised in evaluating dynamics in forest area changes because of differences in the ways that the data were analyzed. For example, evaluation of LUC and harvest effects on changes in area and C were based on forest area in 1992 (unless specified). Thus, the expression indicated relative changes for each state without considering the absolute difference in size among the states. However, when we linked the annual LUC rates with population densities at the state level, the rates were calculated in relation to total

Table 2. Land cover changes at Anderson Level I detected from the NLCD Retrofit Change Product (1992–2001) for 24 northern states based on state-level statistics.

	Water	Urban	Barren	Forest	G/S	Agric.	Wetland	Sum 1992
	(km^2)							
Water	52,796	52	89	194	234	502	672	54,539
Urban	131	175,709	21	226	85	776	162	177,110
Barren	154	28	5,527	44	30	52	44	5,879
Forest	353	2,182	588	657,712	4,120	7,409	2,091	674,455
G/S	1,884	531	56	1,737	388,044	9,197	1,186	402,635
Agric	4,472	4,101	250	5,444	7,468	1,040,500	4,312	1,066,547
Wetland	759	152	21	1,472	928	757	124,472	128,561
Sum 2001	60,549	182,755	6,552	666,829	400,909	1,059,193	132,939	2,509,726

G/S, grass/shrub; Agric., agriculture.

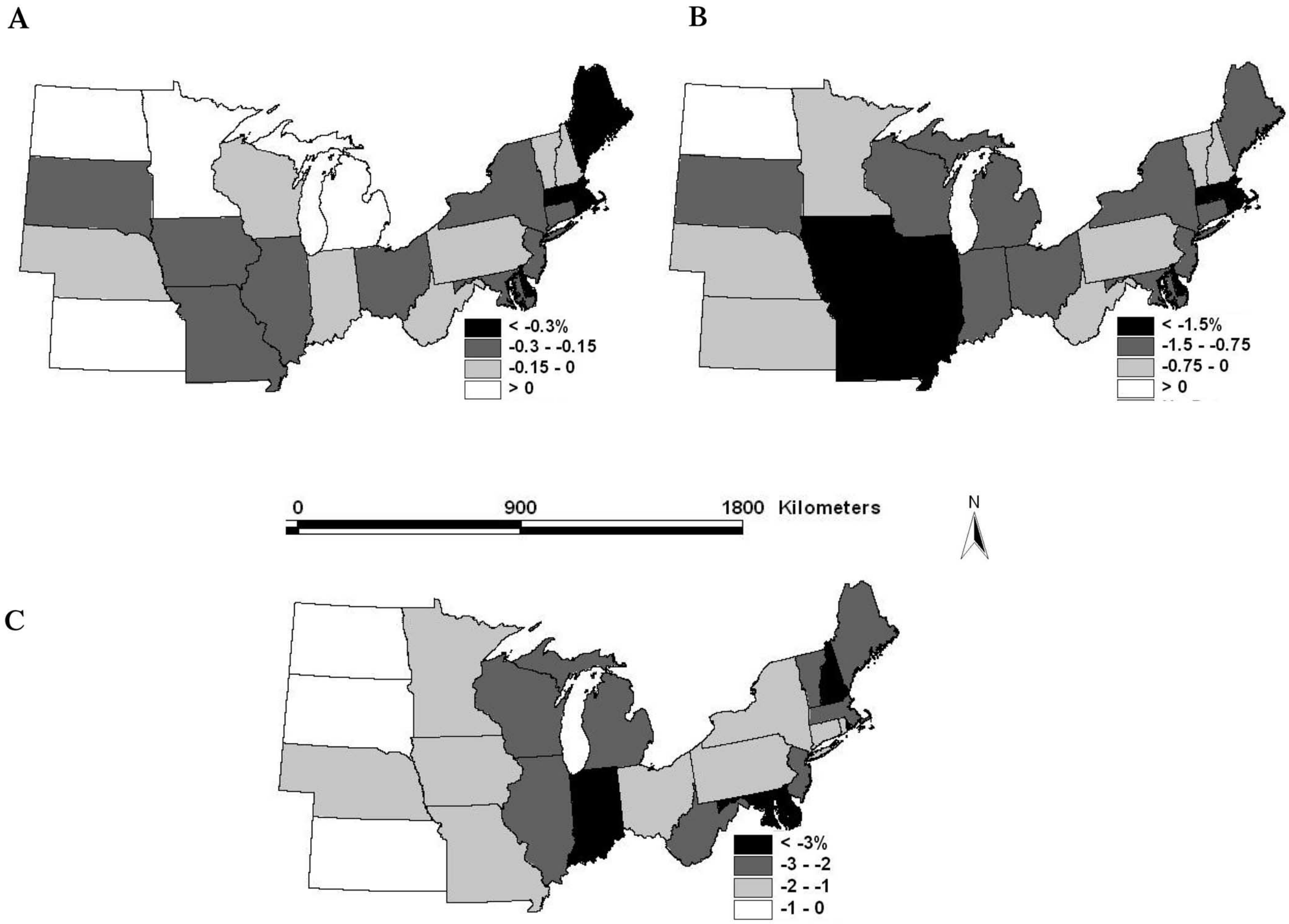

Figure 2. A. Spatial distribution of annual rate (percent) in terms of net LUC effect (afforestation − deforestation) on forest area change for each of the 24 northern states calculated from the NLCD 1992/2001 Retrofit Change Product using Equation 1. Negative rates indicate area loss, whereas positive rates mean area gain. B. Spatial distribution of annual rate (percent) in terms of net LUC effect on C dynamics for each of the 24 northern states based on area change calculations after multiplying by C densities for various forest types identified at county level. Negative rates indicate C loss, whereas positive rates mean C gain. C. Regional distribution pattern of annual rates (percent) in terms of forest harvests on C dynamics for each of the 24 northern states.

land area, which resulted in lower rates than the corresponding rates relative to forest areas even though the observed changes were the same. This adjustment was necessary to make the link valid because the population density from the Esri database was calculated using total land area instead of forest area in each state.

Differences between County- and State-Based Estimates

Forest areas calculated from county- and state-level data differed slightly among the states (less than 0.05% for the region as a whole) as expected and, thus, had little impact on area-related analyses. However, C dynamics calculated using forest type identifications determined at the county level and state level differed substantially. The differences ranged from −54% in South Dakota to 49% in Nebraska with an average of 17.6% (in absolute value). Overall, the C dynamics of a region estimated from state-level species identification was 5% higher than that from county-level identification (Table 3). The C dynamics estimated using county-level forest type identification were improved for the region as a whole compared with the estimation using state-level identification, using the FIA only-based estimation as reference. However, the county-based estimates were not necessarily closer to the FIA survey-based estimates (Smith and Heath 2004) because only 12 of the 24 states showed improved estimates using county-level data and the other half did not (Table 3). On the one hand, county-level data may reflect spatial variation of forest types within a given state, thus improving the state-level estimation. For example, at the state level the common type group of vegetation in Maine is defined as maple/beech/birch, whereas the majority of forest areas in northern Maine are dominated by spruce-fir. The C sequestration rate of maple/beech/birch at age 55 years is 24% higher than that of spruce-fir (Smith et al. 2006). On the other hand, county-level estimates of area by forest type may contain large errors because of too-few inventory plots, compared with the state-level estimates. That forest type is currently determined using an algorithm instead of called in the field may also influence the results. How scaling effects can affect the accuracy in identifying forest type and area is a complicated issue and more focused studies are needed.

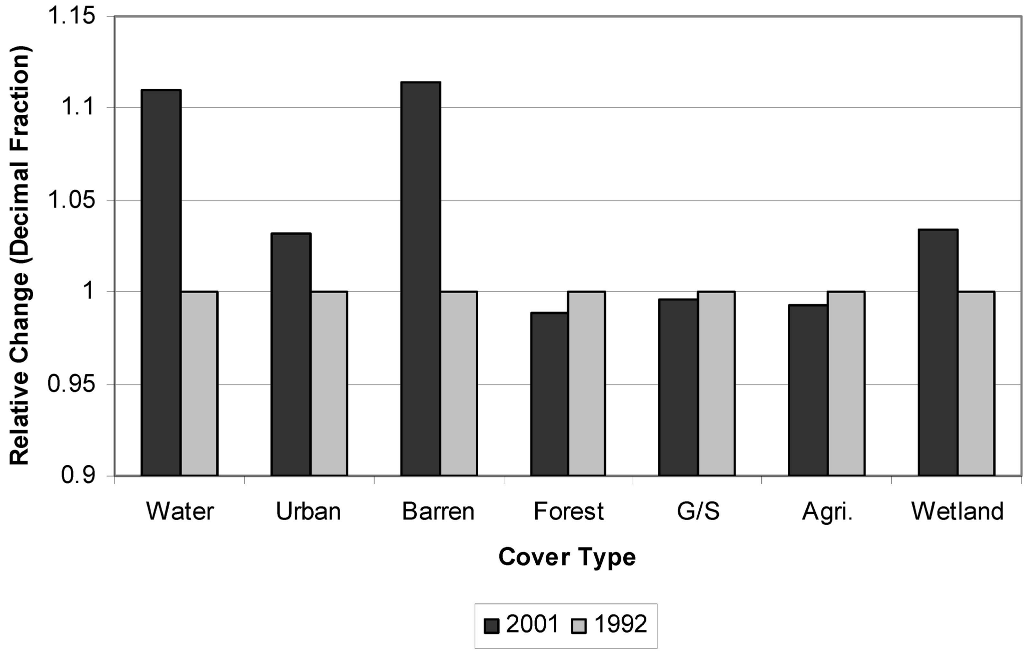

Figure 3. Relative changes in area for the seven cover types at Anderson Level I with the NLCD Retrofit Change Product (1992–2001) between 1992 and 2001 within the 24 northern states of the United States, calculated as $Area_{2001}/Area_{1992}$.

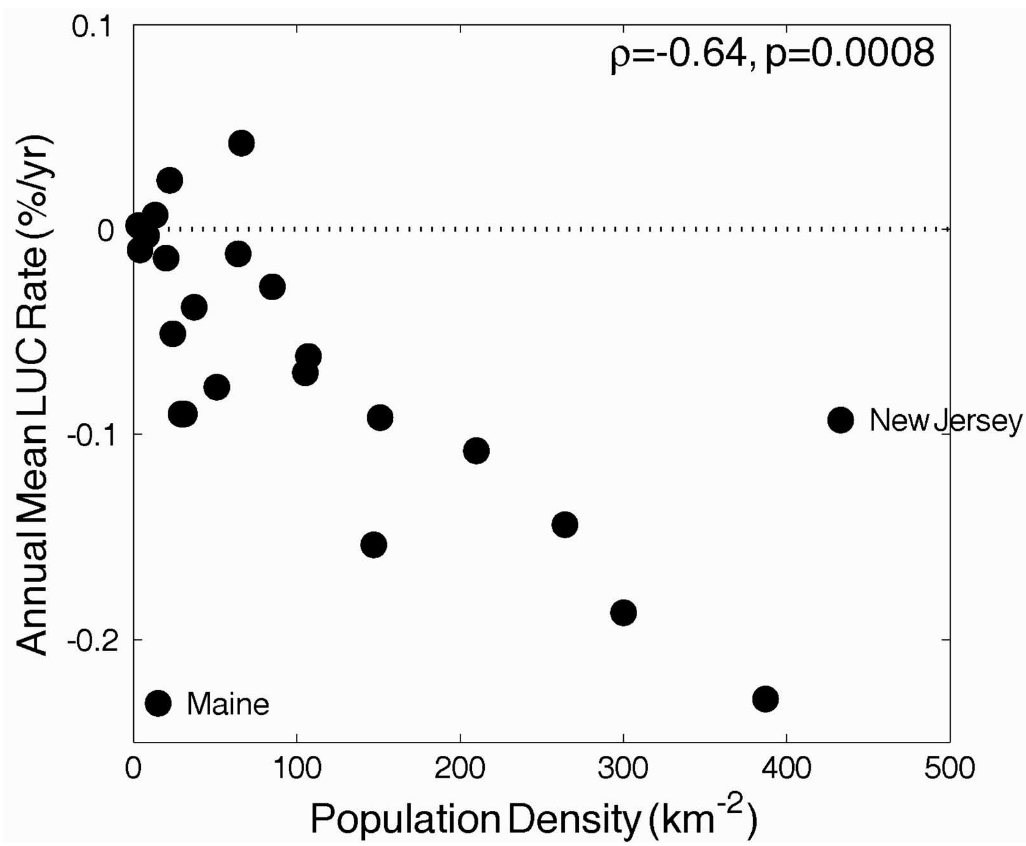

Figure 4. Relationship between annual mean LUC rate from 1992 to 2001: [(afforestation − deforestation)/total land area] × 100/9 and population density in the study area. Negative rates indicate forest losses, whereas positive rates mean forest gains. Each dot represents a state.

C Dynamics

From 1992 to 2001 the region sequestered 11 Tg (1 teragram = 10^{12} g) of C through afforestation and lost 137 Tg of C through deforestation. Simultaneously, forest remaining forest sequestered about 1,041 Tg of C (Table 1) before harvesting effects were included. Northern forests functioned as a C sink of 627 Tg of C after incorporating the harvest data (approximately 287 Tg of C were removed), at

Table 3. Differences in C dynamics estimated using growth and harvest data for forest types determined at county and state levels for the 24 northern states (1992–2001).

State	County-based estimation	State-based estimation	Difference (%)[a]
	........(× 1,000 tonnes)........		
Connecticut	10,867	10,757	−1
Delaware	387	472	22
Illinois[b]	10,435	8,037	−23
Indiana[b]	8,388	7,806	−7
Iowa[b]	7,395	5,588	−24
Kansas[b]	8,724	6,771	−22
Maine[b]	36,312	52,429	44
Maryland[b]	6,463	8,131	26
Massachusetts[b]	8,655	5,369	−38
Michigan[b]	46,537	48,181	4
Minnesota	59,567	57,222	−4
Missouri	45,044	42,344	−6
Nebraska	4,589	6,833	49
New Hampshire	14,030	13,091	−7
New Jersey	7,507	10,394	38
New York	73,566	73,417	0
North Dakota	4,388	4,300	−2
Ohio[b]	41,583	45,086	8
Pennsylvania[b]	91,444	108,511	19
Rhode Island	1,626	1,647	1
South Dakota	10,110	4,609	−54
Vermont	17,222	16,559	−4
West Virginia[b]	67,520	75,961	13
Wisconsin[b]	44,716	47,268	6
Total[b]	627,075	660,783	5

[a] Difference between county-based and state-based estimates: $(EST_s/EST_c - 1) \times 100$ and rounded to integer.
[b] States that indicate improved estimates using county-level data, compared with the FIA only-based (Smith and Heath 2004) C estimates during the same period.

a mean annual rate of 70 Tg of C. The forest-related LUC effect during the 9-year period resulted in a 10.8% reduction of overall forest C accumulation in the region, compared with what would have accumulated without LUC effects. If the C removals from harvests were considered, the influence increased to 28.4% less than the overall regional forest C accumulation. The integrated annual effects of LUC and harvests on forest C dynamics varied substantially within the region, ranging from −0.4% in North Dakota to −5.1% in Delaware, being −3.2% on average (Table 1).

Net change in nonsoil forest C accumulation during the 9-year period ranged by state from 0.4 Tg in Delaware to 91 Tg in Pennsylvania (Table 1). Spatially, in the six states in which forest C was affected the most by LUC, conversion of forestland to agricultural use or urbanization was the primary driver. The exception is the state of Delaware, in which the greatest loss of forestland was to wetland, a land cover type that is sensitive to misclassification error (Wright and Gallant 2007), during the 9-year period (Figure 2b). Among the seven Anderson Level I categories in the NLCD 1992 map, wetlands have the lowest user accuracies using center pixel and mode agreement definitions (Stehman et al. 2003). North Dakota was the only state in which no deforestation was detected. This led to a positive LUC effect for that state.

Forest harvests showed a substantial impact on regional forest C dynamics. For example, the amount of nonsoil forest C removed through harvests was equivalent to 27.6% of total C sequestered by forest remaining forest during the 9-year period (Table 1) ranging from 1.3% in South Dakota to 50.5% in Delaware. In terms of forest C removed by harvesting, the top five states were Maine (42 Tg), Wisconsin (32 Tg), Pennsylvania (30 Tg), West Virginia (26 Tg), and Michigan (25 Tg), three from the Northeastern subregion and two from the Northcentral subregion. In terms of percent loss in forest C, four states exceeded an annual rate of 3% due to harvest alone, with one located in the Northcentral subregion (Indiana) and three in the Northeastern subregion (Delaware, Maryland, and New Hampshire) (Figure 2c).

In terms of forest C loss through deforestation and harvest combined, the state of Maine showed the greatest amount (64 Tg for the 9 years) among the states, indicating a strong influence from human activities. Maine had the largest and most diverse forest products industry in New England and was the second largest paper-producing state in the nation. The industry was a key player in the state's economy, representing more than 36% of Maine's total manufacturing output and providing more than 18,000 jobs for the state (Maine Department of Conservation 2005). Other top states affected by this combined effects were Pennsylvania (42 Tg), Wisconsin (41 Tg), Michigan (37 Tg), and New York (35 Tg) (Table 1).

Spatially, most Northcentral states experienced relatively low rates of effects from harvests (<2%) with exception of the four most easterly states in the subregion (Figure 2c). After area weighting, however, the average annual rate of harvest effect on forest C dynamics was slightly lower (−2.1%) in the Northcentral subregion than that (−2.3%) in the Northeastern subregion.

In summary, the effect of harvest on reducing forest C stocks, assuming that C from harvested wood products was immediately emitted into the atmosphere, was higher than that from LUC in 21 of the 24 states. Taking the region as a whole, harvests removed 287 Tg of C from the regional forests during the 9-year period, 128% higher than that (126 Tg C) resulting from LUC (Table 1). The annual mean integrated effect of both LUC and harvest on forest C accumulation in the Northeastern subregion was −3.4%, 31% higher than the −2.6% in the Northcentral subregion.

Uncertainties

There are several potential error sources in this study. First, NLCD 1992 and 2001 maps were generated using different classification schemes (Vogelmann et al. 2001, Homer et al. 2004). However, the retrofit product uses fewer classifications, and this tends to increase accuracy. For example, overall accuracies in different regions across the eastern United States increased from 43 to 66% at Anderson Level II to 70 to 83% at Level I according to the NLCD 1992 map (Stehman et al. 2003). In general, water, urban, and forest have relatively high classification accuracies, whereas wetland, grass/shrub, and barren have low accuracies (Hollister et al. 2004). Second, some counties with detected forest-related area changes based on the 30-m NLCD map did not have corresponding forest C density data available based on FIA data (Smith et al. 2006). When this occurred, we used the substituted forest types from nearby geographic regions. For example, C dynamics in some counties of South Dakota whose forest types were identified as ponderosa pine were calculated using ponderosa pine data from the Rocky Mountain area. Third, double counting of C removals may occur between deforestation as determined from the NLCD and harvest removals data as estimated using FIA data. The differences between forest cover and forest use definitions used by NLCD and FIA, respectively, affect the estimation of deforestation within each approach. These differences are complicated by the nature of the FIA harvest and removal data, particularly over this time period in which the survey design was changed from periodic to annualized. Two principal types of double counting can be anticipated. In the first, areas that are regenerated silviculturally under even-aged systems could be mapped to nonforest classes in the NLCD data. In the second, timber removals due to terminal harvest and land use conversion associated with correctly mapped deforestation in the NLCD might also appear in the FIA removals. In this study region, a range of quantitative and anecdotal evidence indicates that the vast majority of timber harvests are partial harvests, mitigating the impact of either type of double counting (Kelty et al. 2003, Finley and Kittredge 2006, Maine Forest Service 2008). However, this challenge deserves further exploration. Finally, although our study area in general is not greatly affected by wildfire, we would expect slight changes in our C-related analyses if wildfire data or other natural disturbance data were incorporated.

Conclusions

Spatial variations in integrated effects of LUC and harvest on regional nonsoil forest C dynamics were substantial in the United States northern forests between 1992 and 2001. Between the two components, harvesting effects were greater than those from land cover change. Whereas LUC effects could be quantified from satellite-derived remote sensing products at moderate resolution (e.g., 30 m), growth and harvest data based on ground inventories were needed to improve the accuracy of forest C estimation over large areas. In this study, we also illustrated the effects from LUC and harvests separately because the C dynamics and policy issues relating to LUC (deforestation in particular) and forest management are very different, and thus keeping these items separate is important.

We present a simple, straightforward, and practical method combining remote sensing observations and ground inventory data over large areas for similar studies of this kind across spatial and temporal dimensions with necessary regional adjustments (e.g., effects from forest fires and diseases) in future. The deforestation rate was in general positively related to population density at state level. Our analyses delineate C changes by forest status, which is afforestation, deforestation, and forest remaining forest, which allows for reporting by these categories and allows for calculations to recognize the different forest C dynamics for each land status. Besides the fact the C dynamics are different based on forest status, good practice guidance for national greenhouse gas inventory reporting calls for nations to report their forest C information separately this way, following the Kyoto Protocol. Results were mixed as to whether using forest type identified at the finer county resolution was more accurate than using FIA only-based estimates. Further research is also needed to characterize the uncertainty in this integrated remote sensing field data approach.

Literature Cited

ANDERSON, J.R., E.E. HARDY, J.T. ROACH, AND W.E. WITMER. 1976. *A land use and land cover classification system for use with remote sensing data*. US Geological Survey, Reston, VA. 964 p.

BIRDSEY, R.A., AND H.T. SCHREUDER. 1992. *An overview of forest inventory and analysis estimation procedures in the Eastern United States—With an emphasis on the components of change.* US For. Serv., Rocky Mount. For. Range Exp. Stn., Fort Collins, CO. GTR RM-214.

CANADELL, J.G., C. LEQUÉRÉ, M.R. RAUPACH, C.B. FIELD, E.T. BUITENHUIS, P. CIAIS, T.J. CONWAY, N.P. GILLETT, R.A. HOUGHTON, AND G. MARLAND. 2007. Contributions to accelerating atmospheric CO_2 growth from economic activity, carbon intensity, and efficiency of natural sinks. *Proc. Natl. Acad. Sci. U.S.A.* 104:18866–18870.

COHEN, W.B., T.A. SPIES, R.J. ALIG, D.R. OETTER, T.K. MAIERSPERGER, AND M. FIORELLA. 2002. Characterizing 23 years (1972–1995) of stand replacement disturbance in western Oregon forests with Landsat imagery. *Ecosystems* 5:122–137.

DALE, V.H. 1997. The relationship between land-use change and climate change. *Ecol. Appl*. 7:753–769.

DIXON, R.K., S. BROWN, R.A. HOUGHTON, A.M. SOLOMON, M.C. TREXLER, AND J. WISNIEWSKI. 1994. Carbon pools and flux of global forest ecosystems. *Science* 63:185–190.

FINLEY, A.O., AND KITTREDGE, D.B. 2006. Thoreau, Muir, and Jane Doe: Different types of private forest owners need different kinds of forest management. *North. J. Appl. For*. 23:27–34.

HANSEN, M.C., R.S. DEFRIES, J.R. TOWNSHEND, AND R. SOHLBERG. 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. *Int. J. Remote Sens.* 21:1331–1364.

HAYNES, R.W. 2003. *An analysis of the timber situation in the United States: 1952 to 2050.* US For. Serv., Pac. Northw. Res. Stn., Portland, OR. GTR-PNW-560. 254 p.

HAYNES, R.W., D.M. ADAMS, R.J. ALIG, P.J. INCE, J.R. MILLS, AND X. ZHOU. 2007. *The 2005 RPA timber assessment update.* US For. Serv., Pac. Northw. Res. Stn., Portland, OR. PNW-GTR-699. 212 p.

HEATH, L.S., AND R.A. BIRDSEY. 1993. Carbon trends of productive temperate forests of the conterminous United States. *Water Air Soil Poll.* 70:279–293.

HOLLISTER, J.W., M.L. GONZALEZ, J.F. PAUL, P.V. AUGUST, AND J.L. COPELAND. 2004. Assessing the accuracy of National Land Cover Dataset area estimates at multiple spatial extents. *Photogramm. Eng. Remote Sens*. 70:405–414.

HOMER, C., C. HUANG, L. YANG, B. WYLIE, AND M. COAN. 2004. Development of a 2001 National Land-Cover Database for the United States. *Photogramm. Eng. Remote Sens.* 70:829–840.

HOUGHTON, R.A., J.L. HACKLER, AND K.T. LAWRENCE. 1999. The U.S. carbon budget: Contributions from land-use change. *Science* 285:574–578.

INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE. 2002. *Climate change 2001: The scientific basis*. Available online at www.

grida.no/climate/ipcc_tar/wg1/099.htm; last accessed May 2, 2009.

KELTY, M.J., D.B. KITTREDGE, T. KYKER-SNOWMAN, AND A.D. LEIGHTON. 2003. The conversion of even-aged stands to uneven-aged structure in southern New England. *North. J. Appl. For.* 20:109–116.

MAINE DEPARTMENT OF CONSERVATION. 2005. The 2005 biennial report on the state of the forest and progress report on sustainability standards. Report to the Joint Standing Committee of the 122 Legislature on Agriculture, Conservation and Forestry. Maine Department of Conservation, Augusta, ME. 124 pp.

MAINE FOREST SERVICE. 2008. *2007 Silvicultural activities report.* Department of Conservation, Maine For. Serv. Available online at www.maine.gov/doc/mfs/pubs/pdf/silvi/07silvi.pdf; last accessed April 12, 2009.

MILLS, J.R., AND J.C. KINCAID. 1992. *The aggregate timberland assessment system—ATLAS: A comprehensive timber projection model.* US For. Serv., Pac. Northw. Res. Stn., Portland, OR. GTR-PNW-281.

MULTI-RESOLUTION LAND CHARACTERISTICS CONSORTIUM. 2009. *NLCD 1992/2001 retrofit land cover change project.* Available online at www.mrlc.gov/multizone.php; last accessed Jan. 22, 2009.

PERRY, M.J., AND P.J. MACKUN. 2001. *Population change and distribution: Census 2000 brief*. US Census Bureau, C2KBR/01-2. Available online at www.census.gov/prod/2001pubs/c2kbr01–2.pdf; last accessed Feb. 20, 2009.

POST, W.M., W.R. EMANUEL, P.J. ZINKE, AND A.G. STRANGENBERGER. 1982. Soil carbon pools and world life zones. *Nature* 298:156–159.

PRINCE, S.D., AND S.N. GOWARD. 1995. Global primary production: A remote sensing approach. *J. Biogeogr.* 22:815–835.

RUNNING, S.W., C.O. JUSTICE, V. SALOMONSON, D. HALL, J. BARKER, Y.J. KAUFMANN, A.H. STRAHLER, A.R. HUETE, J.-P. MULLER, V. VANDERBILT, Z.M. WAN, P. TEILLET, AND D. CARNEGGIE. 1994. Terrestrial remote sensing science and algorithms for EOS/MODIS. *Int. J. Rem. Sens.* 15:3587–3620.

RUNNING, S.W., R. NEMANI, D.L. PETERSON, L.E. BEND, D.F. POTTERS, L.L. PIERCE, AND M.A. SPANNER. 1989. Mapping regional forest evapotranspiration and photosynthesis by coupling satellite data with ecosystem simulation. *Ecology* 70:1090–1101.

SMITH, J.E., AND L.S. HEATH. 2004. Carbon stocks and projections on public forestlands in the United States, 1952–2040. *Environ. Manag.* 33:433–442.

SMITH, J.E., AND L.S. HEATH. 2008. Carbon stocks and stock changes in U.S. forests. P. 65–80, C61–C67 in *U.S. Agriculture and forestry greenhouse gas inventory: 1990–2005.* Tech. Bull. No. 1921. US Department of Agriculture, Office of the Chief Economist, Washington, DC.

SMITH, J.E., L.S. HEATH, K.E. SKOG, AND R.A. BIRDSEY. 2006. *Methods for calculating forest ecosystem and harvested carbon with standard estimates for forest types of the United States.* NE-343. US For. Serv., Northeast. Res. Stn., Newtown Square, PA.

STEHMAN, S.V., J.D. WICKHAM, J.H. SMITH, AND L. YANG. 2003. Thematic accuracy of the 1992 National Land-Cover Data for the eastern United States: Statistical methodology and regional results. *Remote Sens. Environ*. 86:500–516.

TELE ATLAS NORTH AMERICA, INC./GEOGRAPHIC DATA TECHNOLOGY, INC. 2005. *U.S. states: Esri data & maps 2005*. Esri, Redlands, CA.

TUCKER, C.J., J.A. GAITLIN, AND S.R. SCHNEIDER. 1984. Monitoring vegetation in the Nile Delta with NOAA-6 and NOAA-7 AVHRR imagery. *Photogramm. Eng. Remote Sens.* 50:53–61.

US DEPARTMENT OF AGRICULTURE. 2008. *FIA DataMart.* Available online at http://199.128.173.17/fiadb4-downloads/datamart.html; last accessed Jan. 4, 2011.

US DEPARTMENT OF AGRICULTURE. 2009. *Forest Inventory and Analysis National Program: User information.* US For. Serv., Washington, DC. Available online at fia.fs.fed.us/tools-data/docs/default.asp; last accessed June 24, 2009.

US DEPARTMENT OF ENERGY. 2009. *Enhancing DOE's voluntary reporting of greenhouse gases (1605(b)) program.* Available online at http://www.eia.doe.gov/oiaf/1605/; last accessed Jan. 4, 2011.

VOGELMANN, J.E., S.M. HOWARD, L. YANG, C.R. LARSON, B.K. WYLIE, AND N. VAN DRIEL. 2001. Completion of the 1990s National Land Cover Dataset for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources. *Photogramm. Eng. Remote Sens.* 67:650–652.

WICKHAM, J.D., S.V. STEHMAN, J.A. FRY, J. H. SMITH, AND C. G. HOMER. 2010. Thematic accuracy of the NLCD 2001 land cover for the conterminous United States. *Remote Sens. Environ.* 114:1286–1296.

WIDMANN, R.H. 2005. *Forests of the Garden State*. US For. Serv., Northeast. Res. Stn., Newtown Square, PA. NE-163.

WOODBURY, P.B., L.S. HEATH, AND J.E. SMITH. 2006. Land use change effects on forest carbon cycling throughout the southern United States. *Environ. Qual.* 35:1348–1363.

WOODCOCK, C.E., S.A. MACOMBER, M. PAX-LENNEY, AND W.B. COHEN. 2001. Monitoring large areas for forest change using Landsat: Generalization across space, time and Landsat sensors. *Remote Sens. Environ*. 78:194–203.

WRIGHT, C., AND A. GALLANT. 2007. Improved wetland remote sensing in Yellowstone National Park using classification trees to combine TM imagery and ancillary environmental data. *Remote Sens. Environ*. 107:582–605.

ZHENG, D., L. HEATH, AND M. DUCEY. 2008. Satellite detection of land-use change and effects on regional forest aboveground biomass estimates. *Environ. Monit. Assess.* 144:67–79.

ZHENG, D., S.D. PRINCE, AND T. HAME. 2004. Estimating net primary production of boreal forests in Finland and Sweden from field data and remote sensing. *J. Veg. Sci*. 15:161–170.