

Forecasts of Forest Conditions in U.S. Regions Under Future Scenarios

A Technical Document Supporting
the Forest Service 2010 RPA Assessment

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Abstract

The 626 million acres of forests in the conterminous United States represent significant reserves of biodiversity and terrestrial carbon and provide substantial flows of highly valued ecosystem services, including timber products, watershed protection benefits, and recreation. This report describes forecasts of forest conditions for the conterminous United States in response to multiple scenarios evaluated by the 2010 Resources Planning Act Assessment. The results are based on the U.S. Forest Assessment System, a modeling system designed to forecast alternative futures for U.S. forests, and provide a forward-looking adjunct to the Forest Inventory and Analysis Program of the Forest Service U.S. Department of Agriculture. Scenarios address a range of future conditions regarding population growth, economic change, global forest product markets, and climate change. Forest forecasts are described for each of four Resources Planning Act regions (South, North, Rocky Mountain, and Pacific Coast) across the Resources Planning Act scenarios. In the Eastern United States, the range of socioeconomic futures leads to greater variation in future forest conditions than does the range of climate projections. Because of the dominance of public forests in the Western United States, socioeconomic changes hold less sway over forest futures there. Built directly from and as a forecasting adjunct to the monitoring system of the Forest Inventory and Analysis Program, the modeling components will be enhanced by additional forest inventory data as they become available.

Keywords: Forecasts, forest inventory, integrated assessment.

INTRODUCTION

Forests develop in response to their physical environment, biological dynamics, and decisions regarding their uses. Acting on different timeframes, these forest dynamics ultimately determine the services that flow from the Nation’s forests. The Forest and Rangeland Renewable Resources Planning Act (RPA) of 1974 mandates a careful analysis of forest conditions as part of a periodic assessment of the condition and trends of the Nation’s renewable resources. The RPA Assessment provides a snapshot of current U.S. forest and rangeland conditions and trends on all ownerships, identifies drivers of change, and projects 50 years into the future. Analyses of the status and trends for forest conditions, recreation, water, timber, wildlife and fish, biodiversity, and range resources as well as land-use change, climate change, and urban forestry are included (USDA Forest Service 2001).

This report describes forecasts of forest conditions for the conterminous United States in response to multiple scenarios evaluated by the 2010 RPA Assessment (fig. 1).¹ The results

¹ Trends and current forest conditions in the United States are examined in Smith and others (2009).

are based on the U.S. Forest Assessment System, a modeling system designed to forecast alternative futures for U.S. forests (Wear 2010). Developed by the RPA Assessment program, this system is a forward-looking adjunct to the ongoing inventories of forest conditions conducted by the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture (fig. 1). The FIA system provides nationwide monitoring through repeated inventories that measure forest conditions, while the Forest Assessment System addresses how biological, physical, and human factors could alter these forest inventories in the future and generates forecasts of detailed forest inventories along with forecasts of land use changes and forest product markets.

The Forest Assessment System represents a new technical approach and a shift in focus for the 2010 RPA. For previous RPA Assessments (Haynes 1990, Haynes and Adams 1985, Haynes and others 1995, Haynes and others 2007, USDA Forest Service 1982) and for Forest Service timber market assessments that predate the RPA (USDA Forest Service 1920, 1933, 1958, 1965, 1974), analysis focused primarily on forecasts of timber production levels and prices. Forecasts

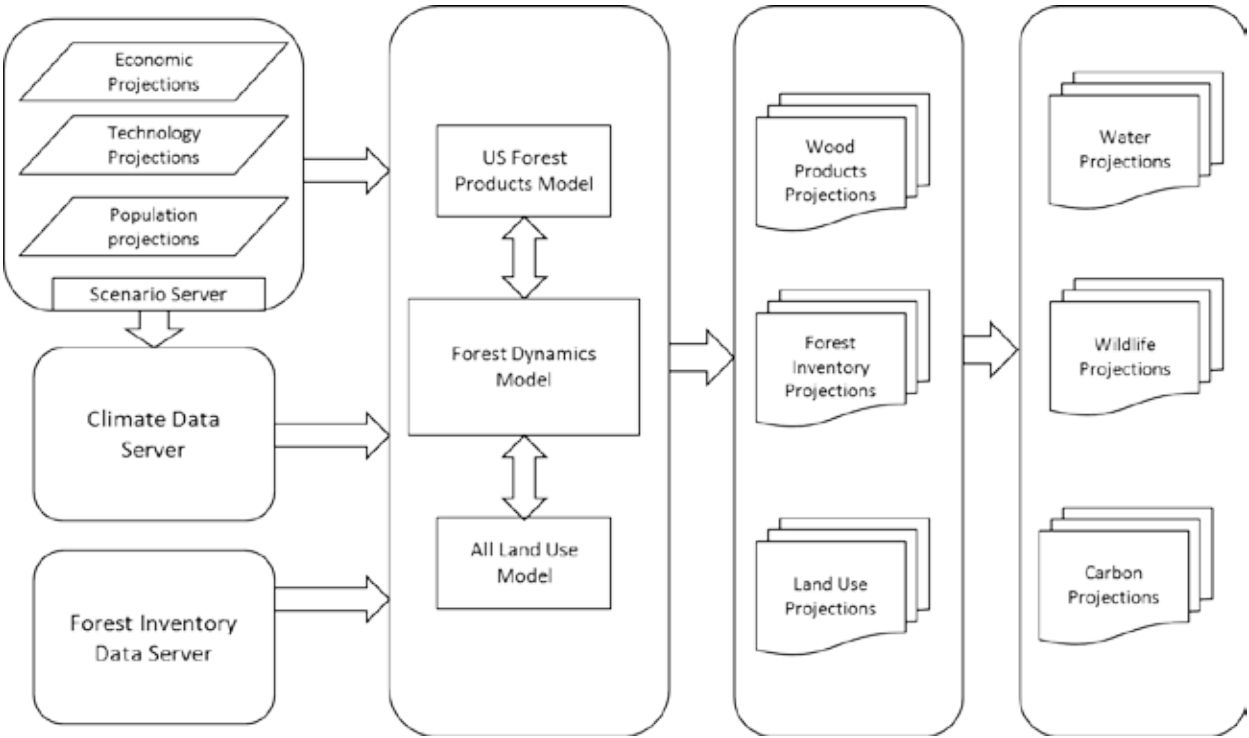


Figure 1—General schematic of the U.S. Forest Assessment System. The first (left) column describes the data sets and projections that initiate analysis and define scenarios. The second column describes the three modeling components of the system. The third and fourth columns describe primary outputs generated and secondary analysis that can be supported respectively.

of timber supply required predictions of timber growth, mortality, and harvests for the various regions of the country and this gave rise to forest/timber inventory projection models based on aggregated forest inventory data (Mills and Kincaid 1992, Mills and Zhou 2007). Timber inventory/supply modeling, conducted at regional scales, provides a useful tool for projecting timber market activities through time and also provided some insights into the future of forest conditions and potential effects on other resource values. While continuing to incorporate the analysis of timber markets, the Forest Assessment System puts the projection of forest conditions at the center of the RPA Assessment, addressing the effects of timber markets but also the effects of other factors such as climate change, natural disturbance, and land use dynamics in the evolution of future forest conditions. The resulting forecasts can support more detailed analysis of ecosystem conditions and services derived from forests in the United States in response to the RPA scenarios.

Overall, the design of the Forest Assessment System aims to allow for integrated assessment of multiple resource issues across common scenarios.

The Forest Assessment System forecasts forest conditions by modeling the effects of changing climate, market-driven timber harvesting/management, and land use changes along with changes driven by disturbance and successional transitions in forest conditions. For the 2010 RPA Assessment, the future of these driving forces is defined through a set of scenarios that contain alternative projections of economic, climate, and population futures. The next sections of this report describe the structure of these scenarios, the modeling approach, and datasets. Subsequent sections describe the forecasts and implications for the future of forests in the four RPA regions of the United States: South, North, Rocky Mountain, and Pacific Coast (fig. 2). A technical appendix provides additional detail on the modeling approach.

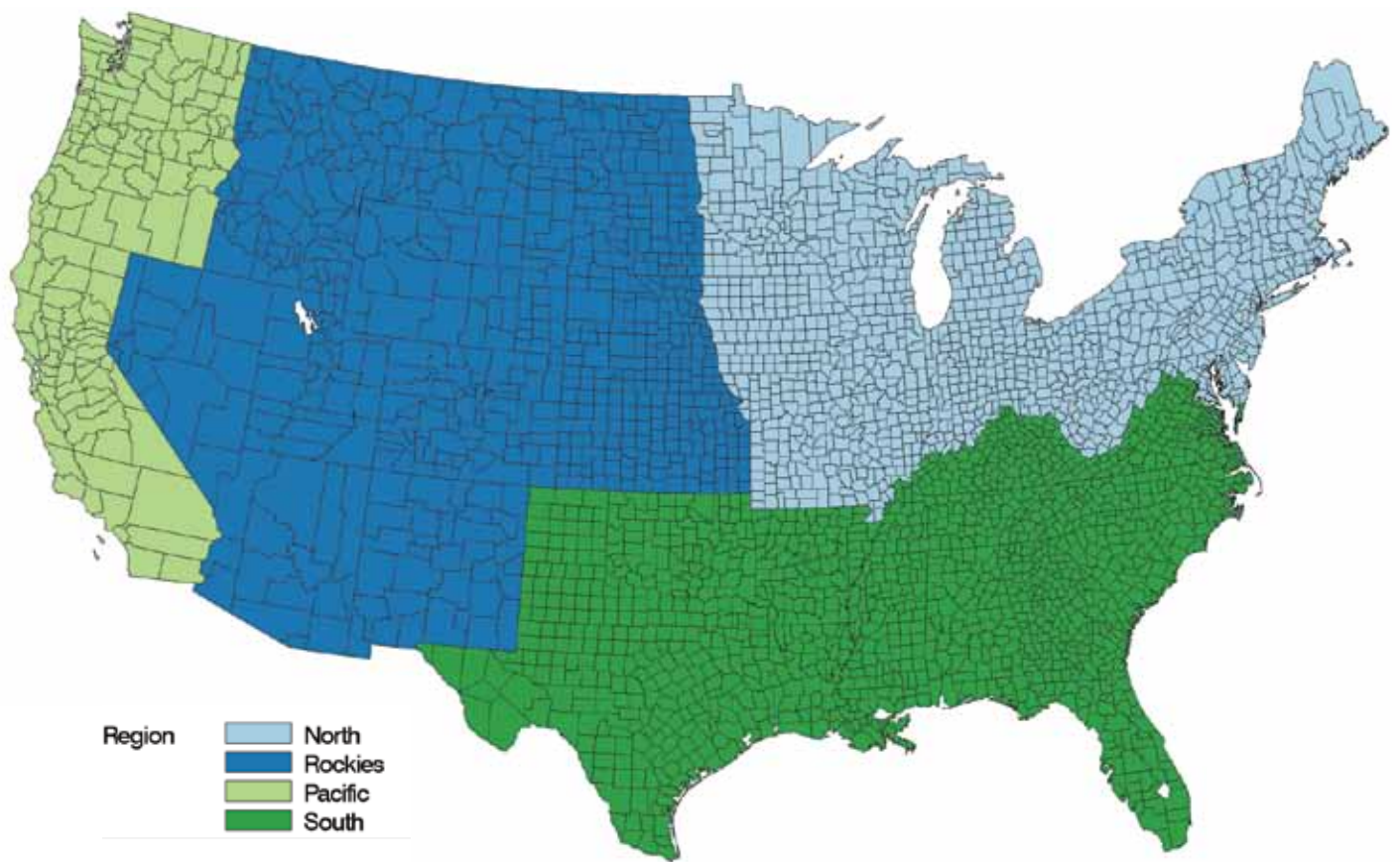


Figure 2—Resources Planning Act (RPA) Assessment regions: South, North, Rocky Mountain, and Pacific Coast.

CHAPTER 1

SCENARIOS FROM THE RESOURCES PLANNING ACT ASSESSMENT

Future renewable resource conditions are influenced by a number of driving forces such as population change, economic growth, and land use change. Three scenarios in the Resources Planning Act (RPA) Assessment are used to characterize the global demographic, socioeconomic, and technological driving forces underlying changes in resource conditions and to evaluate the sensitivity of resource trends to a feasible future range of these driving forces. The use of scenarios links the underlying assumptions of the analyses of various resource conditions and uses and frames uncertainty in these driving forces within the integrated modeling and analysis framework of the 2010 RPA Assessment (see U.S. Department of Agriculture Forest Service, in press, for details on scenario development). RPA scenarios address change over 50 years, from 2010 to 2060.

Three RPA scenarios are linked to global storylines used in the Intergovernmental Panel on Climate Change (IPCC) Third and Fourth Assessments (TAR and AR4, respectively; Intergovernmental Panel on Climate Change 2007a, 2007b). The storylines are potential future states of the world that are largely qualitative, but also include assumptions about global population and economic growth. The storylines were transformed by the IPCC into quantitative scenarios through six integrated assessment models that had varying assumptions about technology change, energy use, and land use change. Of the 40 scenarios produced through this process, seven marker scenarios were subjected to more intensive review and tests of reproducibility by IPCC (Nakicenovic and others 2000).

The RPA selected marker scenarios for storylines A1B, A2, and B2 as the basis for the three RPA scenarios. The IPCC TAR and AR4 storyline labels (A1B, A2, and B2) have been maintained in the 2010 RPA Assessment documentation for continuity (hereafter referred to as RPA A1B, RPA A2, and RPA B2). The global data were scaled to the U.S. national level and sub-national levels for the 2010 RPA Assessment. U.S. gross domestic product and population projections used in the TAR and AR4 analyses were updated, and U.S. population and disposable personal income data were downscaled to the U.S. county level (Zarnoch and others 2010). Climate projections generated from three general circulation models (GCMs) for each of the three IPCC scenarios were also downscaled to the county scale (Joyce and others, in press).

Population and personal income projections for the three RPA scenarios drive forecasts of urbanization and change in the area of forests using the All Land Use Model, as shown in figure 1 (Wear 2011). The RPA A1B population projections are

based on 2004 Census projections for the entire United States, while RPA A2 and RPA B2 depart from these projections as described below. Zarnoch and others (2010) developed county scale projections for each scenario based on forecasts from Woods and Poole's (2007) spatial econometric/demographic model—the Woods and Poole (2007) forecasts are generally consistent with the RPA A1B projection for 2000–30. County-level projections between 2030 and 2060 were disaggregated by extending historical patterns of growth from the Woods and Poole (2007) projections (Zarnoch and others 2010). Projections for RPA A2 and RPA B2 applied the same spatial pattern of population change, but were adjusted to yield county-level projections that add up to the national totals for the respective RPA scenarios.

As shown in figures 3 and 4, RPA A1B corresponds to mid-range population growth and the highest per capita disposable personal income level of the three RPA scenarios. Under RPA A1B, by 2060, the projected population of the United States will be about 446 million, with real per capita personal income around \$80,000. Scenario RPA A2 projects the highest population growth, more than 500 million people by 2060, and the lowest projected per capita personal income, around \$56,000. Scenario RPA B2 projects the lowest population growth, with the population predicted around 397 million people, and mid-level personal income, with per capita personal income predicted around \$60,000.

Population is not forecast to grow across the entire United States. Rather, most projected growth occurs around a number of existing urban centers (fig. 5), e.g., around southern California and between Portland and Seattle in the West, around Minneapolis and Chicago in the Midwest, between Boston and Washington, DC, in the East, and along the Piedmont between Raleigh, NC, and Atlanta in the South. In addition, a large number of rural counties are expected to experience population declines (figure 5 shows these counties in green for RPA A1B). Population loss is forecasted to be especially high through much of the Great Plains and Corn Belt, in the southern Mississippi Alluvial Valley, and in a band from northern Indiana to upstate New York.

For the RPA Assessment, a consistent national database of downscaled climate data were critical to ensure consistency across RPA Assessment resource analyses, as well as consistency with the economic and demographic drivers from the RPA A1B, A2, and B2 scenarios (Joyce and others, in press). For the 2010 RPA analyses, downscaled climate datasets were developed using output from the GCMs used in the

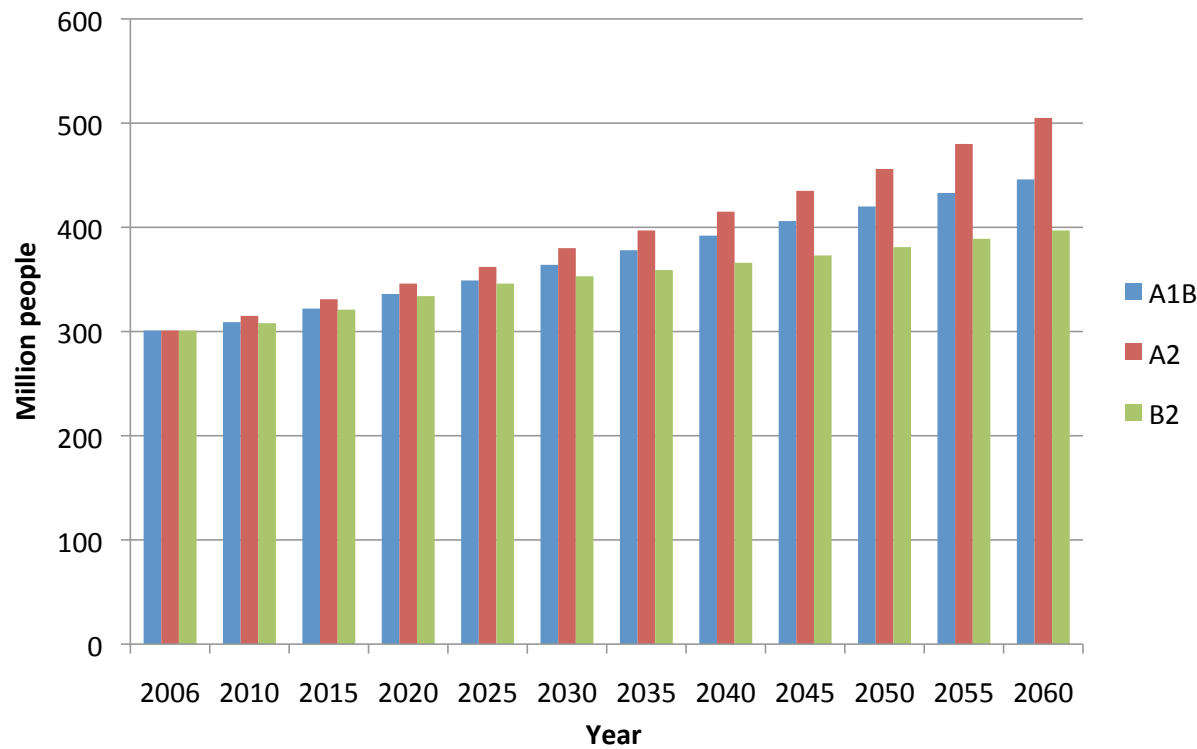


Figure 3—Total projected population in the United States to 2060 for the three Resources Planning Act (RPA) scenarios (A1B, A2, and B2).

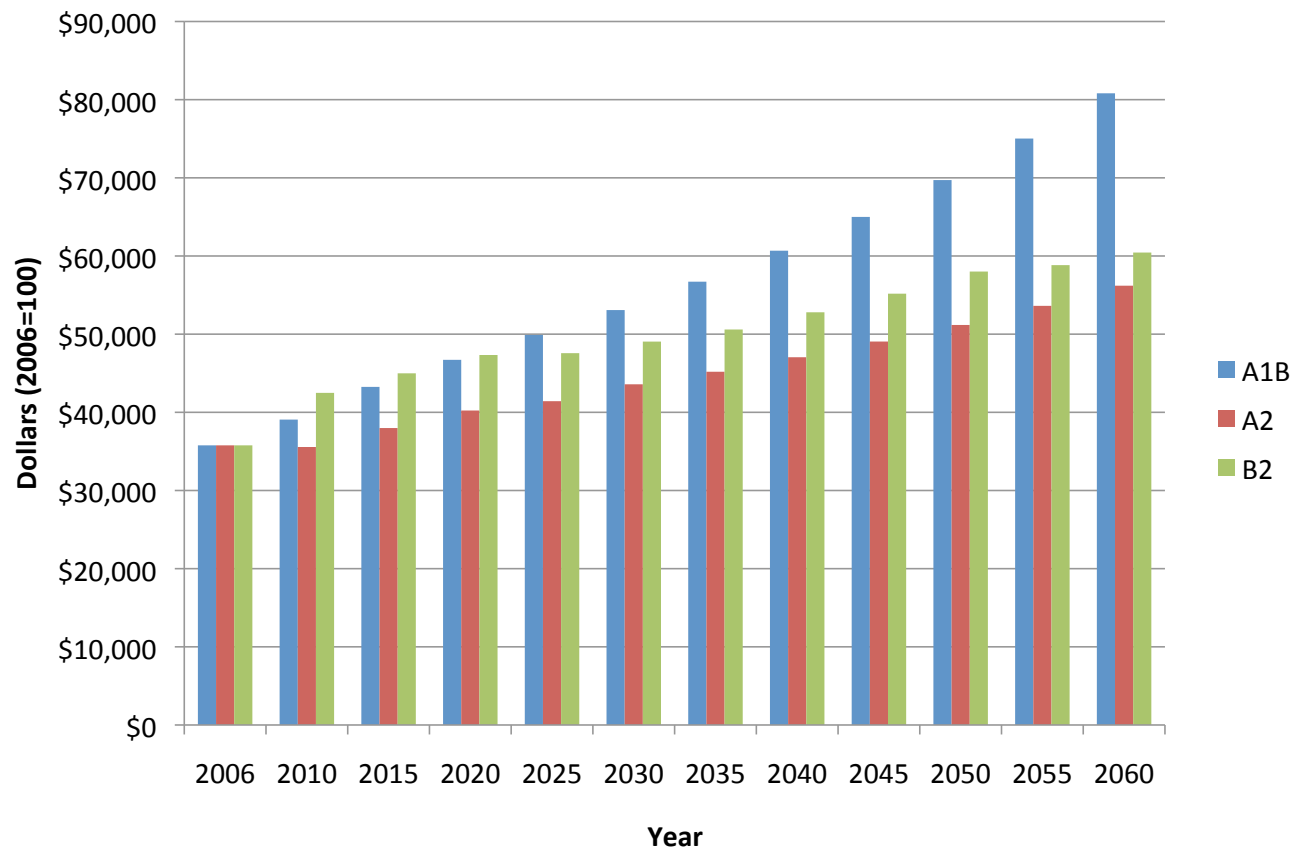


Figure 4—Projected per capita personal income (2006 = 100) for the United States to 2060 for the three Resources Planning Act (RPA) scenarios (A1B, A2, and B2).

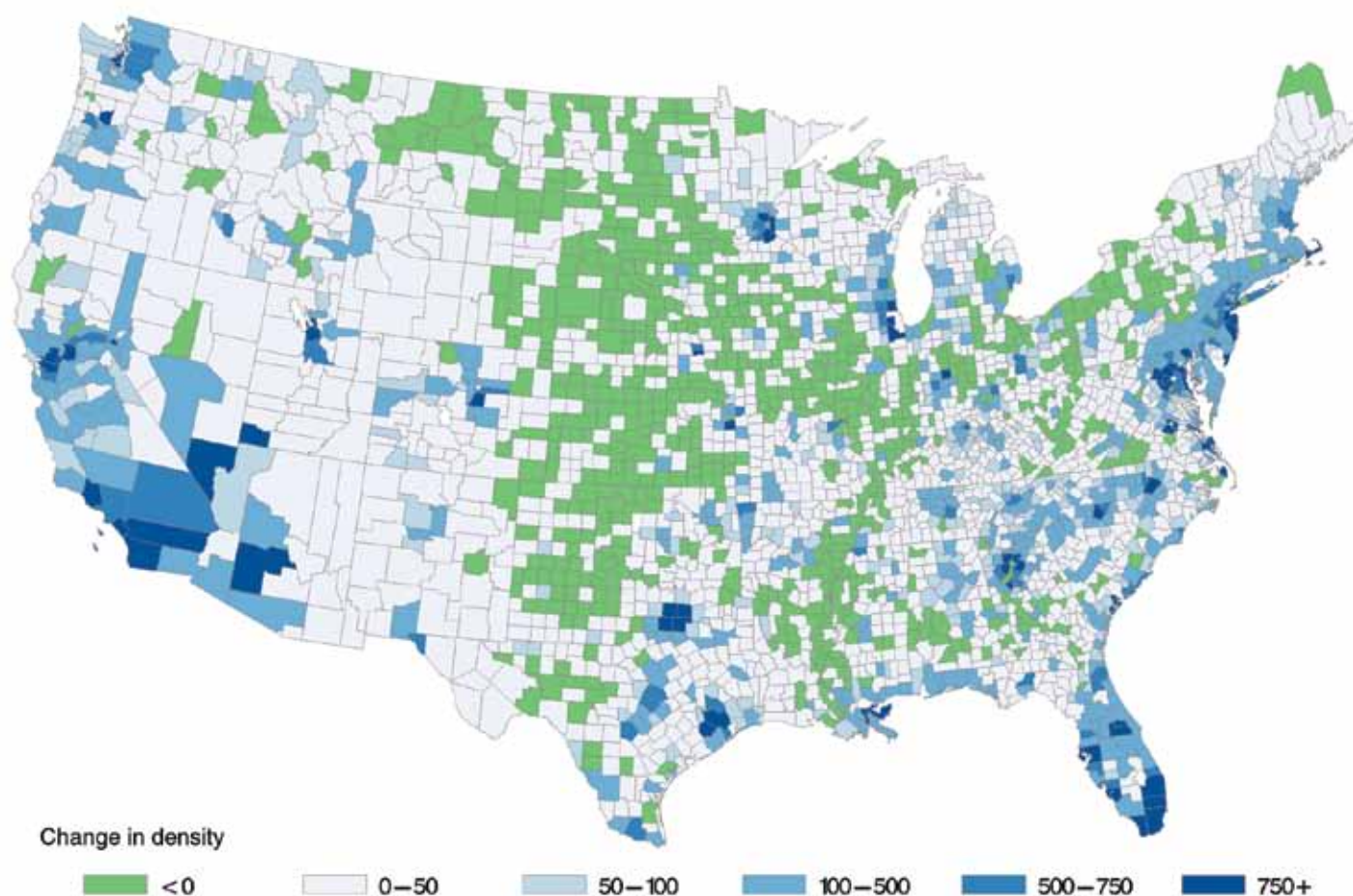


Figure 5—Projected change in population density (people per square mile), 1997–2060, for the Resources Planning Act (RPA) A1B scenario. Areas in blue would experience population increases under this scenario. Areas in green are forecasted to experience population declines over this period.

IPCC AR4 for the A1B and A2 scenarios and for GCMs used in the IPCC TAR for the B2 emission scenario (table 1). The downscaling approach follows Price and others (2004). Data were downloaded from GCM data archival websites, extracted for the regions of the conterminous United States and Alaska (i.e., not including Hawaii) and “downscaled” using the “delta-method” and a well-tested statistical interpolation technique (ANUSPLIN) (Joyce and others 2011). All scenario data were interpolated to a standard 5 arc-minute spatial resolution (0.0833 degree $\approx$ 10 km at mid-latitudes), using latitude and longitude as independent variables. These data were also re-aggregated to generate records for each county (used for the forest forecasts). Details are described in Coulson and others (2010a) for the historical data, Coulson and others (2010b) for the A1B and A2 projections, and Coulson and Joyce (2010) for the B2 projections.

The simulated climate variables include monthly mean daily surface temperature, monthly mean daily maximum surface temperature, monthly mean daily minimum surface

temperature, and monthly total precipitation. Potential evapotranspiration was computed from the downscaled temperature variables. These data were converted to “change factors.” In the case of temperature (monthly mean daily minimum and maximum, or monthly mean), the change factor is computed as the arithmetic difference between the monthly value and the mean for that month computed for 1961–90. For all other variables, the change factor is the ratio of the monthly value to the 1961–90 mean for that month.

The change factors were referenced to the 30-year monthly means for the simulated 1961–90 period and combined with gridded climate normals based on the Parameter-elevation Regression on Independent Slopes (PRISM) dataset for the same 30-year period to create the scenario data needed for the RPA 2010 Assessment (Coulson and Joyce 2010). The PRISM data over the 1961–90 period were used to develop the projections for the 2010 RPA Assessment based on these change factors from the downscaled GCM projections (Joyce and others, in press).

Table 1—Intergovernmental Panel on Climate Change scenarios and general circulation model climate models used for the 2010 Resources Planning Act Assessment^a

Scenario	Integrated Assessment Model (IAM)	General circulation model	Model vintage
A1B	AIM	CGCM3.1(T47) MIROC3.2 CSIRO-Mk3.5	AR4
A2	ASF	CGCM3.1(T47) MIROC3.2 CSIRO-Mk3.5	AR4
B2	MESSAGE	CGCM2 CSIRO-Mk2 UKMO-HadCM3	TAR

^aThe general circulation models are defined as follows: CGCM3.1 - Canadian Centre for Climate Modeling and Analysis Coupled Global Climate Model (CGCM3), Medium Resolution (T47). (Source: <http://www.cccma.bc.ec.gc.ca/models/cgcm3.shtml>); CSIRO-Mk3.5 – Commonwealth Scientific and Industrial Research Organization (CSIRO) (Australia), CSIRO Mk3 Climate System Model. (Source: http://www.cmar.csiro.au/e-print/open/gordon_2002a.pdf); MIROC3.2MR – Center for Climate System Research, University of Tokyo; National Institute for Environmental Studies and Frontier Research Center for Global Change (Japan), Model for Interdisciplinary Research on Climate (MIROC) Version 3.2 Medium Resolution. (Source: <http://www.ccsr.u-tokyo.ac.jp/kyosei/hasumi/MIROC/tech-repo.pdf>); CGCM2 - Coupled Global Climate Model, Medium Resolution (T47). Canadian Centre for Climate Modeling and Analysis. (Source: <http://www.cccma.bc.ec.gc.ca/models/cgcm2.shtml>); CSIRO-Mk2 - Australia's Commonwealth Scientific and Industrial Research Organisation Australia (CSIRO). (Source: http://www.cmar.csiro.au/e-print/open/hennessy_1998a.html#ccm); UKMO-HadCM3 - Hadley Centre for Climate Prediction and Research U.K. (Source: <http://cera-www.dkrz.de/IPC/IS92a/HadleyCM3/hadcm3.html>).

Table 1 describes the nine futures defined by three RPA scenarios linked to three sets of climate projections. Beyond the socioeconomic projections associated with the scenarios and the climate projections from the GCMs, forest futures are also influenced by forest management and timber harvesting driven by forest products markets. In the Forest Assessment System, the U.S. Forest Products Model simulates the future of domestic forest products markets in concert with global markets for each RPA scenario (Ince and others 2011). Initial analysis indicated that timber supply over the next 50 years did not vary substantially among the climate projections for a given RPA scenario. The market futures are driven by alternative projections of wood product demands linked to the RPA/ IPCC global economic outlook and projected socioeconomic conditions for the United States and are most strongly influenced by demands for biomass for bioenergy production—overall, RPA A1B has the highest demand for bioenergy, RPA B2 has the least, and RPA A2 is intermediate. These futures are also influenced by demands for traditional products governed by population growth and levels of economic activity

associated with the scenarios. The linkage between forest forecasts and market forecasts differs across the three Forest Products Model supply regions (South, North, and West, where West is defined by the combination of the Pacific Coast and Rocky Mountain RPA regions).

This report describes forest forecasts for a large number of futures. In all regions, we simulate the future under the nine RPA scenario-climate combinations. In the South we also intersect these nine with market and management assumptions to define a total of 20 futures (table 2). In the other regions, we simulate the nine RPA combinations assuming a continuation of historical (~1995–2005) harvest patterns. We then link forest futures to the market forecasts for RPA scenarios from the Forest Products Model to provide estimates of how market futures would reshape forest conditions. In the South, we selected one future from among the twenty to represent each RPA scenario. In the North and Pacific Coast regions, we generated three separate futures by adjusting inventory removals to match the Forest Products Model outputs (table 3).

Table 2—Labels for 20 futures evaluated in this report for the South Region defined by a combination of Resources Planning Act scenarios (A1B, A2, B2), general circulation models (MIROC, CSIRO, CGCM, and Hadley), timber prices (high for increasing prices, low for decreasing prices), and alternative tree planting rates

General circulation model	Timber prices	Scenarios		
		A1B	A2	B2
MIROC3.2	High	A1_MI_H A1_MI_H_HP ^a	A2_MI_H	
	Low	A1_MI_L	A2_MI_L	
CGCM ^b	High	A1_CG_H	A2_CG_H	B2_CG_H
	Low	A1_CG_L	A2_CG_L	B2_CG_L
CSIRO ^c	High	A1_CS_H	A2_CS_H	B2_CS_H
	Low	A1_CS_L	A2_CS_L	B2_CS_L
HadCM3	High			B2_HA_H
	Low			B2_HA_L
				B2_HA_L_LP ^d

^a Scenario with elevated planting rates.

^b CGCM refers to CGCM3.1 for A1B and A2 and CGCM2 for B2.

^c CSIRO refers to CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2.

^d Scenario with reduced planting rates.

Table 3—Labels for 12 futures evaluated in this report for the North, Rocky Mountain, and Pacific Coast regions defined by a combination of Resources Planning Act scenarios (A1B, A2, B2), general circulation models (MIROC, CSIRO, CGCM, and Hadley), and forest harvesting assumptions

General circulation model	Forest harvesting	Scenarios		
		A1B	A2	B2
MIROC3.2	Historical	A1_MI	A2_MI	
CGCM ^a	Historical	A1_CG	A2_CG	B2_CG
	Market simulation	A1_CG_MKT	A2_CG_MKT	B2_CG_MKT
CSIRO ^b	Historical	A1_CS	A2_CS	B2_CS
HadCM3	Historical			B2_HA

^a CGCM refers to CGCM3.1 for A1B and A2 and CGCM2 for B2.

^b CSIRO refers to CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2.

CHAPTER 2

METHODS

Forest Dynamics Model

This report focuses on inputs to and forecasts from the Forest Dynamics Model, and the discussion of methods concentrates on this component of the U.S. Forest Assessment System (fig. 1). Other components are described in separate reports [the U.S. Forest Products Model is described in Ince and others (2011), and the All Land Use Model is described in Wear (2011)]. The overview of methods that follows is augmented by a detailed description in the appendix to this report.

The primary objective of the Forest Dynamics Model is to forecast change in the forest inventories measured by the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture. Thousands of plots comprise the FIA inventories, and the Forest Dynamics Model forecasts development of each observed forest plot in the inventories.¹ Forecasting at this scale allows for re-aggregation of findings according to different schema (for example, by States, by survey units, or by ecological sections). For example, forecasts described in this report have been used to explore natural resource issues for the Southern Forest Futures Project (Wear and Greis, in press) and the Northern Forest Futures Project (<http://nrs.fs.fed.us/futures/>). Historical FIA plot data provide the information foundation for building forecast models, and results are expanded to broader scales using the area frame design of the forest survey. These methods generate full inventory datasets for each time step of the forecast.

To model and forecast changes in forest conditions, the Forest Assessment System forecasts the condition of each plot in the forest inventory in response to multiple vectors of change. Each plot record contains a set of measured and associated variables combined with an expansion factor that describes the area (portion of the sampled population of forests) that each plot represents. Expansion factors are reconciled at the county level within the FIA system. We define the information set for each plot $I(p)$ as:

$$I(p) = \{S, Z, C, E\} \quad (1)$$

¹ The use of the term “plot” in this report refers to what is technically called a “condition” within a plot in the FIA system. Where plots can have more than one forest condition—e.g., they occur on a boundary between forest types—then multiple conditions are recorded for each plot. Use of the word “plot” simplifies the language in this report without loss of precision.

where

S represents a vector of state variables

Z is a vector of condition variables

C is a vector of climate variables

E is a vector of expansion factors for the plot

S and Z together comprise the measured variables for each plot from phase II (field measurements) of the forest inventory while climate variables are derived from PRISM datasets (Coulson and Joyce 2010), and E is derived from phase I (aerial measurements) of the FIA inventory. We distinguish between state and condition variables to facilitate description of the modeling approach.

Forecasting plot conditions starts with projecting changes in the state variables (S) using transition models and climate variables (C) from downscaled climate projections for the Resources Planning Act (RPA) scenarios (Joyce and others, in press). For example, the future age of a forest plot is a state variable and is defined either by adding the time step of the simulation to the current age or resetting the age to zero due to a disturbance. Forest type may be forecasted based on current forest type and projected climate (C). Once the forecasted state and climate variables have been defined, then a historical plot record with comparable state and climate variable values is used to describe the future condition (including the Z variables). This historical plot record is randomly selected from a database of historical data according to an imputation or resampling algorithm. Changes in the expansion factors (E) for each plot are determined by the land use model that forecasts change in forest area as a function of urbanization and other land use choices that depend on the population and economic variables associated with the RPA scenarios (Wear 2011). Proportional changes in expansion factors were constructed at the county level.

Key decisions in developing the projection models include choosing which variables are state variables, how to project changes in state variables, and how to structure the imputation algorithm. These choices are based in part on the frequency of FIA inventories which varies between the regions of the country. In all regions however, the basic structure of the modeling approach is defined by three modules. The modeling starts with an algorithm that clusters similar plots according to a set of independent variables (the partitioning module). These partitions of plots define the groupings of plots for the imputation module and also define which variables are the state variables that need to be forecasted within the transition module. Changes in key state variables for each forest plot

are forecasted in response to projected forest aging, climate conditions, and human use choices (the transition module). After forecasting the state variables, a historical plot record with comparable conditions is selected to represent the simulated plot in the future inventory (the imputation module) based on clusters chosen in the partitioning module.

In most cases models were developed for individual States because of disparities in inventory dates. In some cases, multiple adjacent States or portions of adjacent States (defined by FIA survey units) are modeled together either because a concurrence of inventory dates allowed for pooling of data—thereby enhancing the information content of the resulting models—or because a State was too small to support model estimation. For example, we pooled southeastern States (Virginia, North Carolina, South Carolina, and Georgia) to allow for more variation in climate conditions across latitudes and a deeper plot donor pool, and we aggregated the Delaware data with adjacent survey units from Pennsylvania due to its small sample size.

The transition and imputation modules define a probabilistic or Monte Carlo modeling framework that was run several times to simulate the variance associated with various model components. Simulation experiments indicated a convergence of variance estimates after about 20 simulations, and we chose to run the model for 26 iterations for each scenario (limits of computing time kept us from constructing more simulations). For the display of forecast results, we chose to use one complete simulated inventory rather than averages for variables because the latter would not be representative of the joint distribution of forest attributes. The iteration with the greatest “central tendency,” defined as minimum proportional distance of six variables from their means over the 50-year simulation period, was selected. These six variables were total growing stock volume (cubic feet), trees per acre, and sawtimber volume for hardwoods and softwoods.

Models were implemented for individual States, aggregates of States, or adjacent Survey Units across States, and results were summed up to display results for the RPA regions. The time step for each model in the East was defined by the time interval of the paired inventories used to build its transition module and in the West was defined as a fixed 10-year step because inventories could not be paired. Projections commenced from the date of the latest inventory available, so the years for which forecasts were generated varied across States. Regional aggregates for the reporting years (2020, 2030, 2040, 2050, and 2060) were constructed by assigning State inventories with most proximal dates to the reporting year, consistent with methods used to generate historical multi-State aggregates with FIA data (Smith and others 2009). See the appendix for details on all elements of the Forest Dynamics Model.

Data Analysis

Climate affects forest forecasts through its influence on transition and plot imputation modules. That is, changes in climate associated with a plot can yield changes in the plot partition from which future conditions are sampled. The specific variables affecting future forest conditions vary by State and by forest type across the RPA regions (table A1). However, average temperature and total precipitation are frequently influential in the resampling. To help interpret forecast results, we analyzed average temperatures and total precipitation from the climate projections using two approaches. For each region, we constructed the cumulative distribution of monthly values for all counties for decadal periods and examined the changes over time and between scenarios. This provides an aggregate measure of shifts in temperature and precipitation for the region.

In addition, for each county, we constructed and compared distributions of monthly values of mean daily surface temperature and total annual precipitation using Kolmogorov-Smirnov (KS) tests, e.g., Press and others (1987), to test the null of no significant difference between decades. Tests were constructed for forecasted decades (2001–10, 2011–20, ..., 2051–60) versus the historical decade (1991–2000). The Kolmogorov-Smirnov test is a nonparametric test based on the distance between the two empirical distributions, where the null hypothesis is that the two samples are generated by the same distribution. We consider the KS test in this application to be a conservative test, in that it is nonparametric (makes no assumptions about the underlying distributions) and is most sensitive to changes at the center of the distribution (NIST/SEMATEC 2012) and not at the tails. Rejection of the null is therefore a strong signal of differences in the distributions and highlights especially strong climate change in these areas. Failure to reject the null should not be viewed as a rejection of change per se, especially given the conservative nature of the test (i.e., higher type II errors; failure to reject false nulls) and the stochastic nature of the climate projections.

These tests define emphatic changes and support general discussion of climate projections as they influence our results. However, other variables are also potentially relevant to our analysis, including seasonal temperature averages, maximum and minimum temperature and precipitation values, or frequency of extreme events that can affect change in biological processes. Joyce and others (in press) indicate important shifts in several seasonal measures with these climate projections even where annual values are less variable.

CHAPTER 3

DATA

For each State, we required plot records from the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture, to construct the partitioning model, conduct the imputation, and build transition models. Analysis for the Eastern United States required two panels of matched plots to estimate transition models. The ideal case was where we had two panels from the national continuous inventory design. However, in many cases we faced a situation where only one continuous inventory was available and we used two older inventories (periodic inventories) to construct transition models for key variables. Because of changes in the plot measurement approach, we determined that it was important to use two inventories of comparable design to construct transition models.

For each inventory that we used, we extracted raw data from publicly available plot records available at the FIA Web site. We were granted access to confidential plot location data which allowed us to conduct the plot matching for evaluating the transitions over time. FIA data are stored in tables, three of which are primary for our analysis (Miles and others 2001). The plot, condition, and tree tables provide information on the overall plot characteristics, discrete landscape features, and measures associated with individual trees larger than an inch in diameter, respectively. As a validation step we used the area frame to generate total values for States and survey units which could then be compared with online report generators and published reports to confirm the accuracy of the algorithms employed in this analysis.

Several other variables were summarized for the plots using plot, condition, and tree tables in the FIA database. In the South, forest type and stand origin were combined to create a broad forest type/management class variable coinciding with the definition in published FIA reports. The six broad classes; natural pine, planted pine, mixed pine-hardwood (further referred to as mixed pine), upland hardwood, lowland hardwood, and non-forest were recoded as binary variables (i.e., $x=0$ or $x=1$). In other regions, forest types were aggregated using standard forest type groups. The dynamics of a forest type group were modeled if the group comprised at least 2 percent of plots in the State's inventory. Minor forest type groups were held constant throughout the forecast period (see the appendix for a list of forest type groupings used in each region).

Estimates of the carbon sequestered on a forest plot were attached to each historical plot using models developed and applied by FIA using the U.S. Forest Carbon Calculation Tool (Smith and others 2007). This tool incorporates estimates derived from field measures and uses the FORCARB2 model to provide carbon inventories that are consistent with standards developed by the Intergovernmental Panel on Climate Change (Penman and others 2003). Carbon estimates for historical plot records contained in the FIA database were attached to future plots through the imputation algorithm and this provided plot-level forecasts of carbon stored for each of eight forest pools under each of the evaluated scenarios.

Climate data records were attached to each forested plot in the inventory as described in the section on future scenarios. Historical data were derived from the PRISM dataset and provided monthly values spanning a 55-year period (1950-2005) at the county level [see Coulson and others (2010a) for details on aggregation of 2.5 arc-minute grid data to define county aggregates]. Using three general circulation models associated with each of the three Resources Planning Act (RPA) scenarios, the nine downscaled climate projections were also attached to each forest plot record based on the county location of the plot. For the analysis of forest conditions in the East, we averaged the climate variables for the life of the forest plot, e.g., if the plot was assigned an age of 25 years, we applied 25-year averages for each of the climate variables used in the partitioning module. In the West, we used a fixed-length average (20 years) to link climate conditions to forest plots.

Fitting the timber harvest models for the South required estimates of potential revenues from alternative treatments of each plot (full harvest, partial harvest, or deferred harvest) based on volume measures derived from the FIA records coupled with timber product prices. Product prices were defined as the average of stumpage prices recorded during the State's inventory period by Timber Mart South, a region-wide price reporting service. Prices for hardwood sawtimber, hardwood pulpwood, softwood sawtimber, and softwood pulpwood were recorded for the Timber Mart South's sub-State regions and assigned to plots on a county basis. Potential revenues further required forecasted volumes, which we estimated using a series of regression equations for each major forest type based on unharvested plots as explained in Polyakov and others (2010).

CHAPTER 4

FOREST FORECASTS FOR THE SOUTH

For the South, forest forecasts were constructed for each of the three Resources Planning Act (RPA) scenarios linked to the general circulation models (GCMs) described in table 2. To explore a range of potential futures for forest conditions we also considered a range of market conditions defined by alternative price paths for timber products: real prices increasing at a compounded 1 percent per year and real prices decreasing at a compounded 1 percent per year from a base year of 2006.

Another key element in the development of forests in the South over the past 50 years and likely for the future is the rate of tree planting. Tree planting is forecasted based on the observed rates of tree planting following a harvest by forest type in the South based on historical inventories by the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture. Future planting rates could be altered by various changes in landowner preferences including the effects of an increasingly dynamic forest ownership base (Butler and Wear, in press). We therefore consider two additional forecasts, one which increased the base planting rates by 50 percent for an RPA A1B storyline (strong economic growth) with high prices and one which reduced the planting rate by 50 percent for the RPA B2 storyline (low economic growth) with low prices.¹

Table 2 provides a summary of the resulting 20 alternative futures (three RPA scenarios by three climate projections, by two price alternatives plus two alternative planting scenarios) evaluated for the South. After considering the range of forest forecasts for these 20 futures, we examine the potential implications of the timber market simulations simulated by the U.S Forest Products Model (Ince and others 2011), by linking one of these 20 futures to represent associated changes in forest conditions.

Climate

To frame the discussion of the forest forecasts, we compare climate projections from the nine RPA scenario-climate combinations with historical conditions for the South. Distributions of monthly values for a projected decade (2010 refers to the monthly values between 2001 and 2010, 2020

refers to monthly values between 2011 and 2020, and so on) are compared with a historical decade (2000 for the monthly values between 1991 and 2000). We start by plotting the cumulative distributions of temperatures/precipitation for a graphical view of regional change over time. We then map where significant differences arise between projected and historical distributions for counties in the region.

Figure 6 shows a comparison of cumulative temperature distributions in the 2060 decade for the nine RPA scenario-climate scenarios and for the historical decade (2000). Projected regional temperature distributions shift to the right of the historical distribution reflecting increasing temperatures. RPA A1B-MIROC3.2 and RPA A2-MIROC3.2 scenarios show the greatest increase in temperatures in 2060, with a 3 °C increase in temperature at the 50th percentile of the distribution and a 4 °C increase at the 90th percentile. The other RPA scenario-climate combinations all show temperature increases that are somewhat less than for the RPA A1B-MIROC3.2 combination (about a 2 °C increase at the 50th percentile and a 2.5 °C increase at the 90th percentile).

A graph of temperature distributions for each of the six decades for the RPA A1B-MIROC3.2 combination, shows temperatures increasing in every decade, with the largest increase between the final two decades compared (2050 and 2060; fig. 7A). A similar pattern holds for the RPA B2-CSIRO-Mk2 scenario (fig. 7B) and for all other RPA scenario-climate combinations (not shown here).

Spatial patterns of change vary across the RPA scenario-climate combinations. Figure 8 shows spatial patterns of change based on the Kolmogorov-Smirnov test ($p=0.05$) at the county level applied to the RPA A1B-MIROC3.2 combination (the scenario-climate combination with the greatest overall increase in temperature by 2060). The black areas indicate counties where there is significant distributional disagreement between historical and projected data for the specified decade. Figure 9 provides the same set of maps for the RPA A1B-CSIRO-Mk3.5 scenario. For the RPA A1B-MIROC3.2 scenario (fig. 8), temperature differences are discernible in the Florida Peninsula in 2020, spreading north into Georgia and Alabama and emerging in Oklahoma and northern Arkansas in 2030. By 2040, most other States, except Tennessee, North Carolina, Kentucky, and Virginia, exhibit significantly different temperatures. By 2060, the entire map is black, indicating a significant outward shift in temperature distributions for all counties under this RPA scenario-climate combination.

¹ A more ideal model would allow planting decisions to be tied to current and anticipated timber market conditions, i.e., allowing planting and other forest investments to be determined as endogenous variables. These relationships proved elusive to our modeling efforts as recent tree planting patterns have proved counterintuitive to economic logic—tree planting expanded by about 30 percent between the late 1990s and 2010, when prices for softwood products declined and remained suppressed.

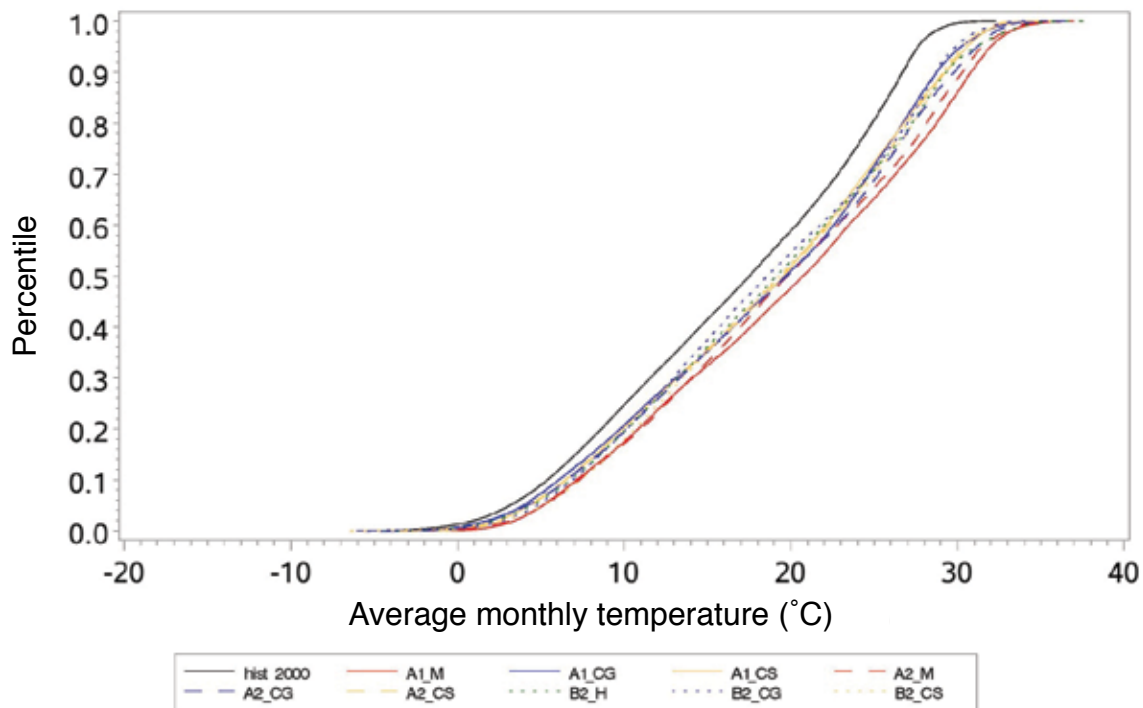


Figure 6—Empirical distributions of monthly temperatures for the South Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–60).

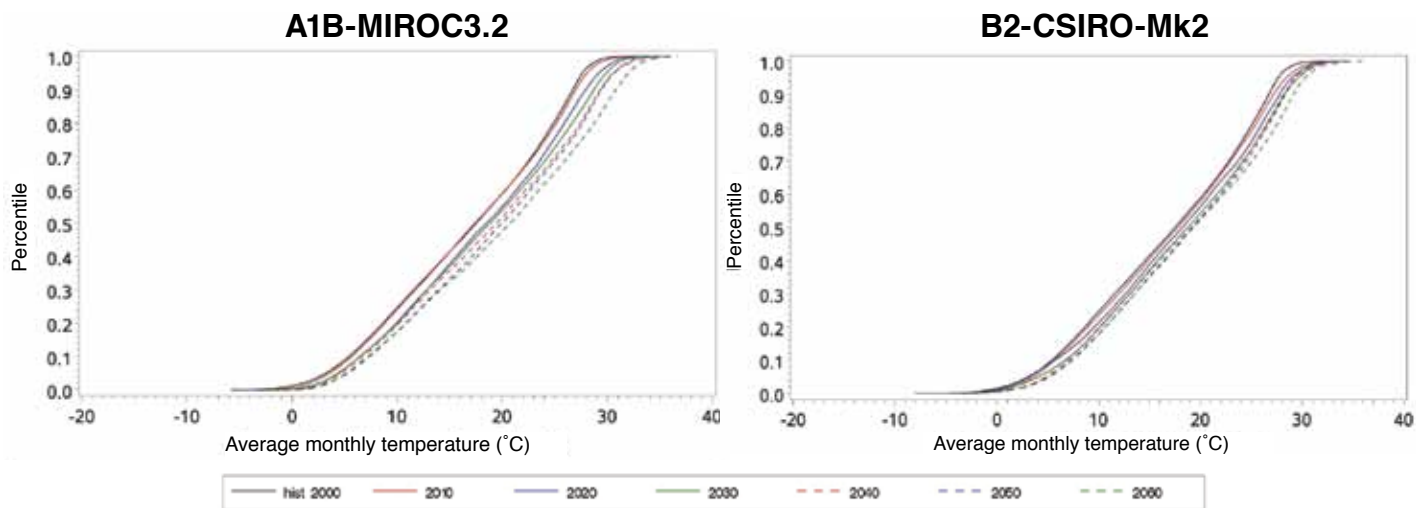


Figure 7—Empirical distributions of monthly temperatures for the South Region for a historical decade (1991–2000) and for 6 successive decades of climate projections (A) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination and (B) for the RPA B2-CSIRO-Mk2 combination.

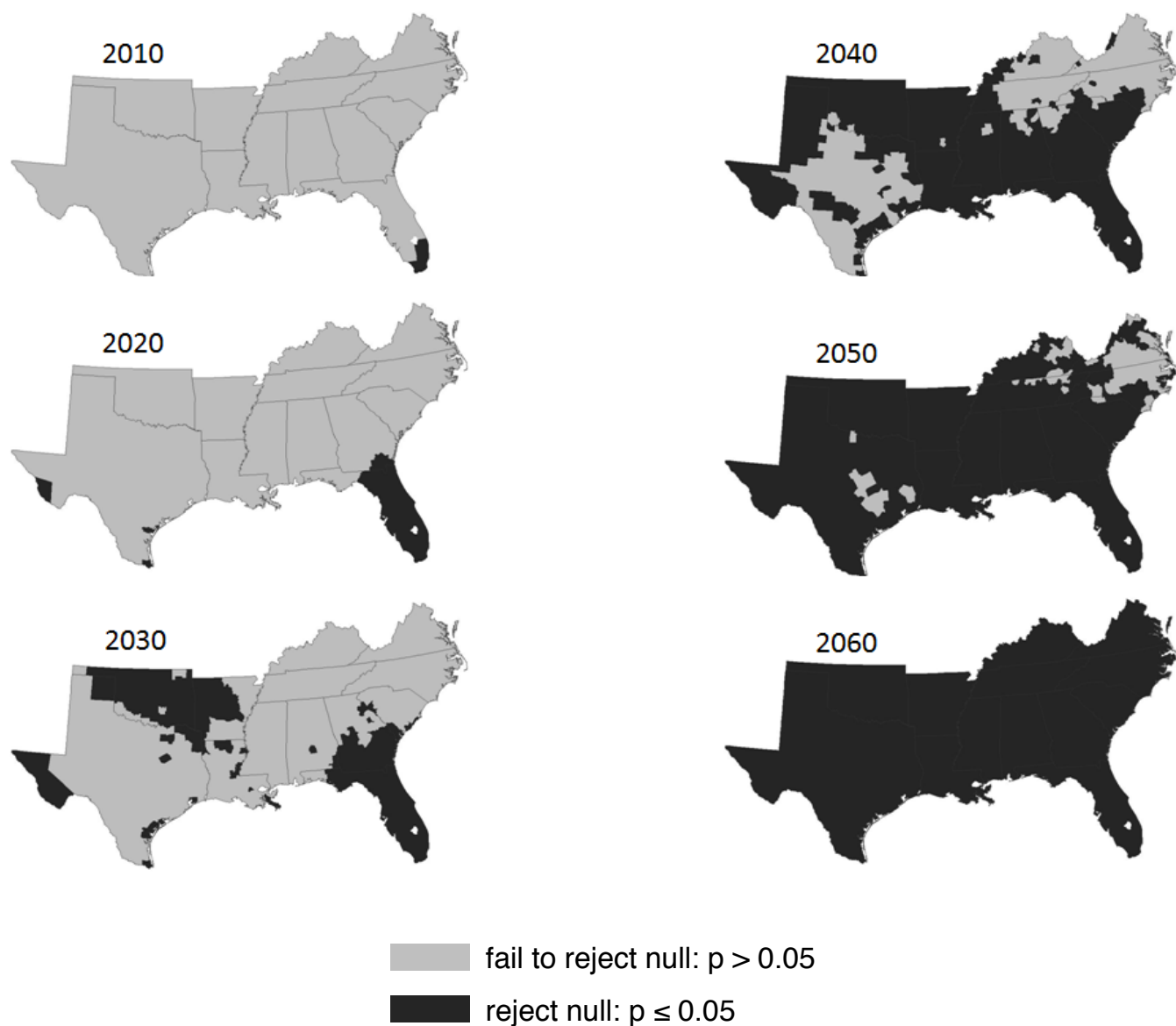


Figure 8—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

The change pattern is quite different for RPA A1B-CSIRO-Mk3.5 (fig. 9). As with RPA A1B-MIROC3.2, temperature increases are first detected in the peninsula of Florida, but “spread” at a slower rate. In 2040, the entire Florida peninsula has significantly higher temperatures. In 2060, significant shifts in temperature distributions are found in Florida, the remainder of the Gulf Coast region and through southern and western Texas.

Figure 10 maps the proportion of the nine RPA scenario-climate combinations that lead to rejection of equivalent temperature distributions between the 2000 and 2060 decades (KS test, $p=0.05$). Temperature distributions are significantly warmer in at least four scenario-climate combinations for a majority of counties. Counties in roughly the southern third of the region have significantly different temperatures in seven or more of the nine climate realizations. Two small sub-regions

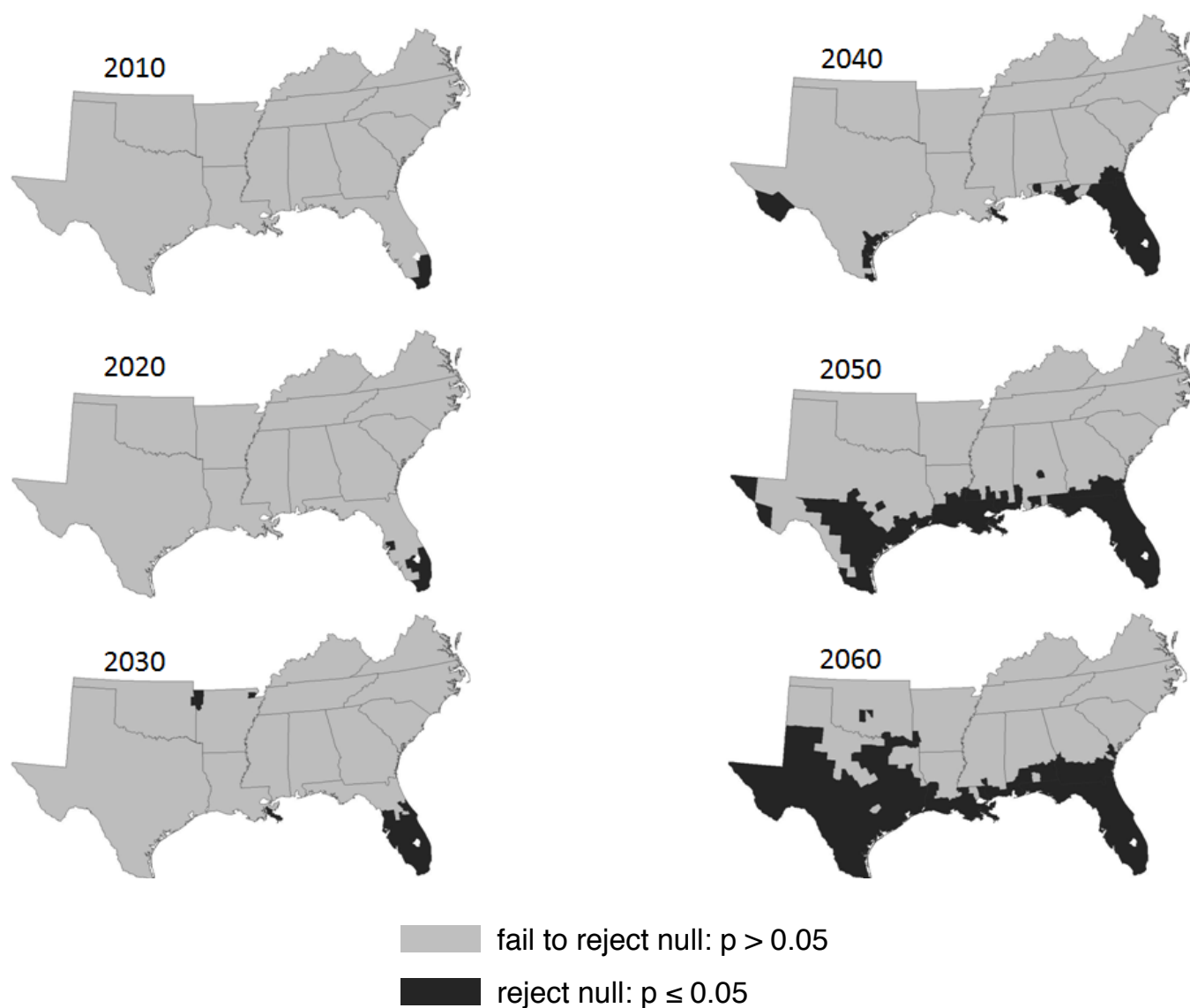


Figure 9—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) scenario A1B-CSIRO-Mk2 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

have less than four significantly different temperature outcomes: the Piedmont and Coastal Plain areas of North Carolina and Virginia and an area that spans north-central Texas and most of Oklahoma.

Projections of precipitation are more variable than temperature projections across the RPA scenario-climate combinations and across the region (Joyce and others, in press). Under some combinations, total regional precipitation declines; under others, total regional precipitation increases. Cumulative distributions of monthly precipitation values show an inward shifting of precipitation (drying) for the RPA A1B-MIROC3.2

and RPA A2 -MIROC3.2 scenarios (fig. 11). For the other scenario-climate combinations, the distributions pivot, indicating that some areas become wetter while others become drier than the historical decade. For the RPA A1B-MIROC3.2 and RPA A2-MIROC3.2 scenarios, the precipitation distribution shifts inward (becomes drier) at every time step, with the biggest shift occurring between 2050 and 2060 (fig. 12).

The spatial pattern of precipitation change is also variable. For RPA A1B-MIROC3.2 (fig. 13), significant declines in precipitation occur across a large area of the South including

the Coastal Plain and much of Texas by 2030. The area of significant drying increases through 2060 to include Oklahoma, Arkansas, and Louisiana. Change in precipitation is different and more sporadic under RPA A1B-CSIRO-Mk3.5 (fig. 14), shifting between drier and wetter conditions between decades in some areas. In contrast, under RPA B2-HadCM3 (fig. 15), little difference in precipitation distributions can be detected across most of the South. Figure 16 maps the proportion of the nine RPA scenario-climate combinations leading to rejection of equivalent monthly precipitation distributions between the 1991–2000 decade and the 2051–60 decade (KS test, $p=0.05$). A large majority of the region shows significant differences in precipitation distributions for one to three of the scenario-climate combinations. Four to six scenario-climate combinations yield significant change in precipitation distributions for counties in the peninsula of Florida, southern and eastern Texas, and central

Tennessee. These models generally show drying in the Florida sub-region and wetter conditions in the Tennessee sub-region, but either drier or wetter conditions are predicted for eastern Texas depending on the model.

In sum, the RPA scenario-climate combinations project significant warming for the South across most models but yield projections of precipitation that vary between models and across time and space within models. However, even in the case of constant precipitation, water availability for plant metabolism would be reduced by rising temperatures. Maps of significant changes highlight areas with emphatic change in these two variables (i.e., these are conservative tests) and other climate variables may also have important influence on future forest conditions but are not examined here.

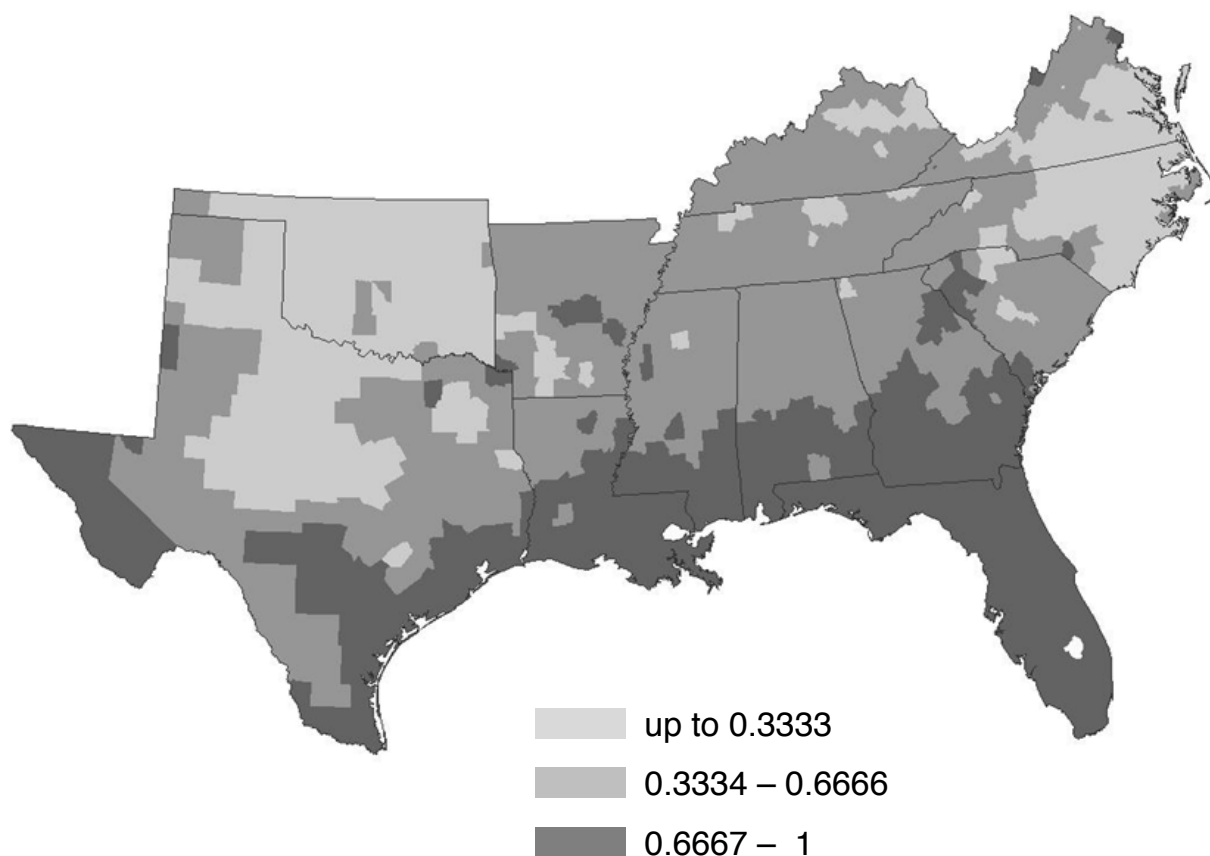


Figure 10—Proportion of the nine Resources Planning Act (RPA) scenario-climate combinations yielding significant differences in decadal temperature distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the South Region.

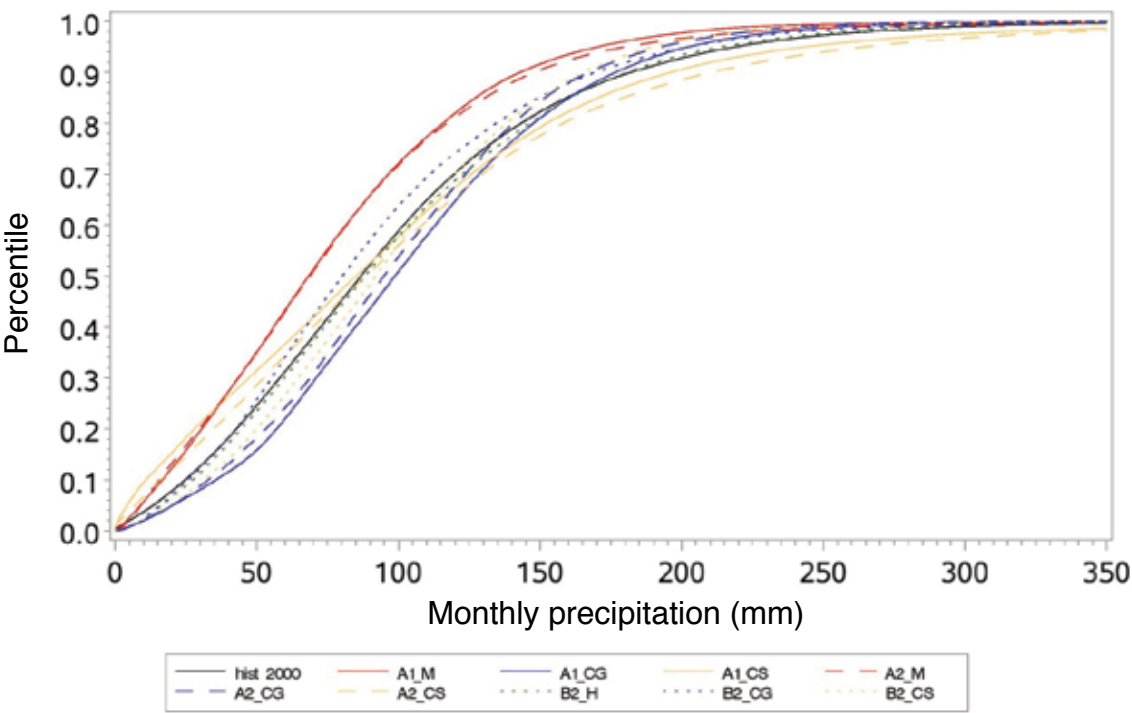


Figure 11—Empirical distributions of monthly precipitation values for the South Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–60).

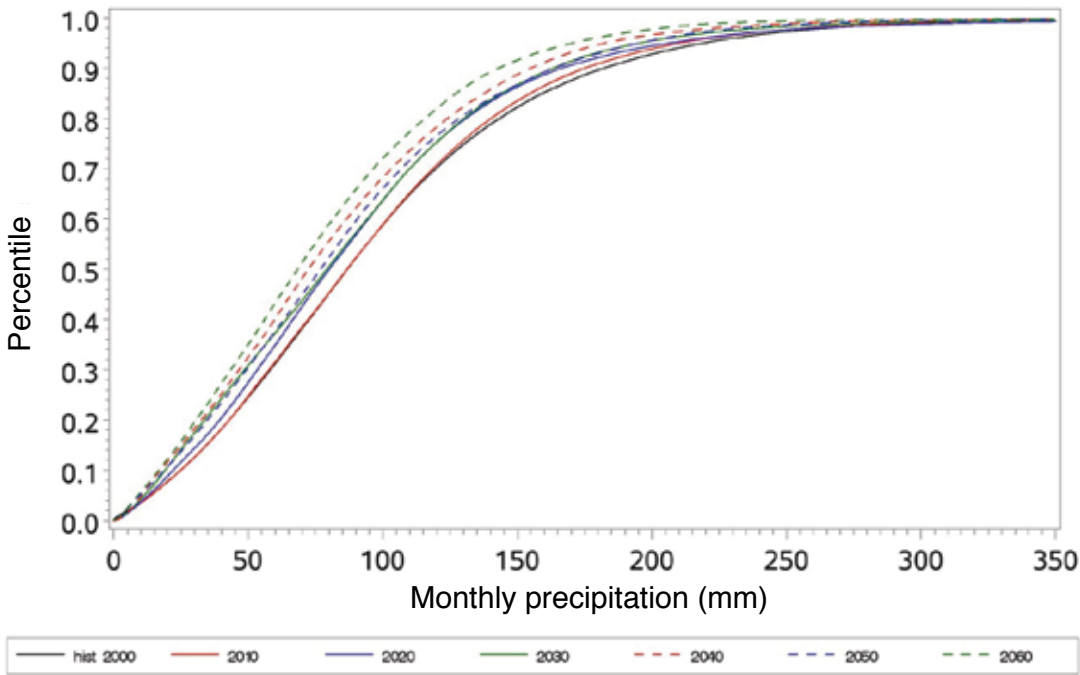


Figure 12—Empirical distributions of monthly precipitation for the South Region for a historical decade (1991–2000) and for 6 successive decades (2010–60) of climate projections for the Resources Planning Act (RPA) A1B-MIROC3.2 combination.

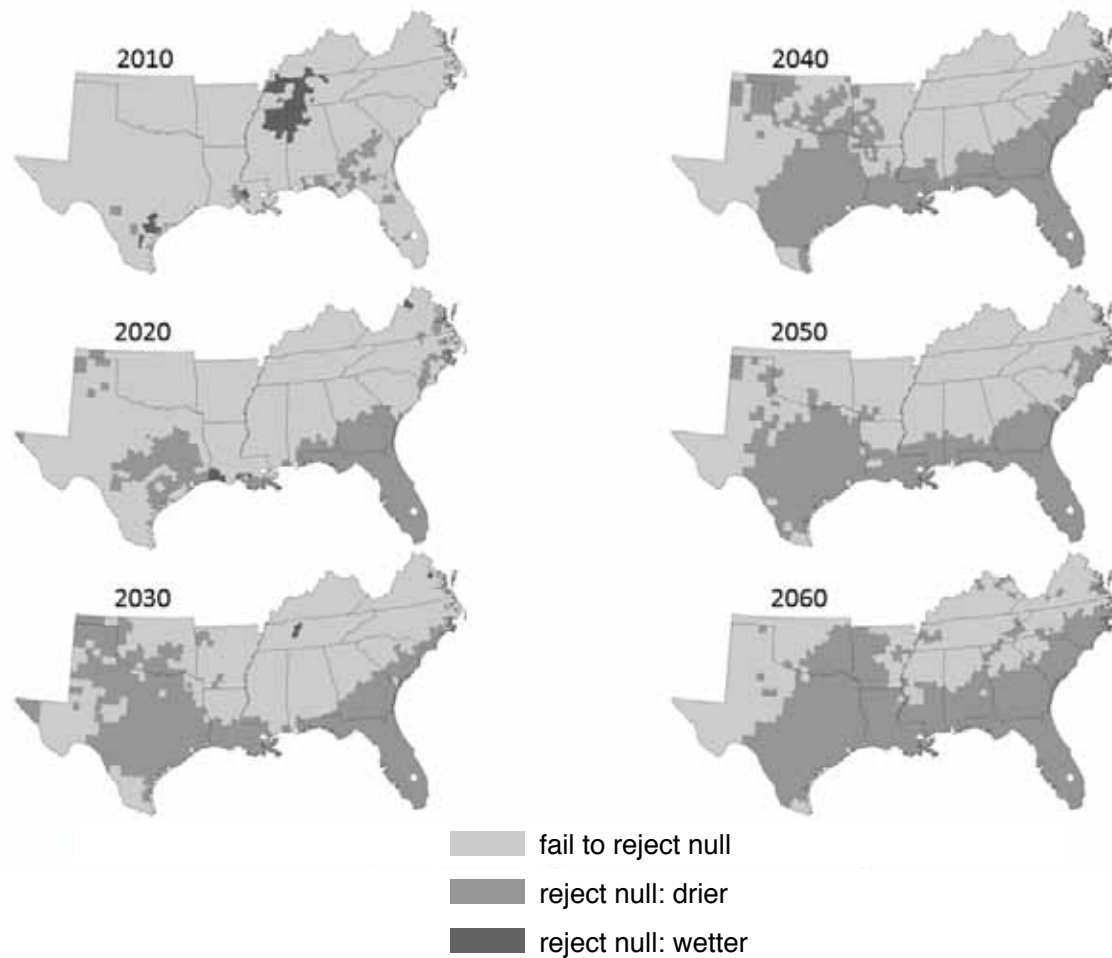


Figure 13—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value < 0.05) and indicate drier and wetter conditions, respectively.

Forest Area

Forecasts of forest area change derive from the land use analysis contained in Wear (2011).² All 20 alternative futures predict declines in forest area, with losses ranging from 4–21 million acres (2–10 percent) between 2010 and 2060, the result of population- and income-driven urbanization and of changes in the relative price of timber products (fig. 17). The smallest loss of forest area is forecasted for scenario RPA B2, with high timber prices, which has the lowest population growth and the lowest income growth resulting in the lowest urbanization, and increasing timber prices resulting in shifts of some rural land toward forest uses. The largest loss of forest area is forecasted

for RPA A1B and low timber prices, where population growth is moderate but income growth is strong (resulting in high urbanization), and timber prices are falling (resulting in shifts of forest land to agricultural uses). Figure 17 also shows that price effects dominate the projection of forest area, with the highest forest loss associated with scenarios that have decreasing prices; the three scenarios with the lowest forest loss have increasing prices.

Forest losses are especially high in a few areas of the South (fig. 18). For all alternative futures, forest losses are concentrated in the Southern Appalachian Piedmont region from northern Georgia through North Carolina and parts of Virginia, the Atlantic and Gulf of Mexico coastal areas, and the area surrounding Houston, TX. The population and income-fueled urbanization in RPA A1B spreads low intensity forest losses across a broader area of the South (Wear 2011). For all alternative futures, the number of acres lost is largest in the Coastal Plain and smallest in the Mississippi Alluvial Valley

² The total forest area changes reported in this report differ from those in Wear (2011) because (1) the analysis in Wear (2011) is based on National Resource Inventory (NRI) data benchmarked in 1997, while this chapter translates those projections into FIA data benchmarked in 2010; and, (2) while the NRI measures only non-Federal land uses, the FIA data address all ownerships.

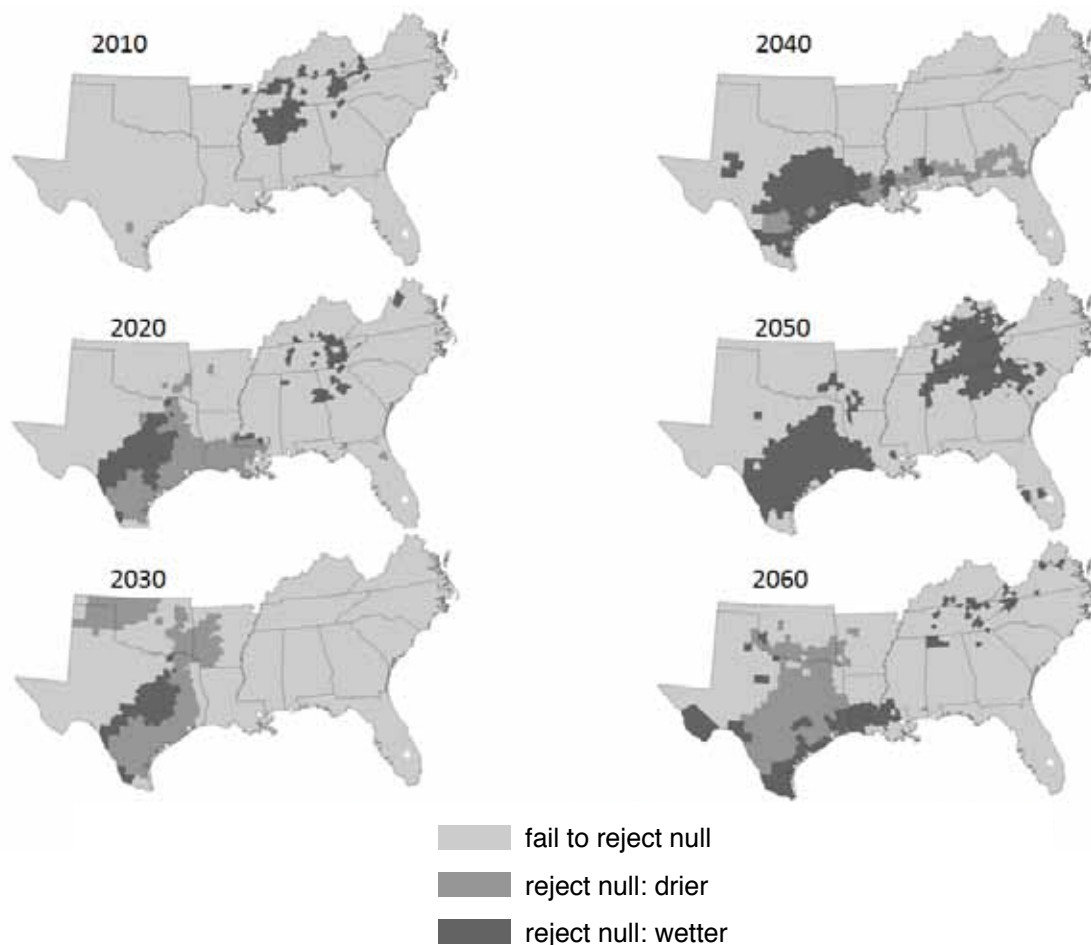


Figure 14—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-CSIRO-Mk3.5 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value <0.05) and indicate drier and wetter conditions, respectively.

and the Mid-South. The percent of acres lost is largest in the Piedmont followed by the Appalachian-Cumberland highlands and the Coastal Plain.

Forest Types

Forest area change also differs among the five forest management types: planted pine, natural pine, mixed pine-hardwood, upland hardwood, and lowland hardwood. The upland and lowland hardwood types are forecasted to comprise between 51 and 53 percent of all forests in 2060, a decline from about 54 percent in 2010. The greatest changes however are found among the softwood types — as planted pine area increases while natural pine and mixed pine-hardwood area declines. These forest dynamics are heavily influenced by the interaction of land use changes and management for forest products, which in turn is driven by timber market conditions, and by the rate of forest planting.

Planted pine—The area of planted pine forests in the South, currently at about 39 million acres or 19 percent of forest area,

is forecasted to increase by 2060 (fig. 19A). Forecasts that apply the historical rate of tree planting for harvested area by forest type and State yield a range of 53.8 million to 59.9 million acres of planted pine by 2060 or an increase of 38–54 percent. Among this group of alternative futures, high prices (lines with triangles in fig. 19A) yield more acres of planted pine than do low prices (lines with circles in fig. 19A). The high and low planting scenarios expand this range to 46.8 million to 67.2 million acres or an increase of 20–72 percent. Even with the high planting rates, planted pine area would grow at rates much lower than those observed between the 1980s and 2010 (e.g., planted pine area expanded by about 30 percent between 1999 and 2010).

Natural pine—Forecasted losses in the area of naturally regenerated pine forest types mirror the gains in planted pine forests and are therefore inversely related to the condition of forest products markets (fig. 19B). The largest decrease in natural pines—a loss of 58 percent from 31.5 million acres in 2010 to 13.5 million acres in 2060—is associated with the highest planting rates. The smallest decline occurs with lower timber prices and planting rates, but losses are still

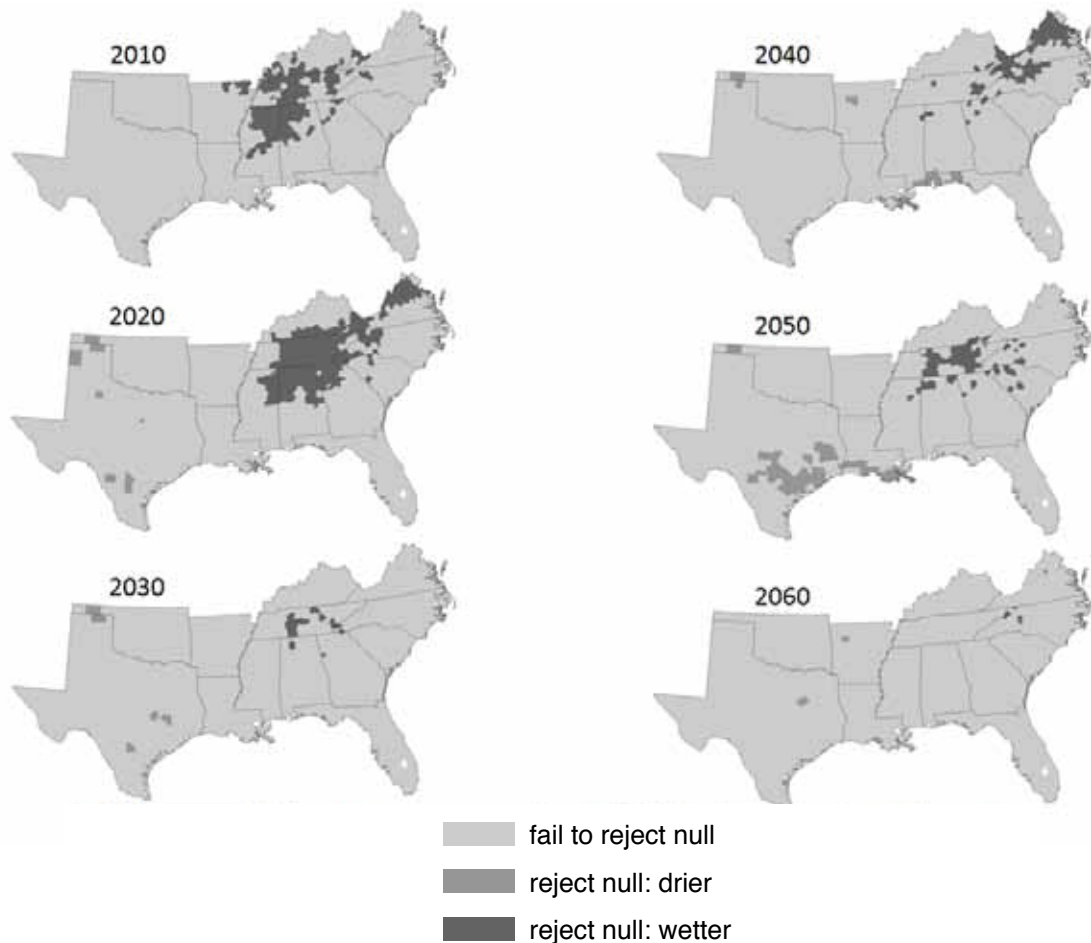


Figure 15—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) B2-HadCM3 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value < 0.05) and indicate drier and wetter conditions, respectively.

substantial—7.6 million acres or 25 percent from 2010 to 2060. Regardless of the future evaluated, naturally regenerated pine types are forecasted to decline, continuing a trend that has dominated forest type dynamics since the 1960s. A strong propensity to harvest mature natural pine forests combined with a strong propensity to use planting as a regeneration technique following harvests in this type of forest drives the changes shown in figure 19B.

Mixed pine-hardwood—The area of the mixed pine-hardwood forest management type also declines for all futures, with a similar pattern of change but smaller acreage and percent changes than is forecasted for natural pines (fig. 19C). As with natural pine, mixed pine-hardwood is more heavily influenced by timber market conditions than by urbanization rates. Mixed pine-hardwood declines range from 8.5 million acres (38 percent) to 3.9 million acres (17 percent) by 2060.

Upland hardwood—At more than 80 million acres in 2010, upland hardwoods are the predominant forest type in the

South, more than double the area of the next largest forest type. Upland hardwoods are forecasted to decline for all futures (fig. 19D), and variations in forecasts are associated more with the rate of urbanization than with timber market futures. The three futures with the lowest upland forest loss are associated with lower urbanization (RPA B2 scenario) and high timber prices, and the three futures with the highest loss are associated with the higher urbanization forecasts (RPA A1B scenario) and low timber prices. Loss of upland hardwood forests ranges from 5.9 million acres (about 8 percent) for RPA B2 with high prices to 11.2 million acres (14 percent) for RPA A1B with low prices. Figure 19D shows little to no separation of forecasts for different GCMs applied to the same future. The set of forecasts demonstrates therefore that prices interact with urbanization forecasts to determine future upland hardwood forest area.

Lowland hardwood—The area of lowland hardwood forests is also more sensitive to the rate of urbanization and less sensitive to forest products markets than the softwood types. For this forest management type (fig. 19E), forecasts indicate

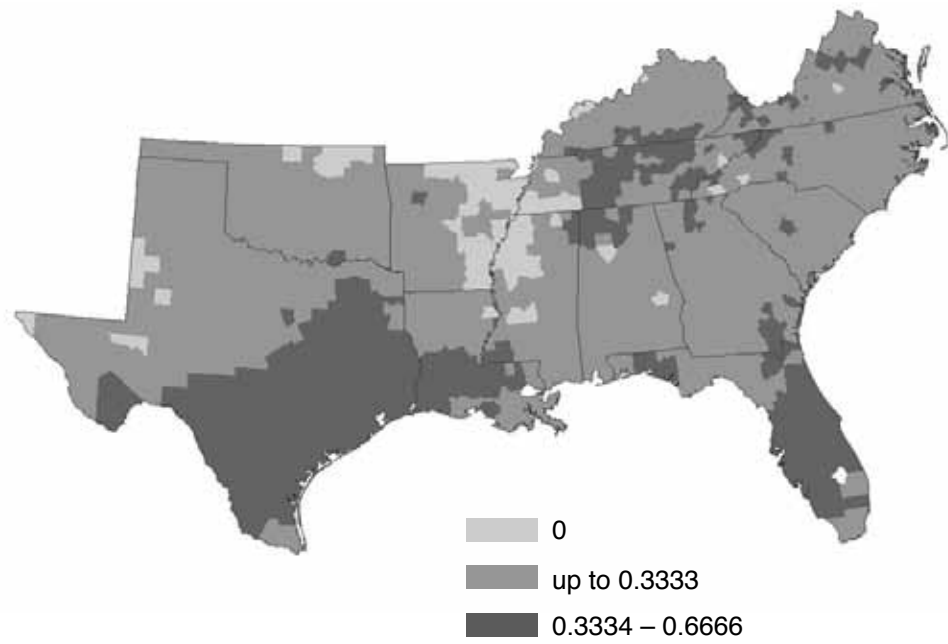


Figure 16—Proportion of the nine scenario-climate combinations yielding significant differences in decadal precipitation distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the South Region.

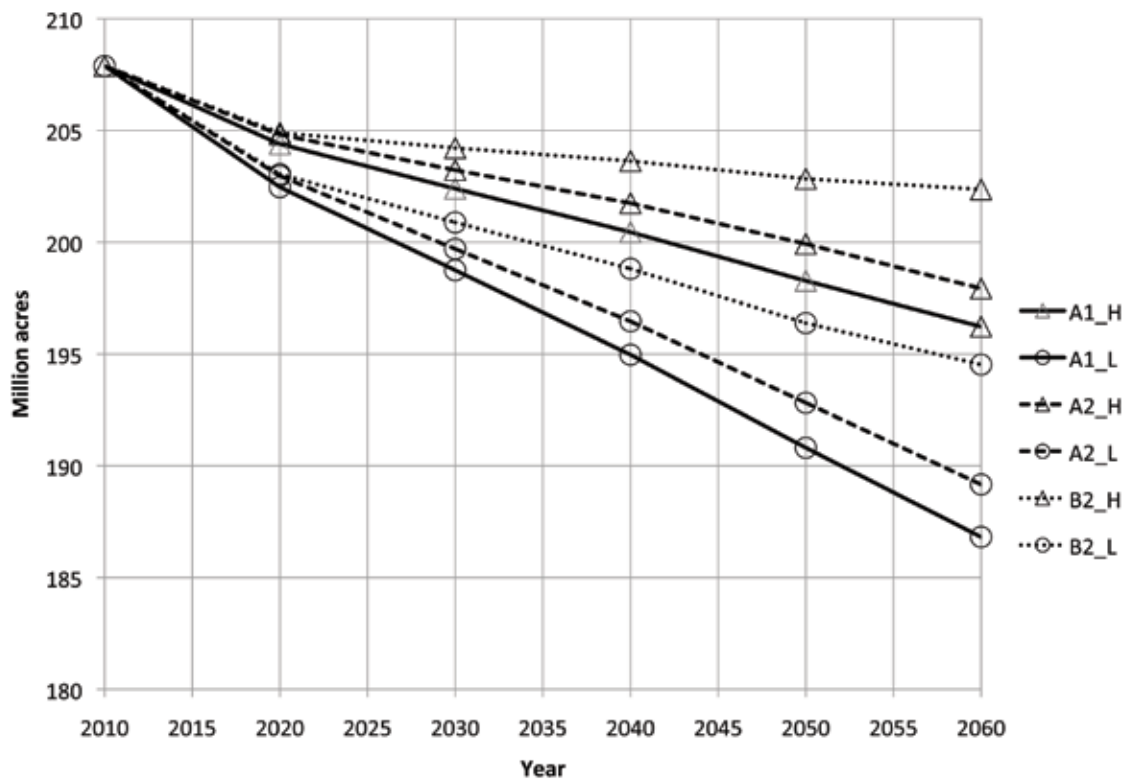


Figure 17—Total forest area for six Resources Planning Act (RPA) scenario-timber price combinations for the South Region. Forest area varies only by RPA scenario and by timber price futures but not by climate projections.

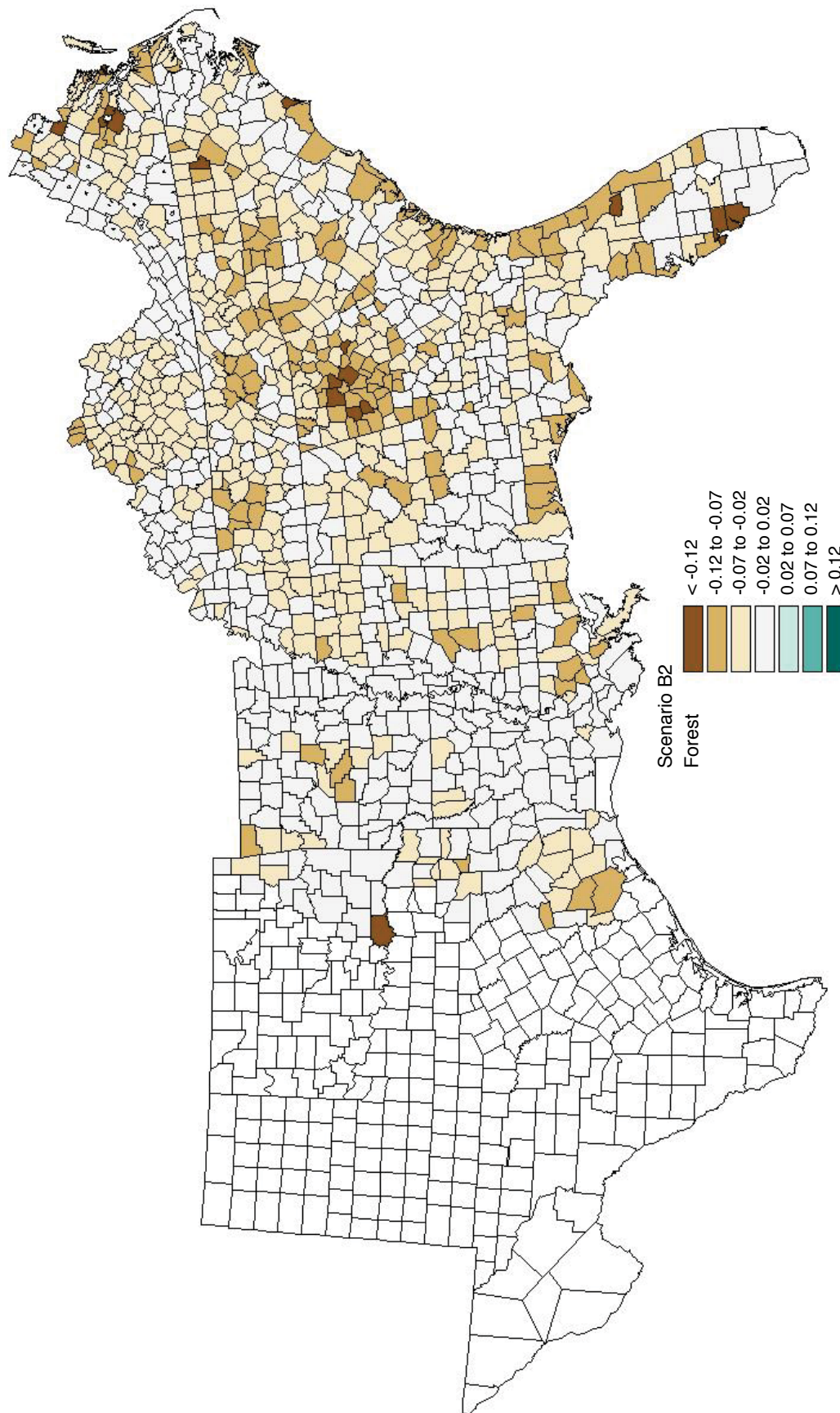


Figure 18—Forecasted change in the proportion of county in forest land, 1997—2060, for the Resources Planning Act (RPA) B2 scenario, which is characterized by high urbanization and low timber prices.

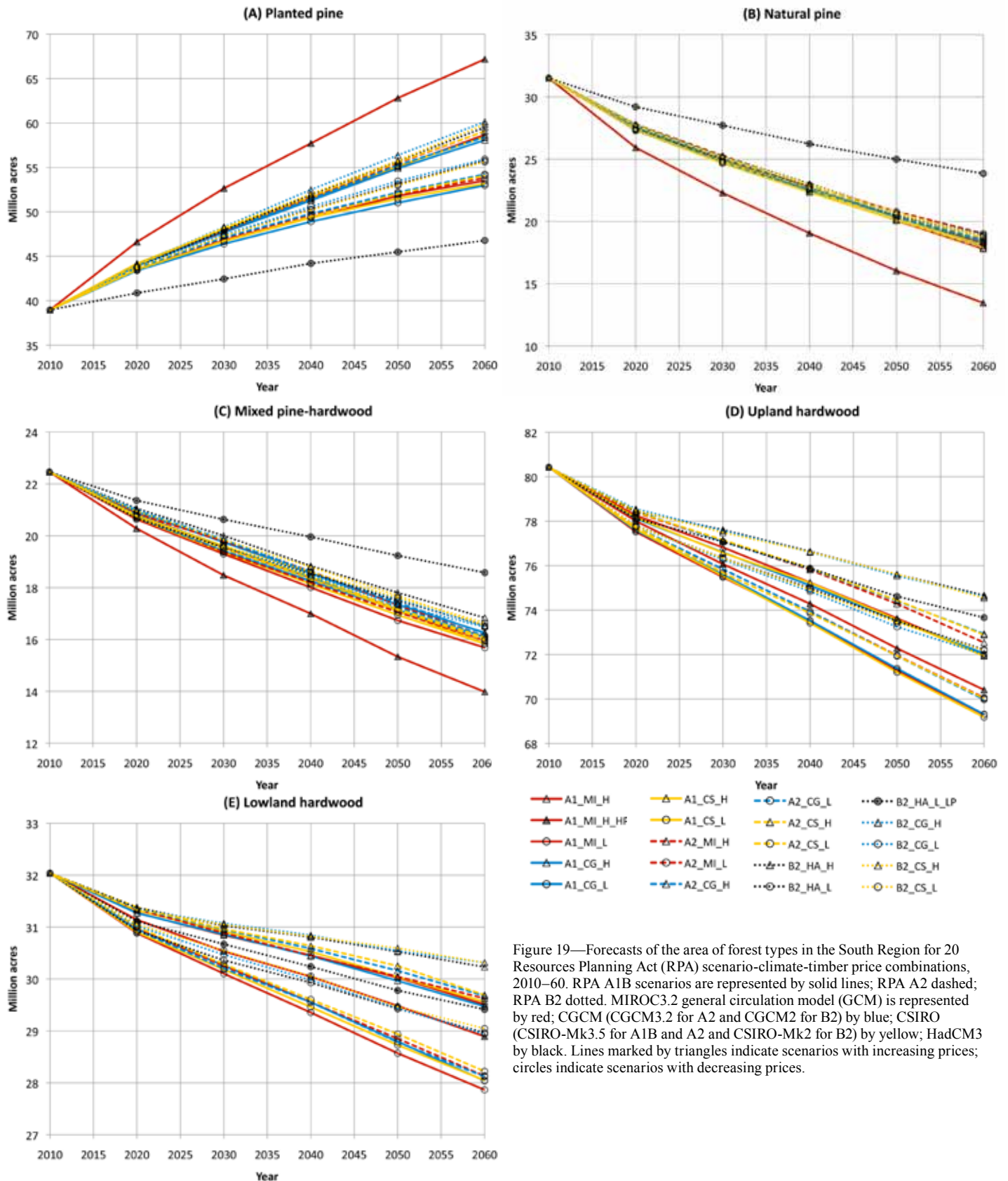


Figure 19—Forecasts of the area of forest types in the South Region for 20 Resources Planning Act (RPA) scenario-climate-timber price combinations, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

losses ranging from 1.7 million acres (5 percent) to 4 million acres (12 percent) by 2060 from a base of 32 million acres in 2010. The relative ranking of change across futures is broadly similar to the forecasts for upland hardwood types. Lowland forests lose proportionally less area than the other forest types that experience losses.

Standing Biomass

Of the various metrics available for measuring biomass changes for a site in a forest inventory, we opted to focus on the volume of growing stock because it is a useful index both for timber analysis and for measuring other ecosystem services. Total growing stock volumes are forecasted to change in response to both land use changes and timber harvesting levels (fig. 20). From a base of about 292 billion cubic feet in 2010, inventories increase at most by about 11 percent in 2060 under the low-urbanization (RPA B2)/low-timber-price future. The smallest increase in total growing stock inventories is found with the high-urbanization (RPA A1B)/high-timber-price future, with an increase in volume to 2030 and then a decline over the remainder of the forecast period. For these futures, the volume in 2060 is about 1 percent higher than values observed in 2010. While at no time during the forecast period does inventory fall below 2010 levels, 16 of 20 futures are trending downward by the end of the forecast period. Growing stock forecasts are more strongly affected by timber price futures than by RPA scenario (population and income), with some separation between GCM projections appearing toward the end of the forecast period.

Patterns of change differ between hardwood and softwood components of the inventory and generate generally countervailing changes. Under all futures, softwood growing stock inventories increase (fig. 21). For the low-urbanization (RPA B2)/low-timber-price future, softwood inventories increase from a base of about 121 billion cubic feet in 2010 to as much as 148 billion cubic feet (37 billion cubic feet or 22 percent). The smallest increase is 15 percent (18 billion cubic feet) for the high-urbanization (RPA A1B)/high-timber-prices future. With the exception of one future, all forecasts indicate at least a slight upward trend in volumes of softwood growing stock between 2050 and 2060.

Hardwood growing stock inventories reveal different patterns of change. Starting from about 171 billion cubic feet in 2010, hardwood growing stock volumes peak somewhere between 2020 and 2040 for all futures and then decline to 2060 (fig. 22). The most pronounced declines are for futures with high rates of urbanization (RPA A1B) and high timber prices. Declines for

these futures are in the range of 15 billion cubic feet (9 percent) from 2010 to 2060. Futures with low urbanization (RPA B2) and low timber prices result in increases of about 3 billion cubic feet (2 percent) for the same period. All forecasts show downward trends in the volume of hardwood growing stock for 2050–60.

These changes in growing stock volume depart from historical patterns of volume accumulation in the South. Between 1963 and 2010 southern forests accumulated about 2.5 billion cubic feet per year or roughly 70 percent. Hardwood forests accounted for most of this biomass accumulation (61 percent). Although growth is projected to continue over at least the next 10 years, growing stock volume reaches a maximum and then declines somewhat over the following 40 years (fig. 23), with hardwood growing stocks declining, especially in response to urbanization, while softwood volumes increase only slightly.

Forest Carbon

Carbon contained in the forests of the South amounts to about 12.4 billion tons at the beginning of forecasts with a majority of the carbon in soil organic matter and living trees (fig. 24). Accordingly, forecasts of forest carbon would be affected by changes in the area of forests and in the amount of biomass as described earlier. Figure 24 shows forecasts of future forest carbon in the South and generally shows a peaking of forest carbon in either 2020 or 2030 followed by a downward trajectory. Figure 24 reveals three clusters of futures. The greatest loss of forest carbon is recorded for high urbanization (RPA A1B)/low price scenarios, with the least area of forest land in the future (see fig. 24). The least loss of forest carbon is recorded for the seven futures with the least urbanization (RPA B2). The middle cluster of futures is occupied by middle urbanization (RPA A2) and high urbanization (RPA A1B) futures with high timber prices. In all cases, within a future, higher prices yield somewhat higher levels of carbon stored in forests when compared to the low price futures.

With only two exceptions, these futures predict carbon stocks in 2060 that are reduced from 2010 values. The two exceptions are for low urbanization (RPA B2) futures with high timber prices. However, the magnitude of overall change is relatively small. For example, the maximum loss of forest carbon between 2010 and 2060 is roughly 5 percent or a loss of 0.6 billion tons.

Estimates of the total carbon stored in forests derive from summing estimates of the carbon stored in eight different compartments or pools in forested ecosystems. Aboveground pools include live trees, understory plants, down and standing dead trees, and litter. Belowground pools include root material for live trees, understory plants, and soil organic matter. The sum of soil organic matter, aboveground live trees, and

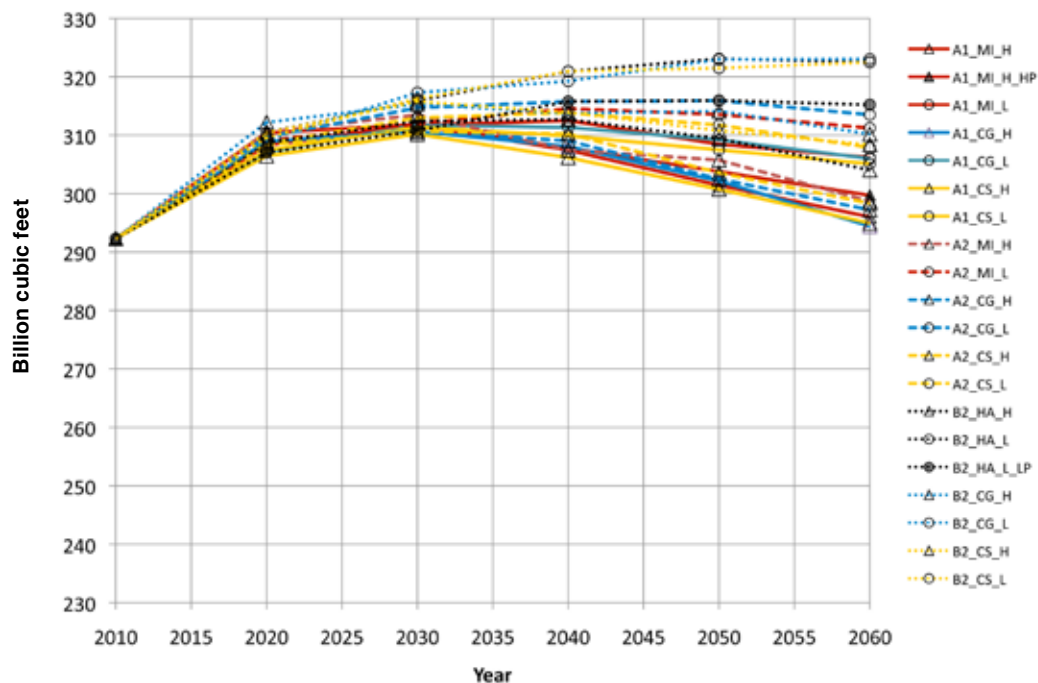


Figure 20—Total biomass measured as growing stock inventory of forests in the South Region for 20 Resources Planning Act (RPA) scenario-climate-timber price combinations (see table 2 for labels), 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

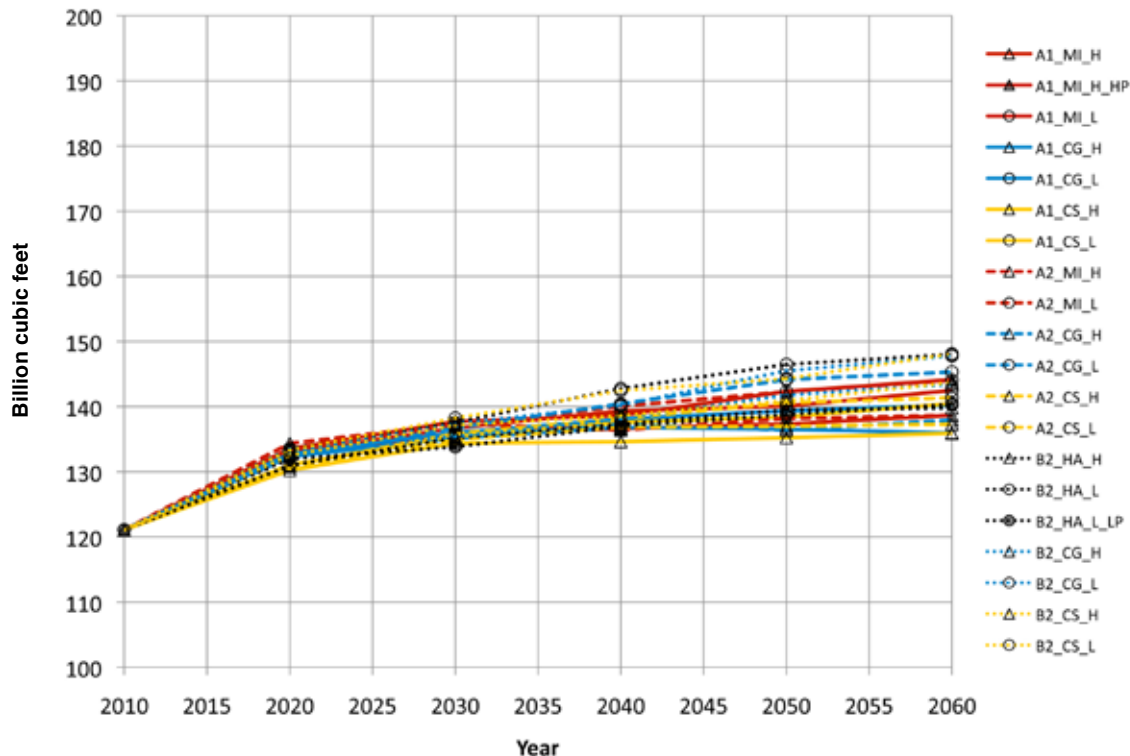


Figure 21—Total softwood growing stock inventory in the South Region for 20 Resources Planning Act (RPA) scenario-climate-timber price combinations, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

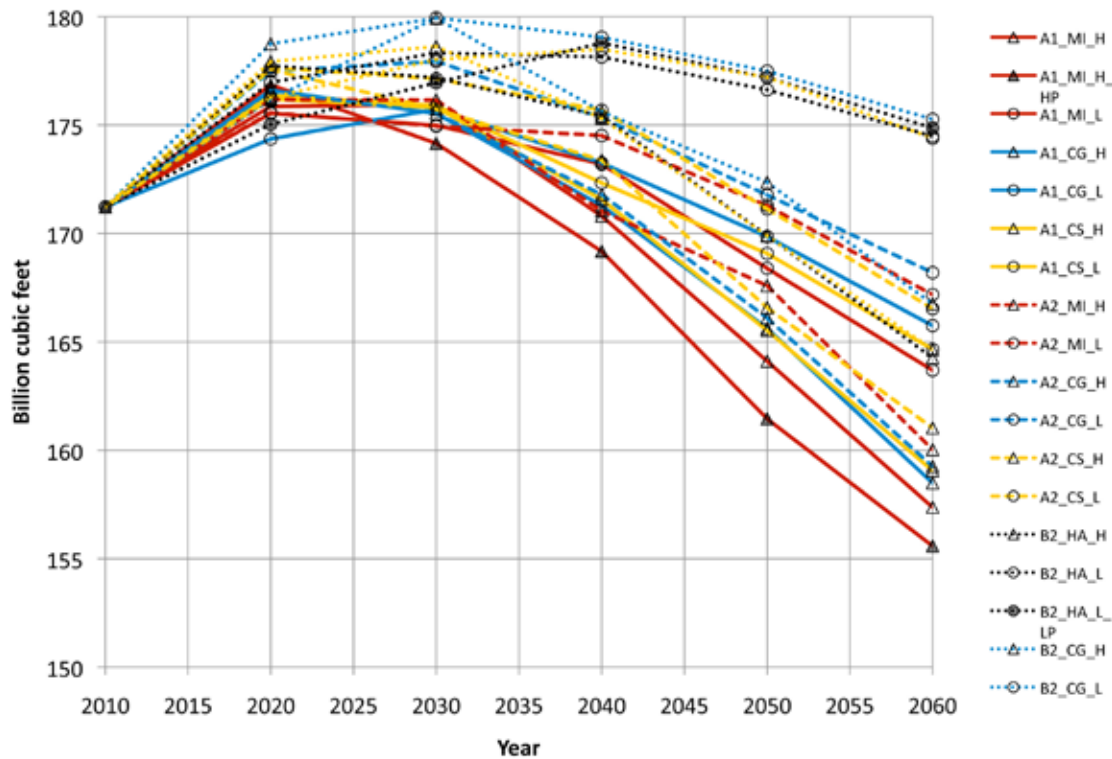


Figure 22—Total hardwood growing stock inventory in the South Region for 20 RPA scenario-climate-timber price combinations, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM2 (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

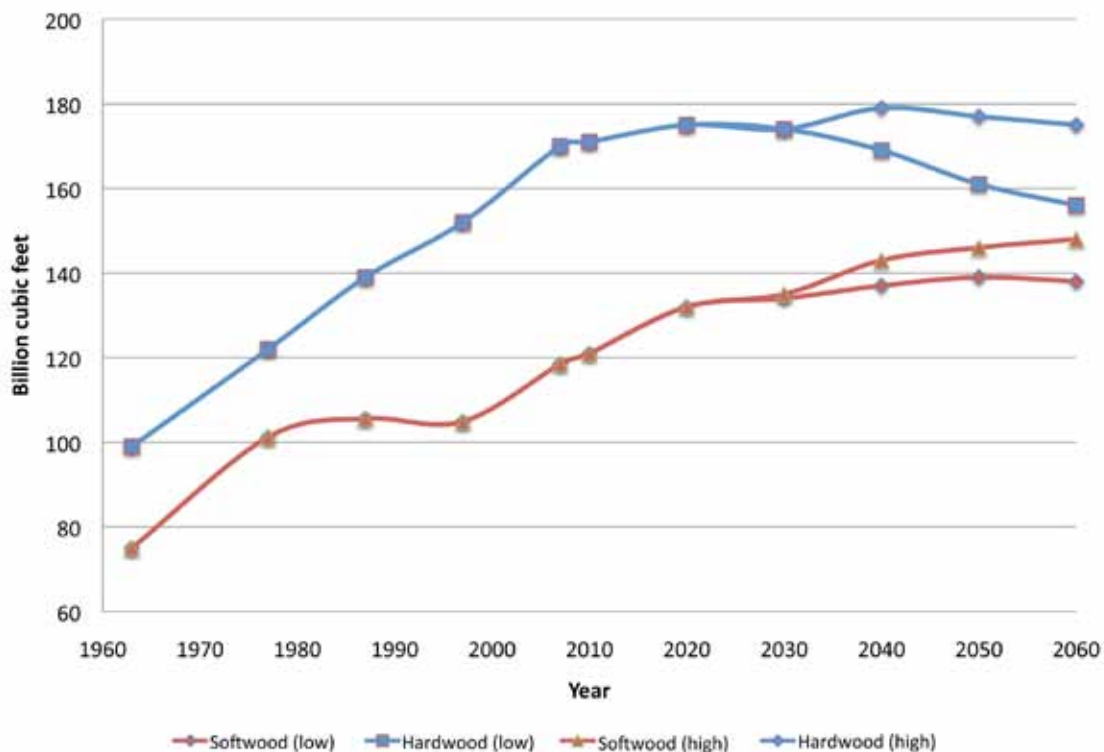


Figure 23—Softwood and hardwood growing stock inventories for the Southern United States, 1962–2060. Forecasts (2010–60) bracket the range of future softwood and hardwood inventories shown in figures 21 and 22, respectively.

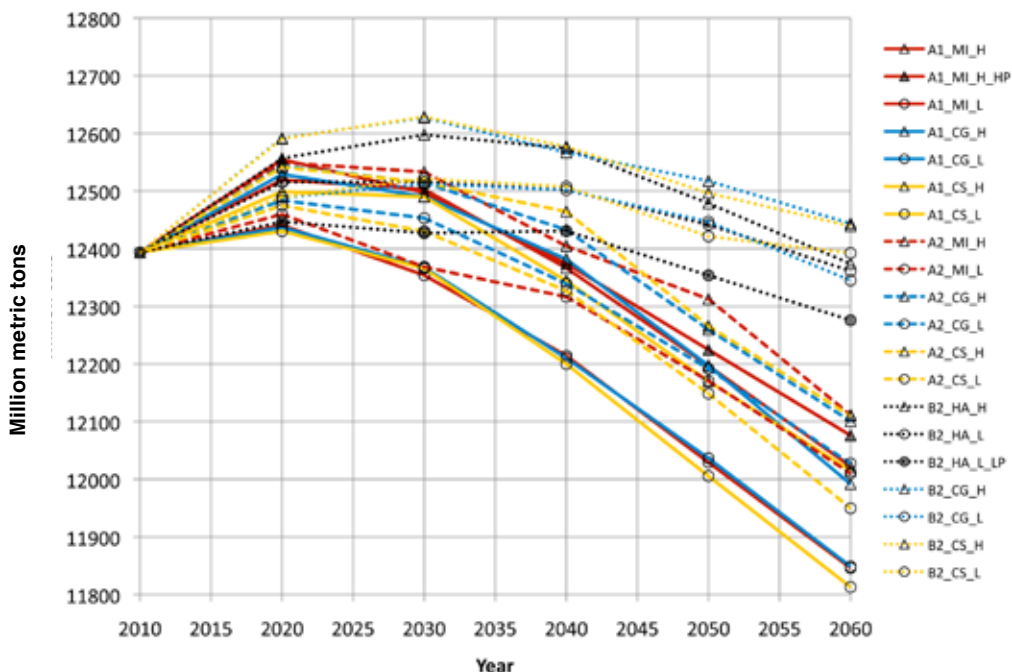


Figure 24—Forecasts of total carbon stored in forests in the South Region, 2010–60, for 20 Resources Planning Act (RPA) scenario-climate-timber price combinations. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

belowground live trees comprises nearly 80 percent of the total, and forecasts of these three pools are shown in fig. 25. The pattern of change for soil organic carbon (fig. 25A) mirrors forest area changes shown in fig. 17. The forecasts are dominated by price futures, with high (low) prices yielding more forest land and higher (lower) soil organic carbon. The forecasts are then organized by future with low urbanization (RPA B2) futures having higher carbon than high urbanization futures (RPA A1B). Live tree above- and belowground carbon pools (figs. 25B and 25C, respectively) have very similar patterns of change. As with soil carbon pools, prices dominate the differences among scenarios except that carbon in these pools is highest with low prices and lowest with high prices.

Removals

Harvest choice models used in the Forest Dynamics Model generate a set of predicted removals associated with each of the 20 futures evaluated here. Total harvest removals displayed in figure 26 are charted for each period of the simulation. Note that the time step associated with the removals is different from that associated with measures of the inventory; removals are labeled with midpoint values (2015, 2025, etc.) because these values represent the average annual removals for the decade, rather than an accumulated value. Figure 26 shows that price futures dominate future harvesting with increasing prices

(lines with triangles in fig. 26) leading to increases in total removals (average increase of about 36 percent). Declining prices are not, however, associated with declines in harvests. Rather, these futures (lines with circles in fig. 26) show a slight increase to 2025, and then harvest levels stabilize.

Additional information can be derived from examining removals forecasts for softwoods and hardwoods separately. Figure 27A shows that softwood harvests are more variable than total harvests. Increased prices yield as much as a 45 percent increase in harvest output with the high planting future yielding the most timber. For declining prices, harvests also increase by as much as 15 percent—the lowest removals occur with the lower planting rates. This strong harvest response reflects the strong growth in planted pine area experienced in the 1990s and 2000s and forecasts of additional growth in planted pine area. In addition, it reflects a financial maturation of naturally regenerated pine and mixed forests.

The story for hardwoods is quite different (fig. 27B). Increases in prices yield expanded removals (generally about an 18 percent increase). Decreases in prices yield a decline in harvests of roughly the same magnitude. This suggests that supply is relatively stable over time for hardwoods, likely reflecting an offsetting of the losses of hardwood forest area with the financial maturation of the remaining forests.

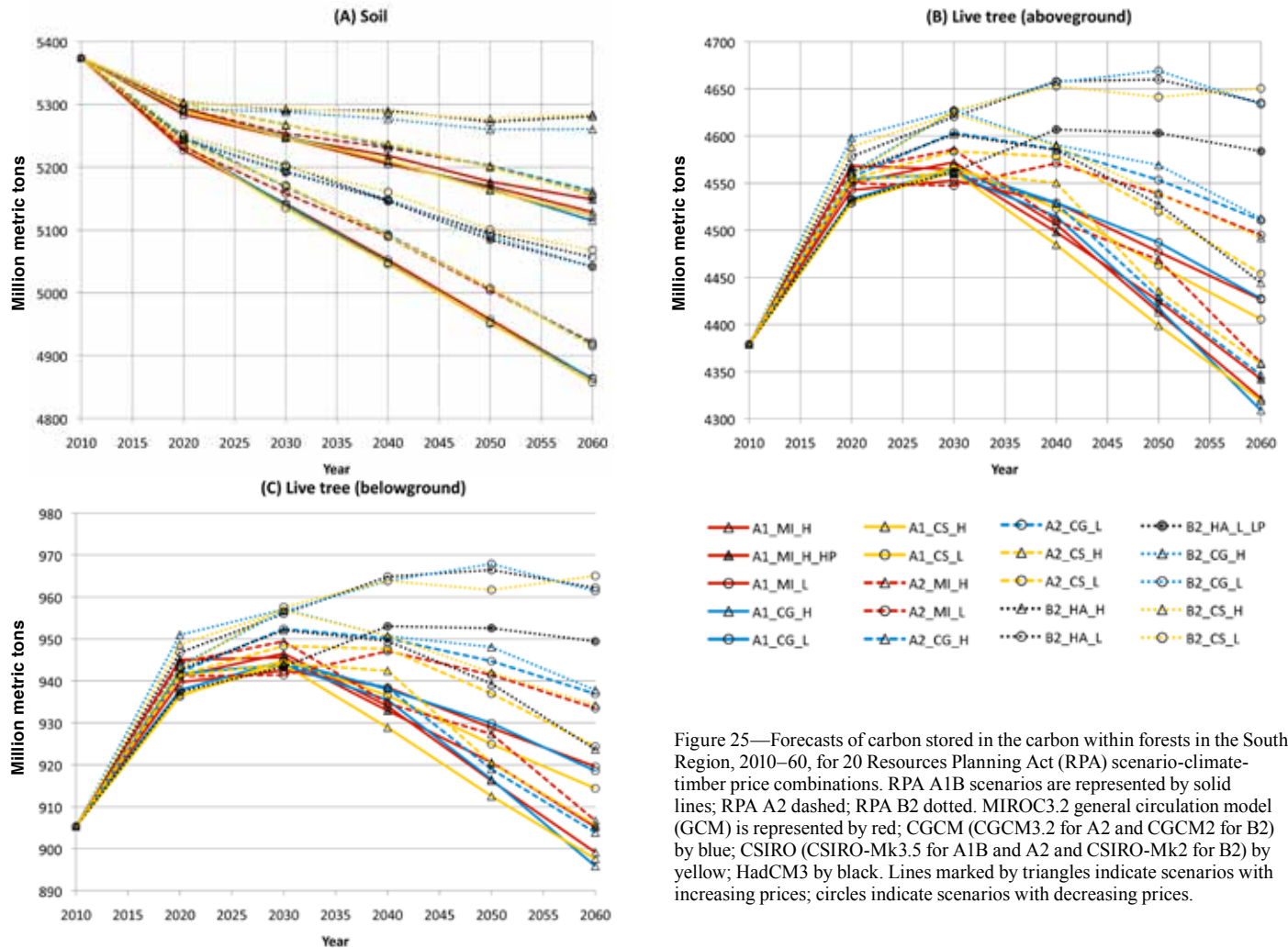


Figure 25—Forecasts of carbon stored in the carbon within forests in the South Region, 2010–60, for 20 Resources Planning Act (RPA) scenario-climate-timber price combinations. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

Removal forecasts can be further examined in light of a longer historical record. Figure 28 shows estimates of timber removals for the South between 1962 and 2060 and indicates that softwood and hardwood removals were roughly equivalent in 1962 at about 2.8 billion cubic feet. Softwood removals expanded by more than 132 percent between 1962 and 1998, and hardwood removals expanded by about 37 percent. As a result, softwood output was about 75 percent higher than hardwood output in 1996. Harvest outputs declined after 1996 and have not recovered to date (the data labeled as 2010 may actually overstate most recent removal levels). Forecasts of timber removals are based on price projections that start with prices in 2006 and then move upward or downward by about 1 percent per year (high and low price scenarios, respectively). All of these forecasts show an increase in harvests and a return to output growth. These increases are driven by two factors: (1) a strong accumulation of biomass over the past 15 years, partially explained by the decline in harvests, i.e., wood has been accumulating on the stump in lieu of harvests, and (2) a strong growth in timber investments through the planting of

pine, i.e., reflecting the 30 percent expansion between the late 1990s and 2010. Forecasts of softwood removals span a range between a return to 1980s levels of growth and a leveling of output about 38 percent above current prices.

The forest forecasts described for the South are driven by futures defined with exogenous price paths and this range of price paths, along with climate, population, and income projections, show a range of plausible futures for forests in the region. The removals forecasts from these and other runs of the Forest Dynamics Models were used to generate the supply functions for four specific products incorporated in the U.S. Forest Products Model as described by Ince and others (2011). Set within a model of global forest products markets called the Global Forest Products Model (Buongiorno and others 2003, 2012), the Forest Products Model provides detailed forecasts of market outcomes to simulate the effects of the global economic forecasts and energy forecasts (notably, forest biomass used to generate energy) associated with each of the three RPA scenarios. The latter involves downscaling continental-scale demands for wood in

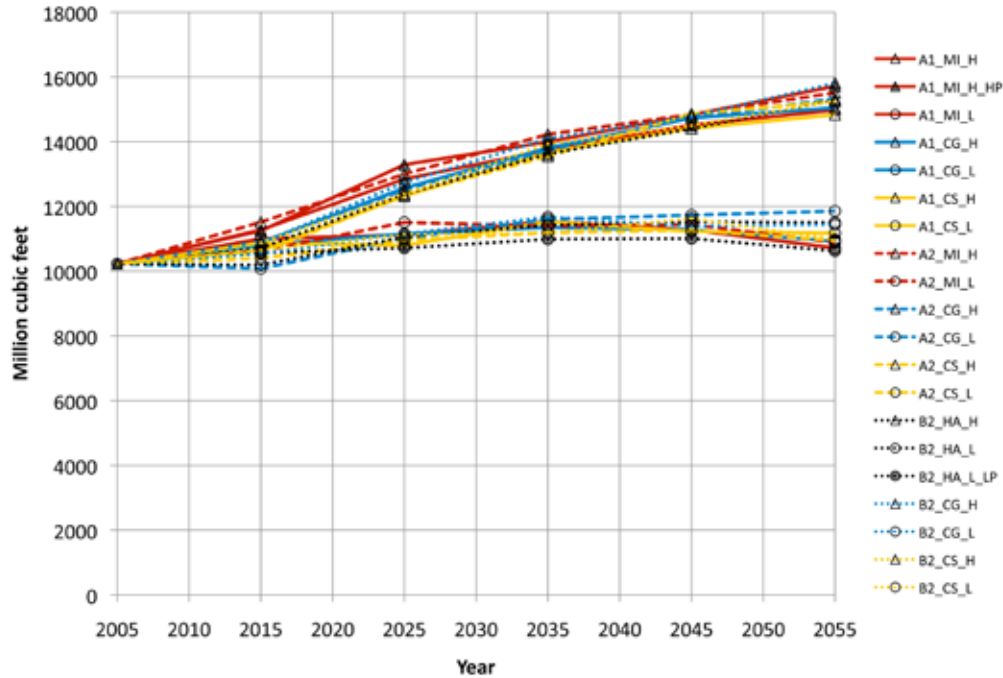


Figure 26—Total harvest removals from inventory in the South Region for 20 Resources Planning Act (RPA) scenario-climate-timber price combinations, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

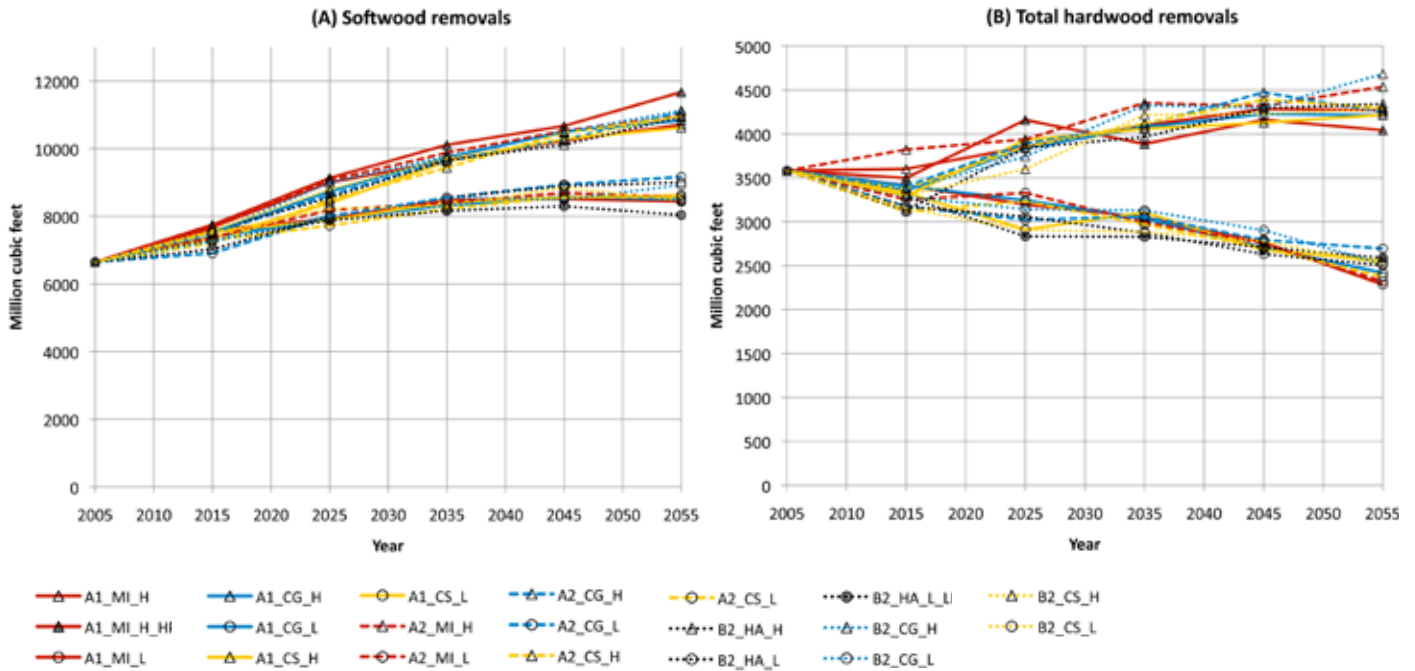


Figure 27—Total removals by broad forest type in the South Region for 20 Resources Planning Act (RPA) scenario-climate-timber price combinations, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

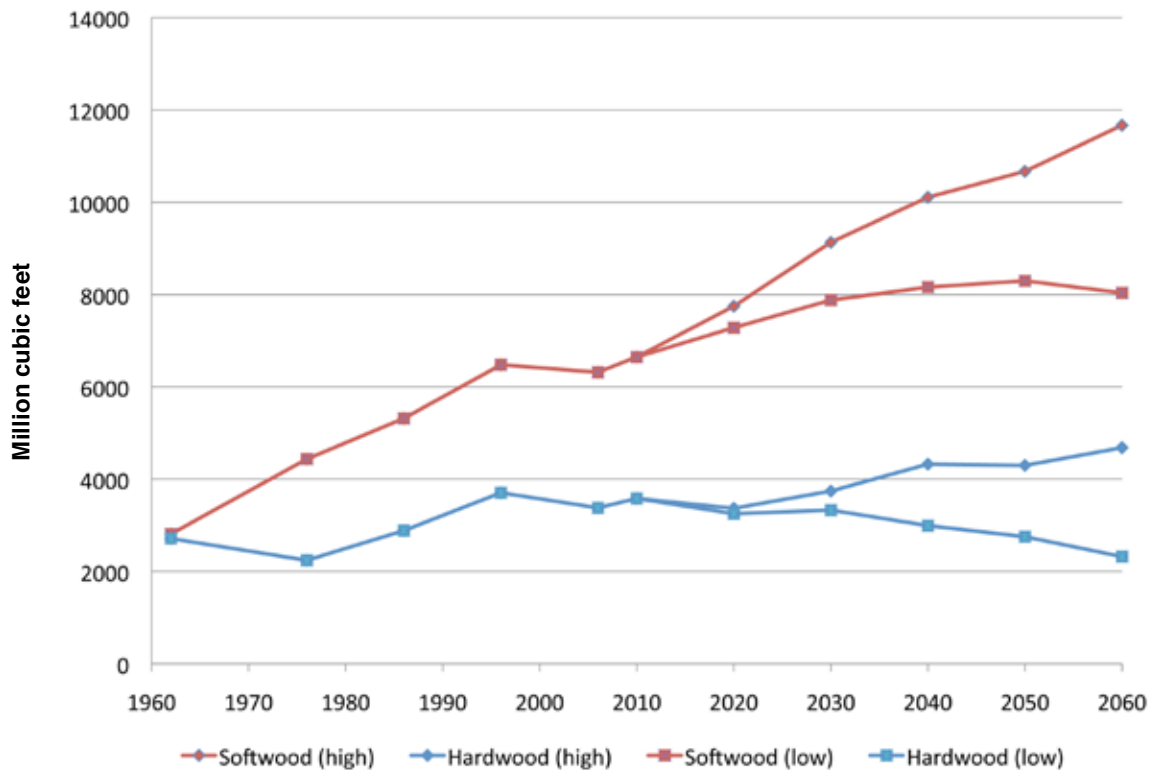


Figure 28—Softwood and hardwood growing stock removals for the South Region, 1962–2060. Forecasts (2010–2060) bracket the range of future inventories shown in figure 27.

bioenergy applications to individual countries and simulating the effects on fiber markets and trade. In the United States, the RPA A1B scenario is associated with high bioenergy demands, RPA B2 is associated with much lower bioenergy demands, and RPA A2 is intermediate to RPA A1B and B2.

Within the Forest Products Model then, timber supply from the South is derived from the land use and forest dynamics components of the U.S. Forest Assessment System, and so is consistent with each RPA scenario's projections of population growth and income growth (at a county scale) and with shifts in forest conditions affected by harvesting, successional dynamics, climate change, and land use changes. However, differences in removal forecasts are not readily discernable between GCMs (figs. 26 and 27).

To examine the resource implications of the market outcomes associated with each of the three RPA scenarios, we assign a forest simulation to each RPA scenario defined by the Forest Products Model projections. Due to the stochastic nature of the models and the inherent variability of removals estimates in the FIA inventory, we did not expect to find an exact match for harvests; instead we sought a simulation with a close approximation of the harvest pattern and harvest totals for the

model run.³ Figure 29 compares the South's timber harvest forecasts from the Forest Products Model with the implied harvests from the selected runs of the Forest Dynamics Model, and shows that total harvest forecasts are largely consistent between the models for the specific futures. This includes the productivity enhancement for pine plantations under the RPA A1B-high price future. Forest Dynamics Model harvest removals are within 10 percent of harvest removals from the Forest Products Model for all periods and scenarios, with one exception. For the last 2 decades, the RPA A1B Forest Products Model projection is roughly 20 percent higher than the Forest Dynamics Model projections. For 2055, RPA A2

³ As with any sampling scheme, FIA inventories are designed to provide estimates with a certain level of precision. Forest area projections require a sampling error of 3 percent per 1 million acres of timberland, and FIA guidelines target an error rate of 5 percent in the East and 10 percent in the West for volume, removals, and net annual growth (Woudenberg and others 2010). Removals forecasts across the 26 runs for each FDM simulation reflect this level of variability, and the translation of removals into harvest estimates introduces another source of error. Overall, we sought to produce Forest Dynamics Model simulations that were within 10 percent of the Forest Products Model simulations as representative of forest conditions under a particular scenario. An evaluation of total harvest levels over the length of the simulation provided a means for evaluating bias, i.e., whether the differences between the two models were consistently greater or lesser.

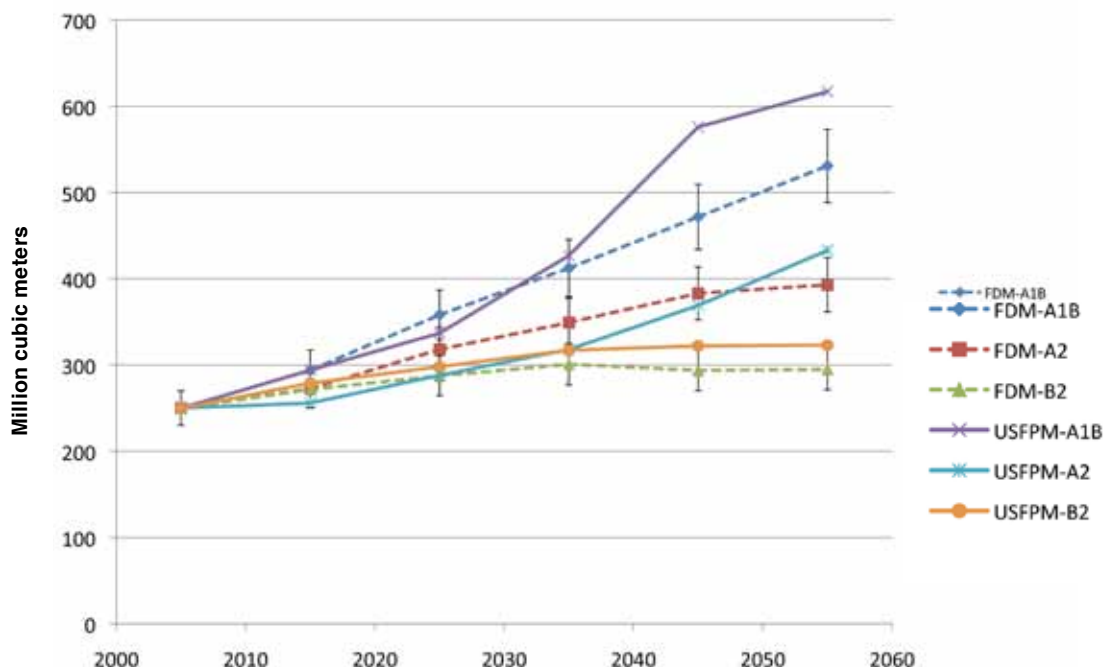


Figure 29—Comparison of harvests predicted by U.S. Forest Products Model and the Forest Dynamics Model scenario associated with the U.S. Forest Products Model scenario for the South Region.

Forest Products Model projections are about 11 percent lower than the Forest Dynamics Model projections. Total removals match fairly closely for the entire simulation period for the RPA B2 scenario. The Forest Dynamics Model projects 93, 103, and 95 percent of removals forecast across all decades by RPA A1B, A2, and B2 scenarios, respectively. Based on these comparisons, we use RPA A1B-MIROC3.2 with high prices, RPA A2-CSIRO-Mk3.5 with high prices and RPA B2-CGCM2 with low prices to represent futures under these RPA scenarios consistent with the market analysis conducted by the Forest Products Model.

Age Structure/Habitat

Simulated inventories can be used to evaluate various aspects of future forest conditions. One aspect of significance to wildlife habitat conditions in the South is the distribution of forests by age class, and the implications for the provision of early, middle, and late age forest conditions. We evaluate changes in the age class distributions of forests of various type using two charts. One displays the aerial age class distribution by decade for the most recent inventories of the 13 Southern States. We then summarize changes in age class resulting from the 20 futures between 2010 and 2060 using box plots. Figure 30 shows the current age class distribution for planted pine forests in the South by 10-year age classes. Each box plot describes the distributions of changes in age classes.

The bottom of the box represents the 25th percentile of the predicted changes, the top of the box represents the 75th percentile of the predicted changes, the line in the box indicates the median forecast, and the plus in the box indicates the mean forecast. The “whiskers” of the box show the extreme values of the forecasts.

Not surprisingly, a large majority of planted pine forests are between the ages of 0 and 30, with the largest share between the ages of 11 and 20 (fig. 30). By 2060, all age classes are forecasted to gain area except the 11–20 class, which would decline but still be comparable in area to the 0–10 and 21–30 age classes. Increases in older planted pine forests indicate that, while the probabilities of harvest are high, forecasted planting is higher than that demanded for additional harvesting over the next 50 years. However, only a tiny proportion of planted pine forests is expected to exceed 60 years of age by 2060.

Age dynamics differ strongly for natural pine (fig. 31). Recalling that this forest type is forecasted to lose substantial area by 2060 irrespective of future, forecasted declines in nearly every age class are consistent with overall trends (fig. 31). For this forest type, the area of forest in the 0–10 age class remains relatively constant—harvests not followed by planting essentially “recharge” this age class. However the area of forests in age classes between 11 and 70 years are forecast to decline substantially. The only age class forecasted to gain substantial area is the 81-plus age class. Early age habitats

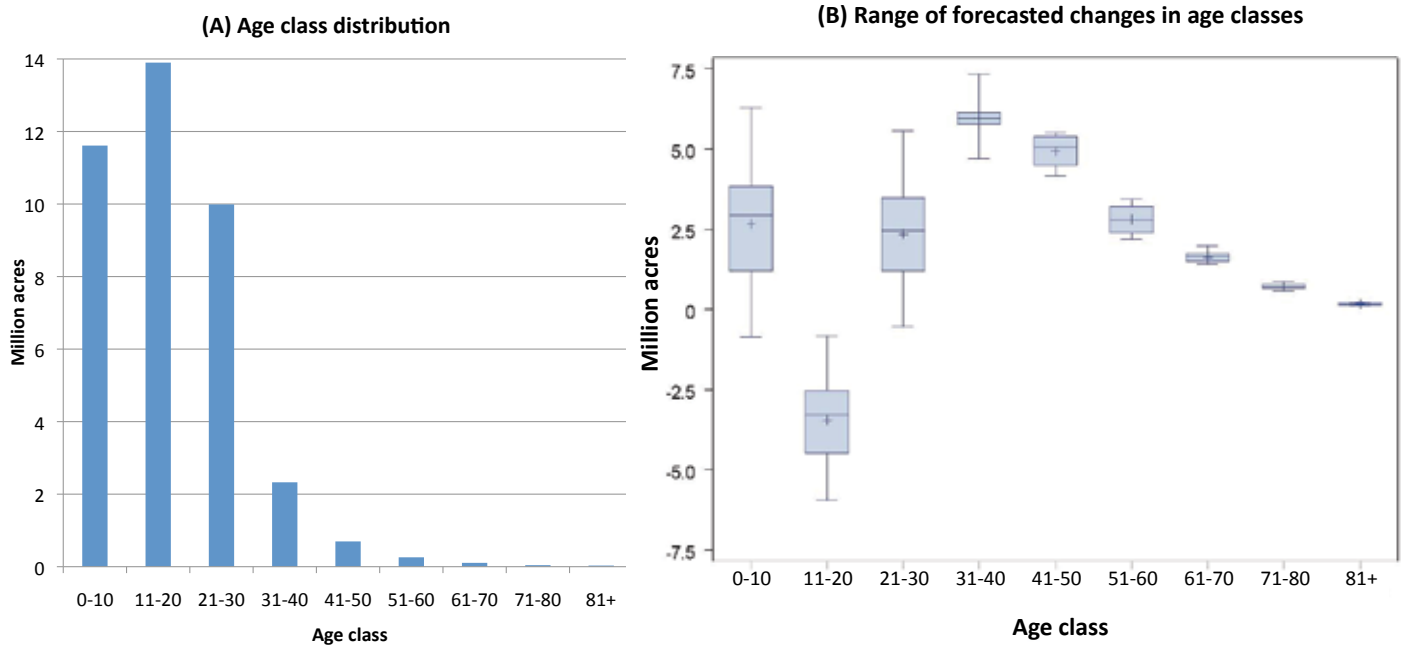


Figure 30—(A) Age class distribution for planted pine forests in the South Region, 2010, and (B) the range of forecasted changes in age classes for planted pine forests, 2010–60, using forest forecasts for the 20 Resources Planning Act (RPA) scenario-climate-price combinations. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

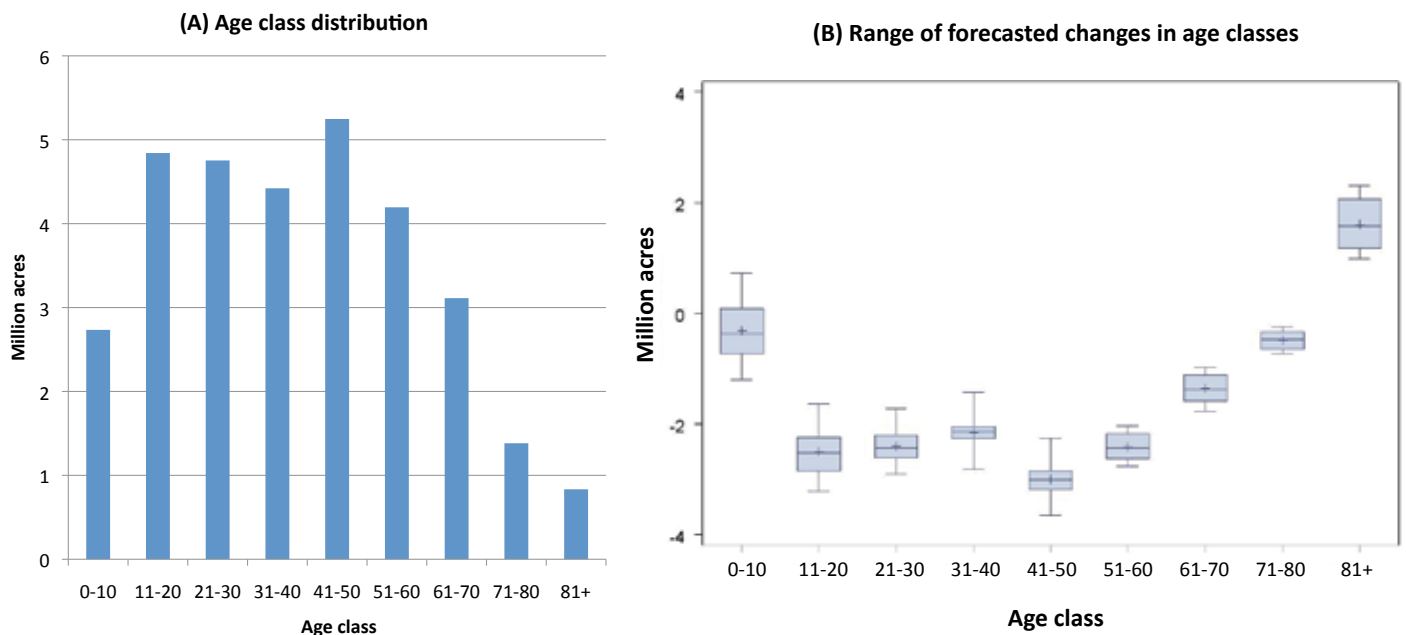


Figure 31—(A) Age class distribution for natural pine forests in the South Region, 2010 and (B) the range of forecasted changes in age classes for natural pine forests, 2010–60, using forest forecasts for the 20 Resources Planning Act (RPA) scenario-climate-price combinations. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

are relatively constant, while middle age classes decline substantially and old age classes increase somewhat.

Mixed pine-hardwood forests are forecast to experience declines in the earliest age classes, smaller declines in the middle age classes, and slight gains in the oldest age classes (not shown). The current age class distribution of upland hardwoods shows a U-shape with a large area in the 0–10 age class, much lower area in the 11–40 age classes, and majority of area in the 41–70 age classes (fig. 32). Forecasts show a strong downward shift in early and middle age classes, with a strong growth in the older age classes (>70 years). The early age class grouping would decline by about 50 percent, and the middle age classes would decline by about 30 percent from a currently low value. While the area of upland hardwood forests may decline only slightly, their age class composition is forecasted to be substantially different by 2060 (fig. 32).

The pattern of the current age class distribution of lowland hardwoods is similar to the pattern for upland hardwoods (not shown). Patterns of change are also comparable, but with a lower magnitude. Early and middle age classes decline in area while the area in the oldest age class increases substantially by 2060 (from about 2.7 million acres to about 7 million acres).

Discussion

The 20 futures considered for the South Region provide a range of future forest conditions that reflects uncertainty inherent in projecting the future as well as the state of knowledge regarding the response of forests and land uses to future conditions. In many cases, consistent trends are revealed but perhaps more importantly, variation across futures suggests which variables are most important in determining future conditions.

Climate futures reveal a gradual change in climate conditions across the South between 2010 and 2060 with the greatest changes associated with the RPA A1B-MIROC3.2 and A2-MIROC3.2 combinations. Significant changes in temperature and precipitation values begin to arise over substantial areas beginning in 2030. Given the ways in which climate factors into the forest forecasts, the biggest impacts of climate are realized in regenerated forests. For unharvested forests, these types of gradual changes are unlikely to generate substantial changes in forest conditions in the 50 years of the forecasts. This is reflected in the clustering of biomass and removals forecasts around price and scenario forecasts and with little separation in forecasts across GCMs for most variables at the regional level.

Future forest area is most strongly determined by the future price of timber products but also almost as strongly influenced by the population and income forecasts associated with the RPA scenarios. Urbanization, driven by the latter, would shift

away from forests and toward agricultural lands as timber prices increase. For example, RPA A1B has the highest level of urbanization with a forest loss of about 21 million acres between 2010 and 2060 under the low timber price scenario. With the high timber price scenario, forest loss is reduced to about 11 million acres.

Timber prices also influence the condition of forests, especially through forest planting. Across the 20 futures, the middle forecast is for about 56 million acres of planted pine in 2060 from a base of about 39 million acres in 2010. With high prices, the future area of planted pine area would range from 58 to as much as 67 million acres. Higher timber prices therefore suppress overall forest losses but shift the condition of forests toward more planted pine—at least 50 percent of the urbanization offset (and as much as 100 percent) described earlier is accounted for by increased planted pine area. Currently, planted pine represents about 19 percent of forest area in the South. By 2060, planted pine could represent between 24 and 34 percent of the region's forests, depending on market conditions.

Biomass accumulated substantially in the South over the past 50 years: total growing stock inventory expanded by 67 percent between 1962 and 2010. However, forecasts for the next 50 years suggest a change in this pattern. Due largely to the aging of forests, but also because of land use and forest type changes, the accumulation of biomass would slow substantially, with net increases in total biomass amounting to 1–10 percent between 2010 and 2060. This trend in total inventory volume is based on forecasted increases in softwood volume with simultaneous decreases in hardwood volume. As a result the share of softwood in the inventory shifts from about 41 percent in 2010 to about 46 percent in 2060, with little variation across the futures.

Forest carbon pools are determined by the area of forests and the distribution of forest conditions. The net impact on forest carbon pools of land use changes, forest type changes, and forecasted removals is essentially a stasis. Forest growth largely offsets losses accruing to forest area losses so that in 2060 the forest carbon pool ranges from 99–105 percent of its value in 2010. This is not a complete accounting for all land-based carbon pools—forests converted to agricultural or urban uses will retain some amount of stored carbon—nor does it account for the amount of carbon stored for long periods in solid wood products. These findings do suggest that there is little opportunity to expand standing forest carbon pools except where land use conversions can be prevented. It should also be emphasized that these scenarios include no policy incentive to retain or sequester additional carbon on forest lands.

Forecasts of removals based on disaggregate harvest choice models indicates the potential for a substantial expansion in the harvest of timber products from the South. Even with steadily declining prices, removals are forecast to increase,

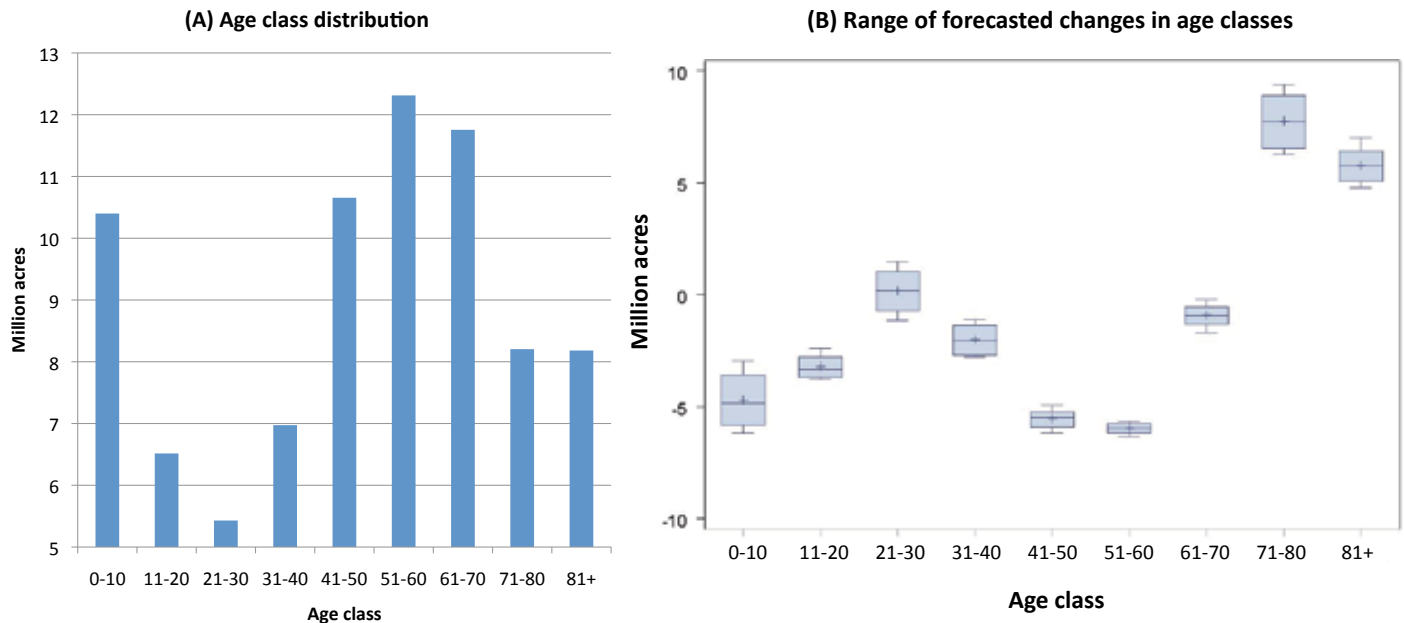


Figure 32—(A) Age class distribution for upland hardwood forests in the South Region, 2010, and (B) the range of forecasted changes in age classes for upland hardwood forests, 2010–60, using forest forecasts for the 20 Resources Planning Act (RPA) scenario-climate-price combinations. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines marked by triangles indicate scenarios with increasing prices; circles indicate scenarios with decreasing prices.

reflecting the substantial expansion in supply from the area of planted pine forests in the region over the past 20 years as well as a “backlog” of unharvested forests stored “on the stump.” These forecasts also reveal that forecasted forest losses do not suppress removals due largely to the location and types of forests affected by urbanization. Supply expansion can be viewed as an ongoing transition to agricultural-style forestry in the South. This also indicates changes in the removals to inventory ratio, which increases substantially between 2010 and 2060 as harvests increase by as much as 90 percent while inventories of standing biomass grow by only 1–10 percent.

Actual harvests will be determined, not only by the supply relationships simulated here, but also by forecasted demand for various forest products. The market future associated with each of the three RPA scenarios has been taken up by Ince and others (2011) for the 2010 RPA Assessment. Their analysis, using supply estimates derived from the analysis described here, indicates widely varying market futures for the three RPA scenarios. RPA B2, with its low economic growth, lower population growth, and low demands for wood-based bioenergy yields market futures that are most similar to the RPA B2-low price futures explored in this report. Under these futures, we would expect a moderate loss of forest land (about 12 million acres), forecasts of planted pine area at the lower end (47–55 million acres in 2060), expanding standing biomass inventories through 2050 followed by a leveling, and very moderate long run growth in removals.

RPA A2 yields a price future that is quite comparable to RPA B2 through 2040, after which, timber prices rise somewhat. Through 2040 then the RPA A2 low price future would hold, but with price levels reaching the area of RPA A2 high price future by 2060. For RPA A2 then, forest area losses would be somewhat higher than for the RPA B2 case, and inventories would level off about 20 years earlier (but would be at 2010 levels in 2060). For both the RPA B2 and A2 scenarios, changes between 2010 and 2060 would be orderly, with paths of change quite comparable to the paths of change experienced over the past 50 years.

The RPA A1B scenario suggests structural changes in timber markets and forest conditions by the end of the forecast period. Prices for harvested products are projected to increase substantially beginning in 2025 and reach beyond the price forecasts of the 20 futures by 2040. These price signals would provide strong incentives for forest landowners to intensify investment in planted forests suggesting that the RPA A1B-high price and high planting scenario would provide a start for examining the effects of this future. Under this future, the area of planted pine forests would increase to about 67 million acres and planted pine would represent about 34 percent of forest area in the region. Harvests would begin to expand substantially, and inventories would begin to trend downward in about 2030. Forest carbon stocks under this future would trend down slightly but would remain at 97 percent of 2010 values in 2060.

The future captured by the RPA A1B scenario involves price increases beyond 2040 that are far outside the historical data upon which this analysis is based, implying structural changes that would not be captured by the models. Such price changes would encourage changes within the forest sector including more planting and more intense management on planted forests. Recent research in the South (McKeand and others 2003) suggest that a doubling of the fiber production from planted pine forests is plausible given new methods of genetic selection, fertilization, and other intensive silviculture. Beyond the forest sector, other changes are possible including price-induced switching to non-wood feedstocks for bioenergy or movement toward other energy technologies such as wind or solar. While the RPA B2 and RPA A2 scenarios are consistent with orderly changes given the condition and management of southern forests, demands at the level anticipated by RPA A1B would involve substantial structural changes.

CHAPTER 5

FOREST FORECASTS FOR THE NORTH

For the North, forest forecasts were generated for each of the nine Resources Planning Act (RPA) scenario-climate combinations. For these nine combinations, we apply timber harvest models that reflect historical harvest relationships—that is, probabilities of harvest are functions of plot attributes based on observed harvesting over the previous inventory interval. In addition, we generate separate forest forecasts that simulate timber market projections generated by the U.S. Forest Products Model for the economic futures attached to the three RPA scenarios. These three forecasts use the climate projections from the CGCM3.1 GCM for RPA A1B and A2 and the CGCM2 GCM for RPA B2. To match the harvests from the Forest Products Model, we adjust a scaling parameter on the set of harvest probability models (see appendix, equation 4) to reflect Forest Products Model runs for the respective scenario. Harvest outcomes in the Forest Products Model are partially determined by an aggregate model of timber supply for the region. Table 3 defines labels for the 12 futures evaluated in this section.

Climate

To frame a discussion of the forest forecasts, we compare climate projections from the nine RPA scenario-climate combinations with historical conditions for the North. Distributions of monthly values for a projected decade (2010 refers to the monthly values between 2001 and 2010, 2020 refers to monthly values between 2011 and 2020, and so on) are compared with a historical decade (2000 for the monthly values between 1991 and 2000). We start by plotting the cumulative distributions of temperatures/precipitation for a graphical view of change across time. We then map where significant differences arise between projected and historical data for counties in the region.

Figure 33 shows a comparison of empirical temperature distributions for the 2060 decade for the nine RPA scenario-climate combinations with the historical period (2000). For all forecasts, the distributions shift outward over time indicating temperature increases. The RPA A1B-MIROC3.2 combination shows the greatest increase in temperatures between the 2010 and 2060 decades, with a 4 °C increase in temperature at the

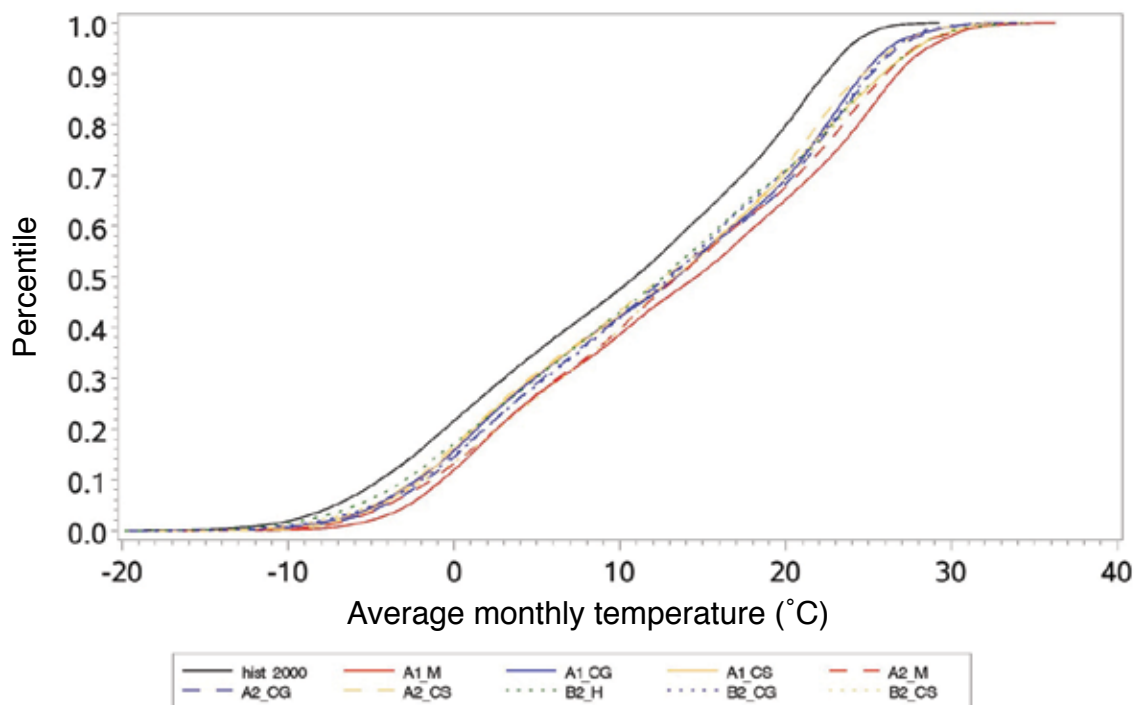


Figure 33—Empirical distributions of monthly temperatures for the North Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–60).

50th percentile of the distribution and a 4.5 °C increase at the 90th percentile. The other combinations yield roughly half the temperature increase shown for RPA A1B-MIROC3.2 (about a 2 °C increase at the 50th percentile and a 2.5 °C increase at the 90th percentile).

Comparing forecasts by decade shows that under RPA A1B-MIROC3.2 (the warmest scenario in the North), temperatures increase in every decade, with the greatest increase between the final 2 decades compared (2050 and 2060; fig. 34A). For the RPA CSIRO-Mk2 combination (fig. 34B) temperature distributions also shift outward between decades, but greater increases are shown for the earlier decades. The other seven RPA scenario-climate combinations (not shown here) also show outward temperature shifts in every decade.

Spatial patterns of change vary across the scenario-climate combinations. Figure 35 shows spatial patterns of change based on the Kolmogorov-Smirnov test for monthly temperatures at the county level applied to RPA A1B-MIROC3.2 (the combination with the greatest overall increase in temperature by 2060). The black areas indicate counties where there is distributional disagreement between historical and forecasted temperatures for the specified decade. Figure 36 provides the same set of maps for RPA A1B CSIRO-Mk3.5. For RPA A1B-MIROC3.2 (fig. 35), discernible temperature differences appear beginning in 2030 in small portions of Iowa, Missouri, and Illinois. By 2040 temperature increases consolidate across these three States and in peripheral States. By 2050, significant temperature increases are indicated for much of the Corn Belt, the lower peninsula of Michigan, and parts of the mid-Atlantic States of Pennsylvania, West Virginia, and Maryland. By 2060, the entire map is black for this scenario, indicating a significant outward shift in temperature distributions for all but two counties in the North.

The change pattern is quite different for RPA A1B-CSIRO-Mk3.5 (fig. 36). Unlike with MIROC3.2, significant temperature increases do not appear throughout the region until 2060. In 2060, the northwestern corner of the region, including Minnesota, Wisconsin, Iowa, northern Missouri, and much of Michigan has significantly higher temperature distributions.

Figure 37 maps the proportion of the nine RPA scenario-climate combinations leading to rejection of equivalent temperature distributions in the 2000 and 2060 decades (KS test, $p=0.05$). Four or more of the nine climate realizations have significantly different temperatures across roughly the western half of the region. Seven or more of the nine climate realizations have significantly different temperatures in counties in a sub-region to the west of Lake Michigan in Illinois, Iowa, and Wisconsin, and in some counties in the upper peninsula and the upper part of the lower peninsula of Michigan.

Projections of precipitation are much more variable than temperature projections across the nine RPA scenario-climate combinations and across the region. Under some scenario-climate combinations, overall precipitation declines by 2060; under others precipitation increases by 2060. Cumulative distributions of monthly precipitation for the nine climate projections for the 2060 decade compared with the historical decade (2000) show an inward shifting of precipitation (drying) for RPA A1B-MIROC3.2 and RPA A2-MIROC3.2 combinations and a strong outward shift (increase) in precipitation for RPA A2-CSIRO-Mk3.5 and RPA A1B-CGCM combinations (fig. 38). For the other scenario-climate combinations, the distributions pivot, indicating that some areas are wetter while others are drier in 2060 than in 2000. For the various combinations (including RPA A1B-MIROC3.2 which is drier in 2060), the precipitation distribution shifts vary between time steps, in some cases alternating between wetter and drier decades (fig. 39).

The spatial pattern of precipitation change also varies between scenario-climate combinations and across the region. For RPA A1B-MIROC3.2 (fig. 40) significant differences in the precipitation distribution arise largely in the northeast, with a drying trend between Massachusetts and Maine in the 2010 and 2020 decades. While these effects shrink or expand over the remaining decades, the northeast is generally drier under this scenario-climate combination. Additional drying is evident by 2060 in parts of Missouri, Illinois, and Michigan. Precipitation change follows a different pattern and is more sporadic under RPA A1B-CSIRO-Mk3.5 (fig. 41) and under RPA B2-HadCM3 (not shown).

Figure 42 maps the proportion of the nine climate realizations leading to rejection of equivalent monthly precipitation distributions between the historical (2000) decade and the 2060 decade (KS test, $p=0.05$). Very few counties show no significant difference across all models, with northwestern Minnesota being an exception. For much of New England, at least four model runs show significantly different precipitation between 2000 and 2060, with the highest degree of concurrence along the coast. Models generally show a drying trend for the New England States.

Maps of significant shifts in mean temperature and total precipitation highlight areas with emphatic change in these two variables, i.e., these are conservative tests. Other climate variables may also have important influence on future forest conditions but are not examined here.

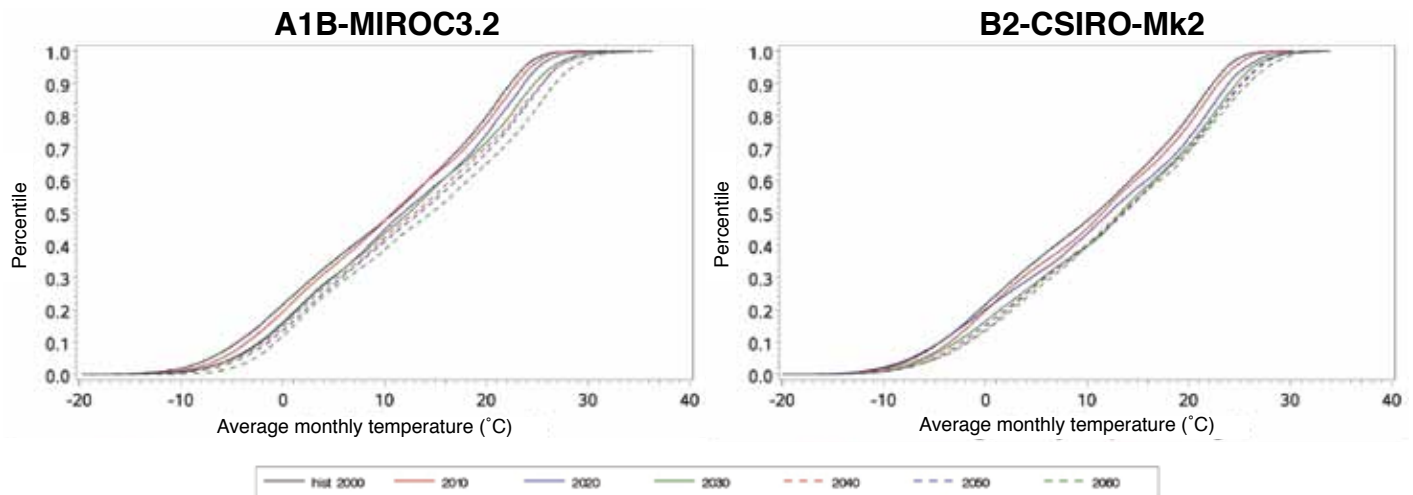


Figure 34—Empirical distributions of monthly temperatures for the North Region for a historical decade (1991–2000) and for 6 successive decades of climate projections for the (A) Resources Planning Act (RPA) A1B-MIROC3.2 combination and (B) RPA B2-CSIRO-Mk2 combination.

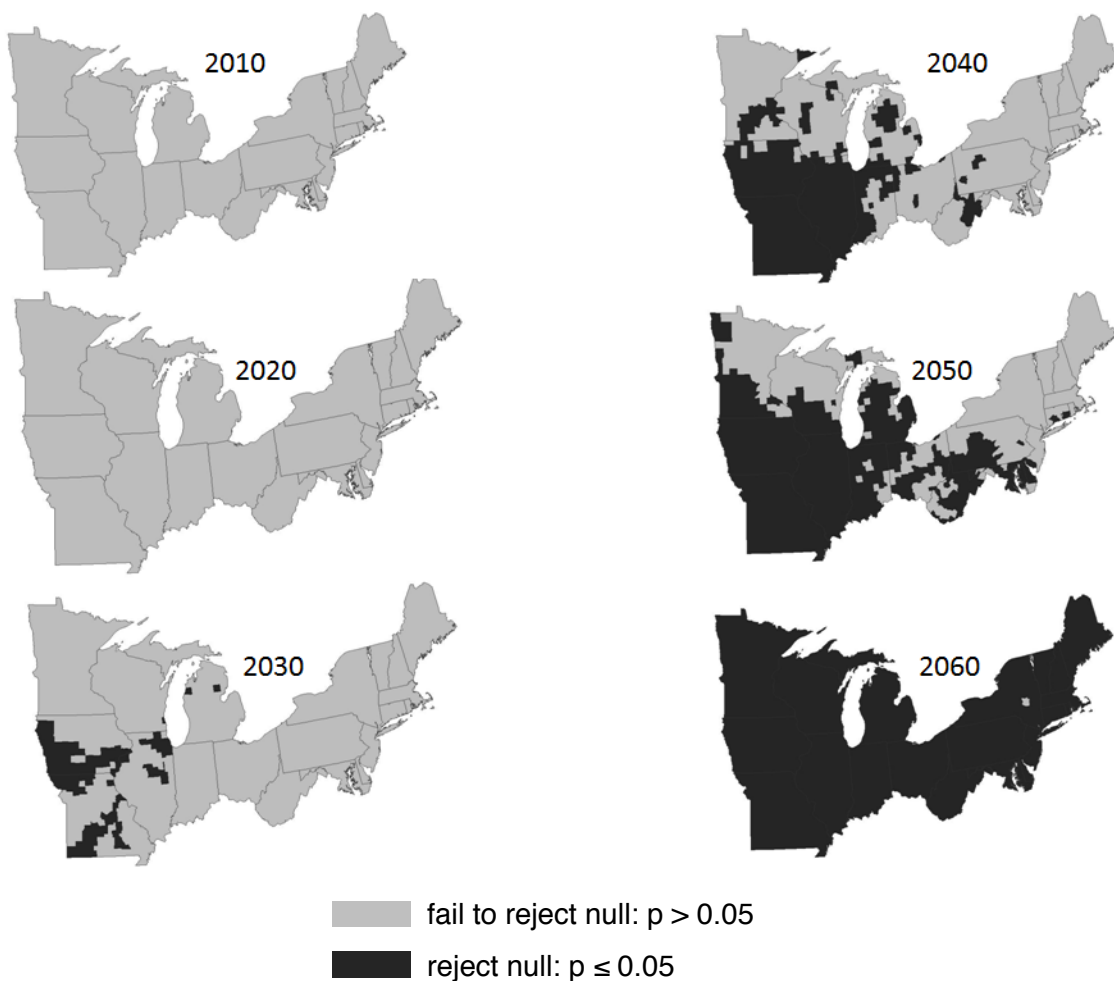


Figure 35—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

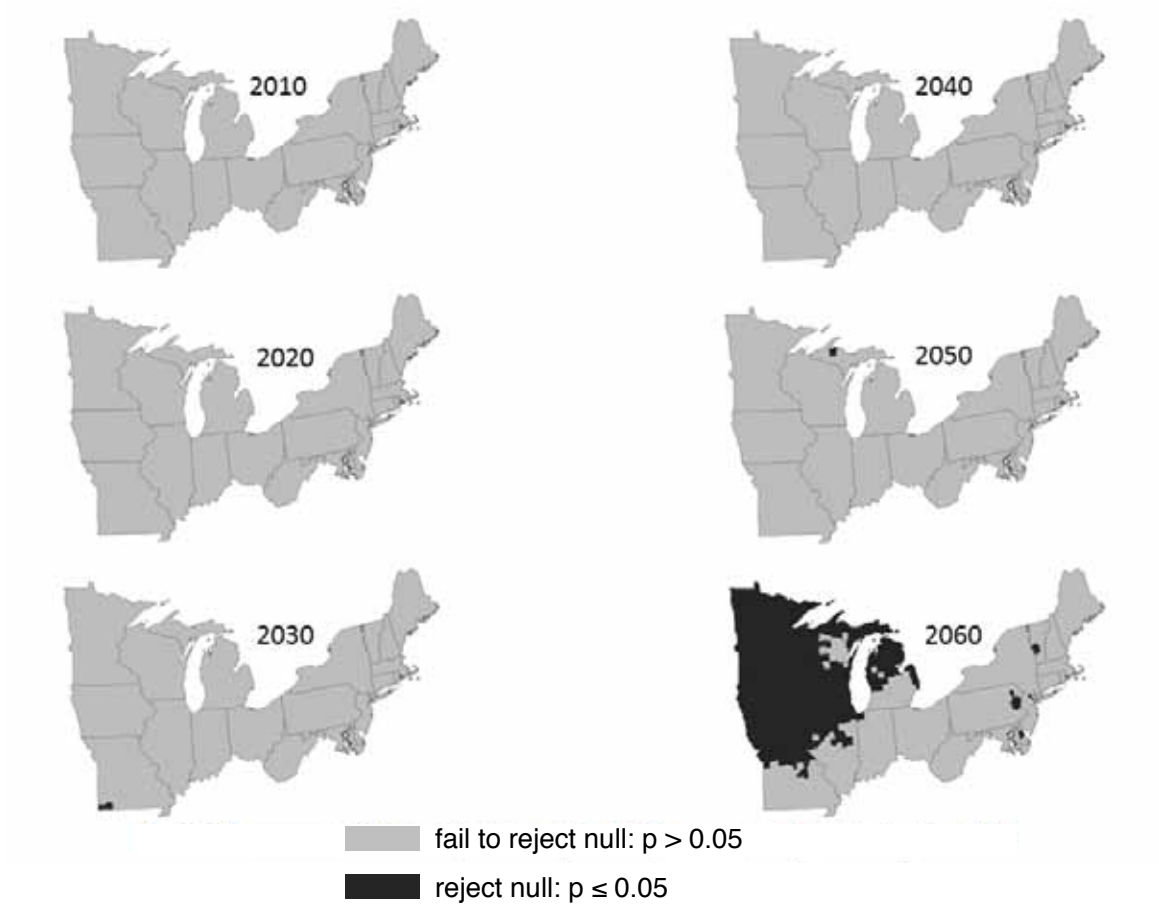


Figure 36—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-CSIRO-Mk3.5 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

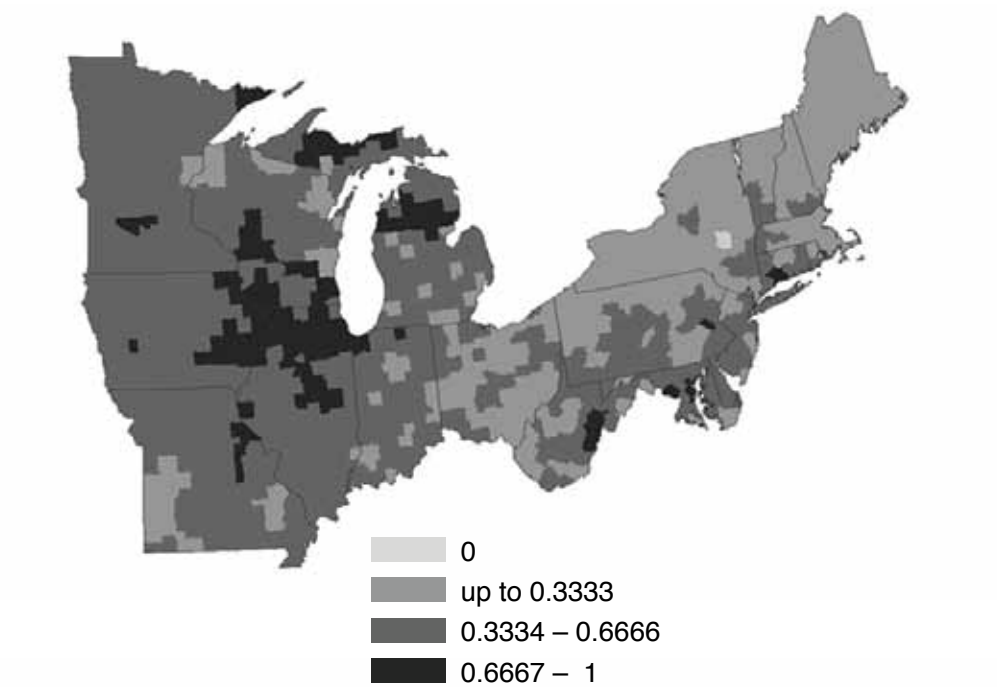


Figure 37—Proportion of the nine scenario-climate combinations yielding significant differences in decadal temperature distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the North Region.

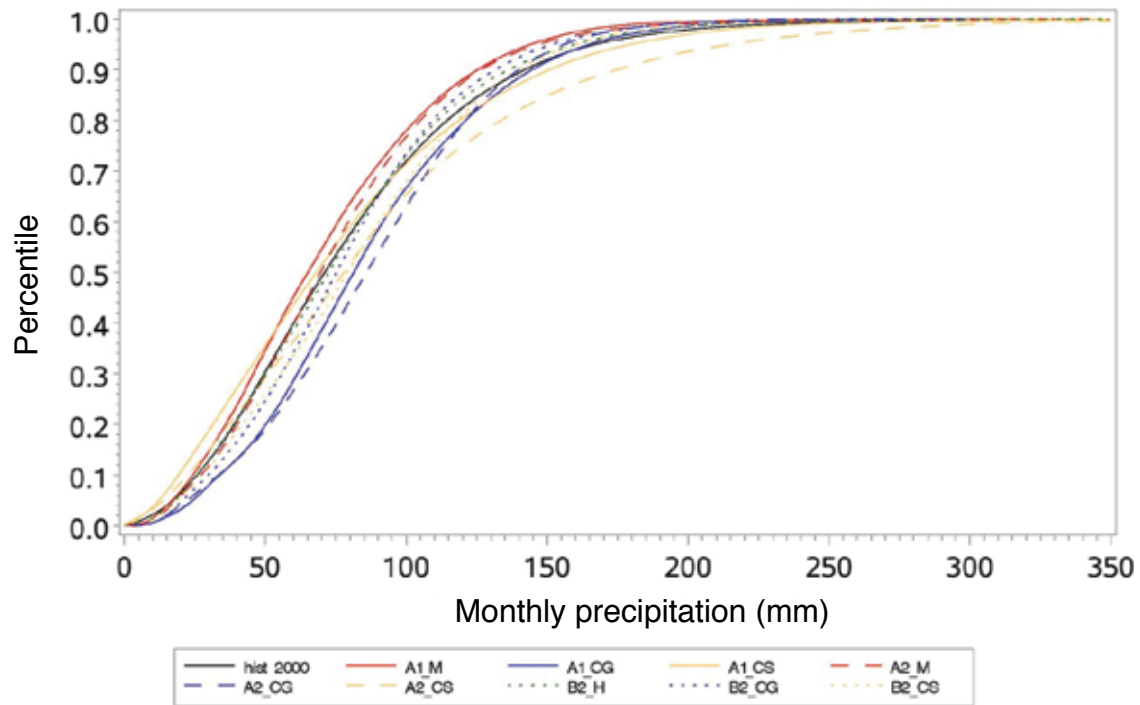


Figure 38—Empirical distributions of monthly precipitation values for the North Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–60).

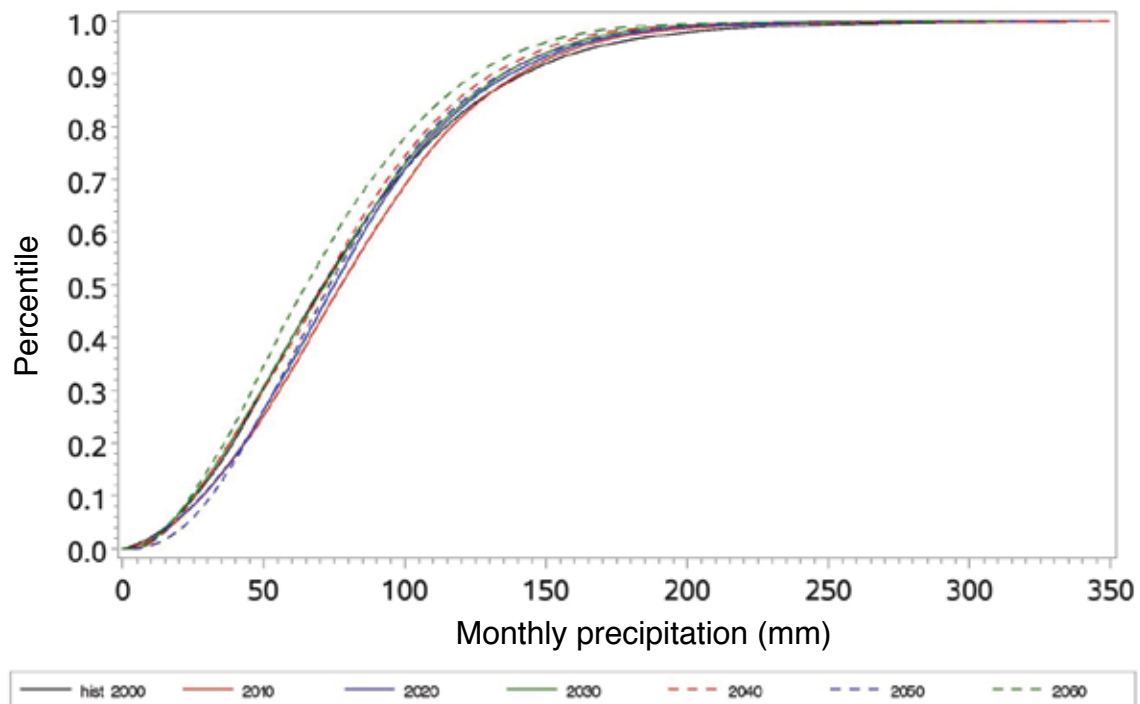


Figure 39—Empirical distributions of monthly precipitation for the North Region for a historical decade (1991–2000) and for 6 successive decades (2010–60) of climate projections for the Resources Planning Act (RPA) A1B-MIROC3.2 combination.

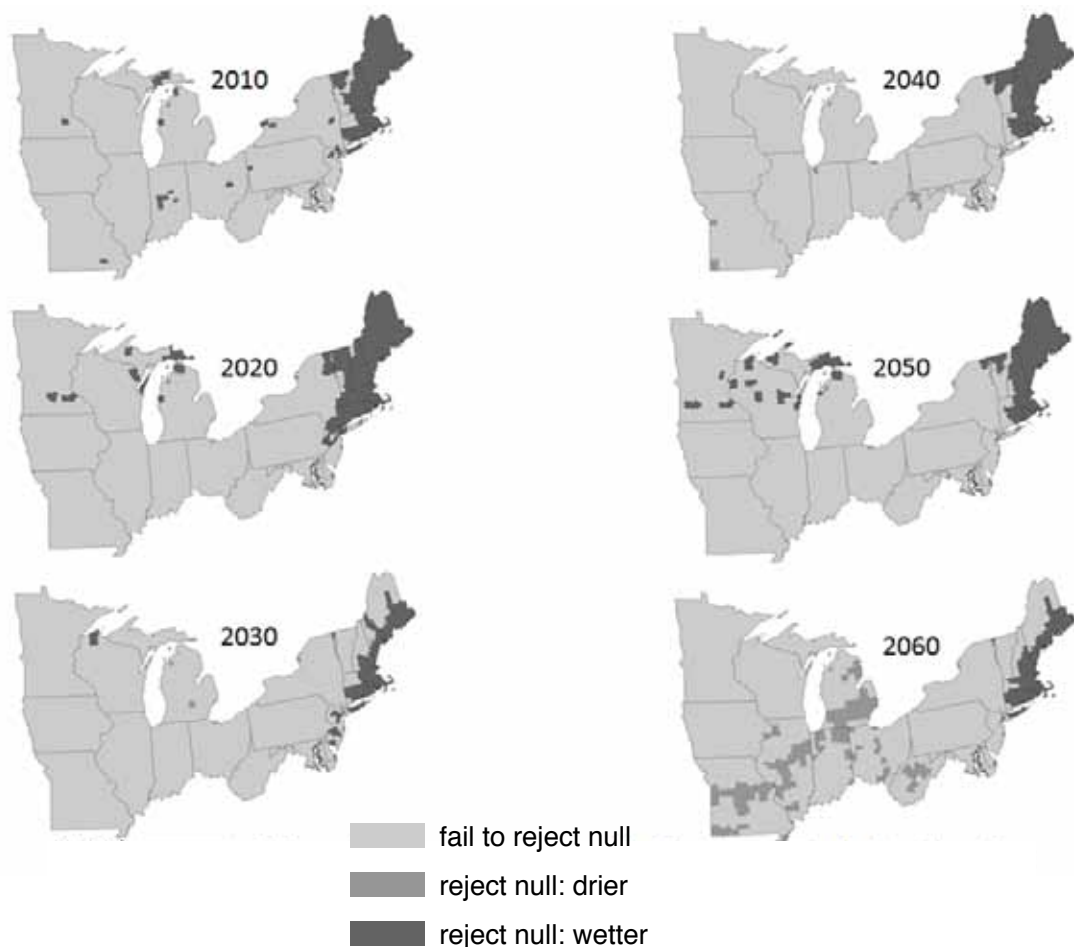


Figure 40—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value < 0.05) and indicate drier and wetter conditions, respectively.

Forest Area

Forecasts of forest area change derive from the land use analysis contained in Wear (2011).¹ All RPA scenarios predict declines in forest area with losses ranging from 6 million to 11 million acres (3–6 percent) between 2010 and 2060, the result of population- and income-driven urbanization (fig. 43). The smallest loss of forest area is forecasted for scenario RPA B2 (6 million acres), which has the lowest

population growth and the lowest income growth resulting in the lowest urbanization. The largest loss of forest area is forecasted for RPA A1B (11 million acres), where population growth is moderate but income growth is strong—this combination results in higher rates of urbanization. Under scenario RPA A2, where population growth is highest but income growth is lowest, forest loss is intermediate between RPA A1B and B2 (9 million acres).

Forest losses are especially high in a few areas of the North (fig. 44). Under the RPA A1B scenario (with the highest rate of urbanization), the largest contiguous area of forest losses is along the eastern seaboard stretching from Boston to Washington, DC, and extending inland to include all of

¹ The total forest area changes reported in this report differ from those in Wear (2011) because (1) the analysis in Wear (2011) is based on National Resource Inventory (NRI) data benchmarked in 1997, while this chapter translates those projections into FIA data benchmarked in 2010; and, (2) while the NRI measures only non-Federal land uses, the FIA data address all ownerships.

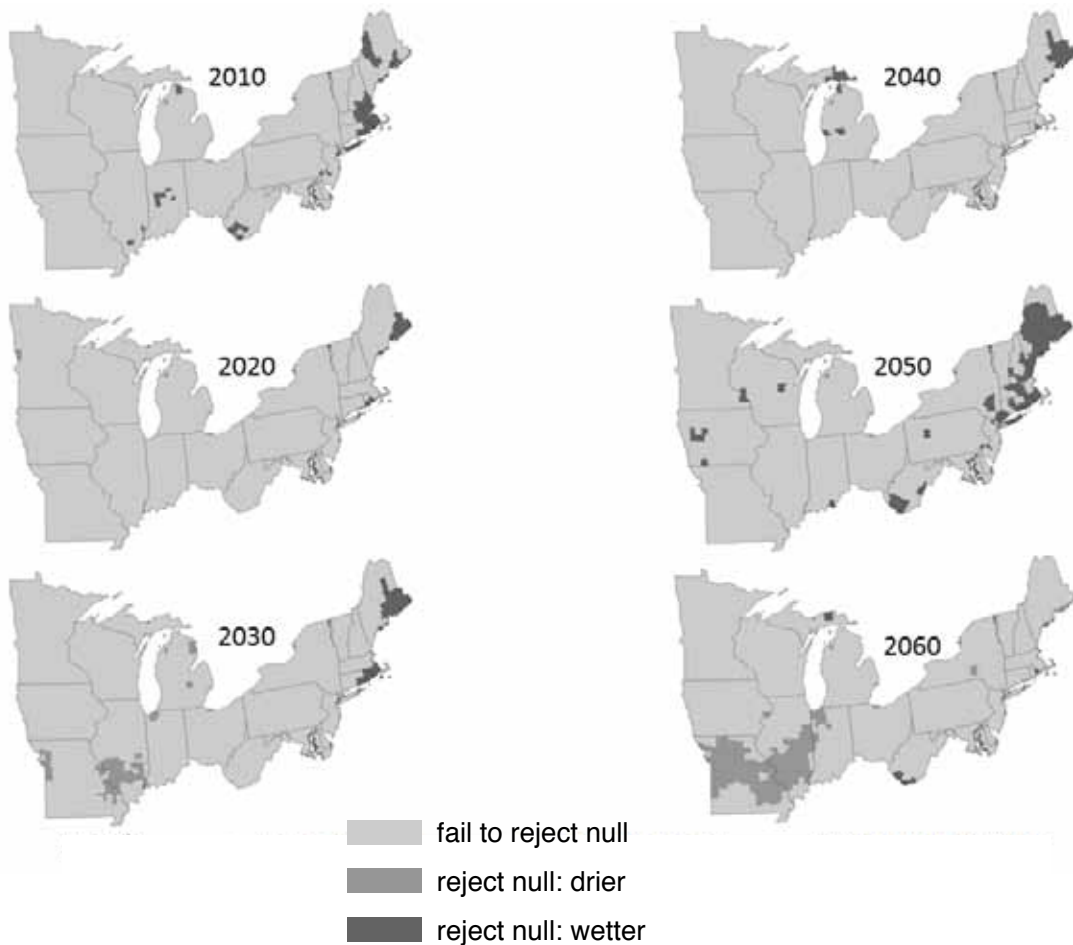


Figure 41—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-CSIRO-Mk3.5 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value < 0.05) and indicate drier and wetter conditions, respectively.

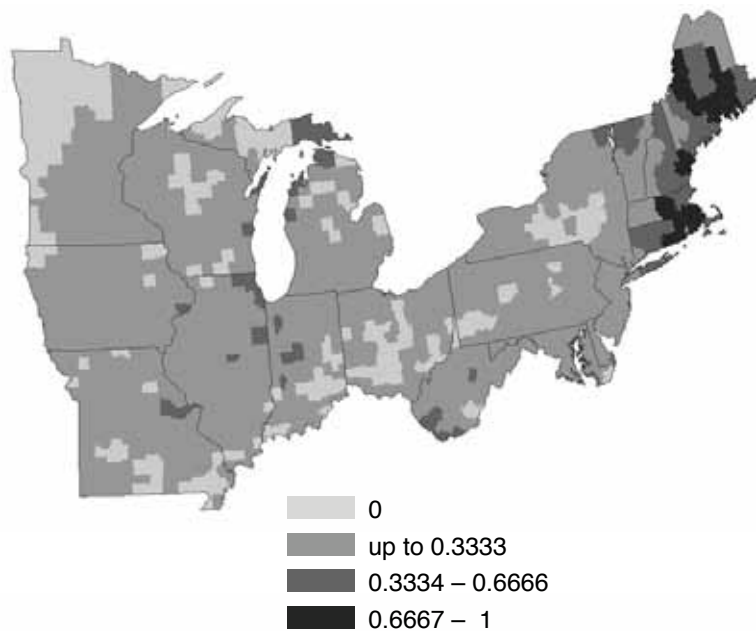


Figure 42—Proportion of the nine scenario-climate combinations yielding significant differences in decadal precipitation distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the North Region.

Maryland, parts of West Virginia, and much of southeastern Pennsylvania. In addition, parts of New Hampshire-Maine and northern Michigan have areas of high forest losses. Areas with lesser but still substantial losses are found in central Missouri and in an area stretching northwest and southeast of Minneapolis. In contrast to the population and income-fueled urbanization in RPA A1B, scenario RPA B2 has less forest losses, and losses are more concentrated around the metro areas that anchor growth under RPA A1B.

Forest Types

Hardwoods dominate forest types in the North, accounting for about 83 percent of forest area. Among hardwood forest types, maple-beech-birch and oak-hickory groups are the largest, accounting for 26 and 36 percent of total forest area in 2010. Among softwood types, spruce-fir (9 percent) and white-red-jack pine (5 percent) account for the largest shares of total forest area, and these forest types are concentrated in northern parts of the region. For the all forecasts, there is little change in the overall shares represented by hardwoods and softwoods. However, different shifts among forest types arise within the hardwood and softwood groups (fig. 45).

The area of oak-hickory, the largest forest type in the North, declines between 2010 and 2060 for all scenario-climate combinations (fig. 46A). Declines range between 3 million and 6 million acres (5–10 percent) over this period with the highest losses for the RPA A1B scenario-climate combinations and the least losses for the RPA B2 scenarios. The clumping of projections around scenarios indicates that land use changes (driven by the socioeconomic components of the scenarios) dominate forecasts of change for oak-hickory forests. There is little variation among projections of this forest type based on different GCMs for a given scenario; even the market-based scenarios do not significantly alter the area of oak-hickory.

In contrast, the area of maple-beech-birch increases between 2010 and 2060 for all scenario-climate combinations, with increases ranging between 1 million and 3 million acres (3–7 percent) (fig. 46B). Results are similar across all of the RPA scenario-climate combinations, with no clear separation between the scenarios. Among the hardwood types, elm-ash-cottonwood forests decline by the greatest percentage across all RPA scenario-climate combinations, falling by 13–20 percent (1–2 million acres) (fig. 46C) between 2010 and 2060. Aspen-birch forecasts are the most variable among hardwood types and all scenario-climate combinations lead to losses in aspen-birch area. Minimum losses are 1.4 million acres

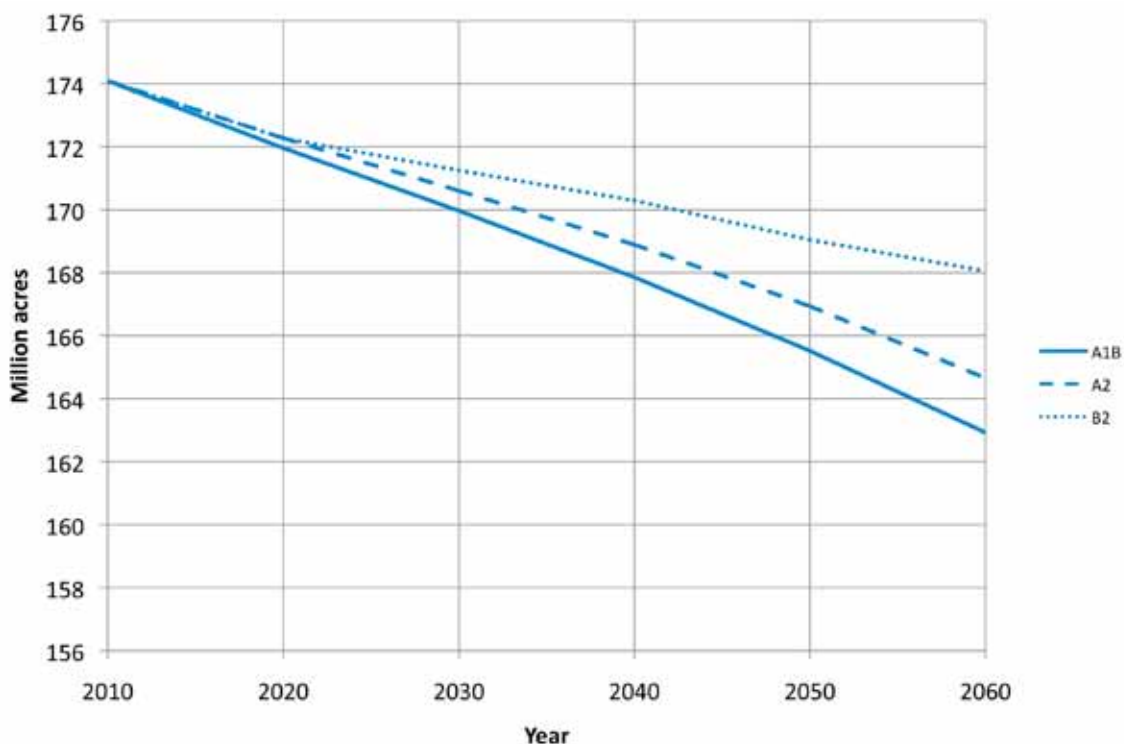


Figure 43—Total forest area for three Resources Planning Act (RPA) scenarios for the North Region. By model construction, forest area in the North varies only by RPA scenario and not by climate projection.

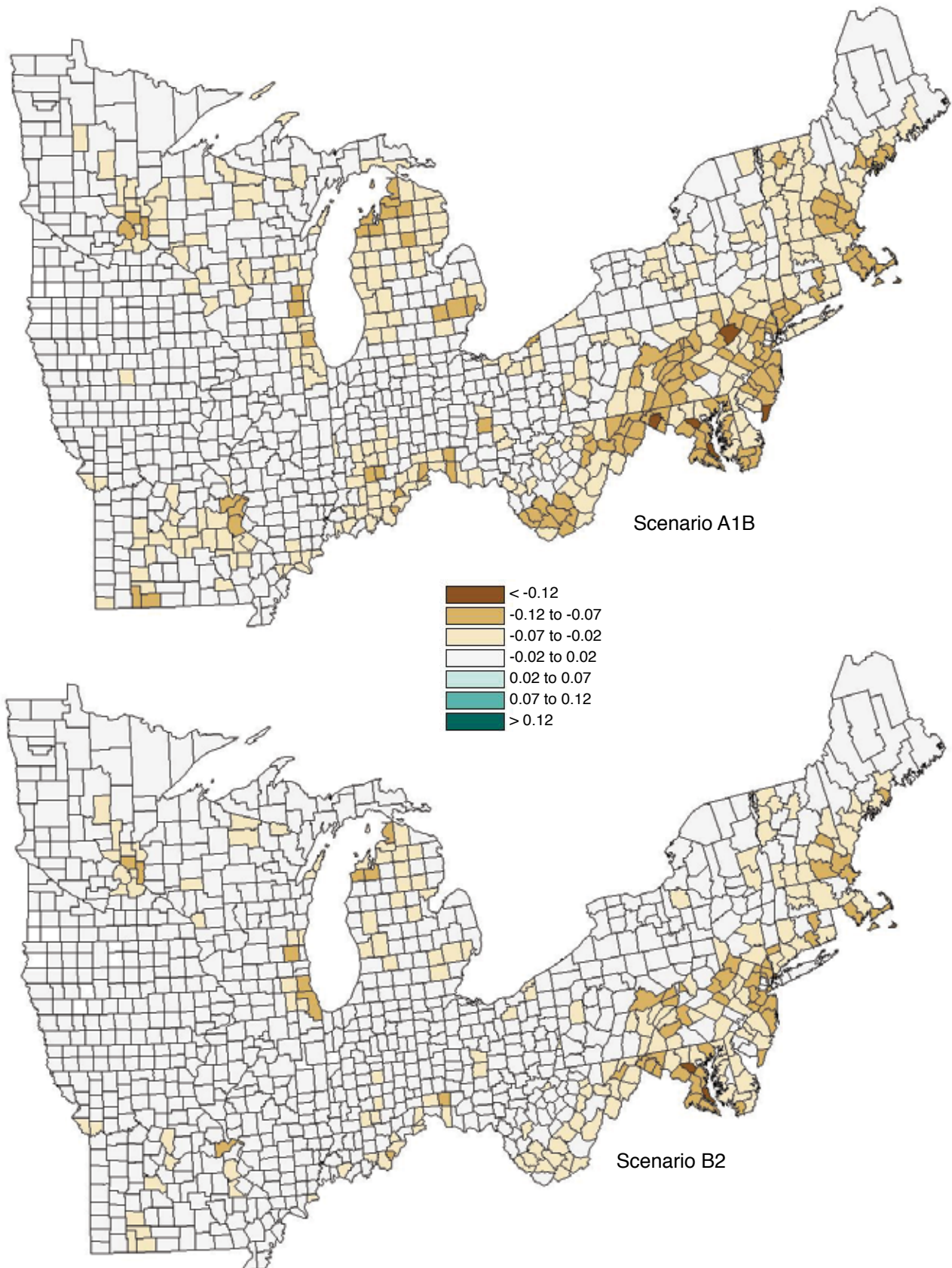


Figure 44—Forecasted change in the proportion of county in forest land, 1997–2060, for Resources Planning Act (RPA) A1B and B2 scenarios.

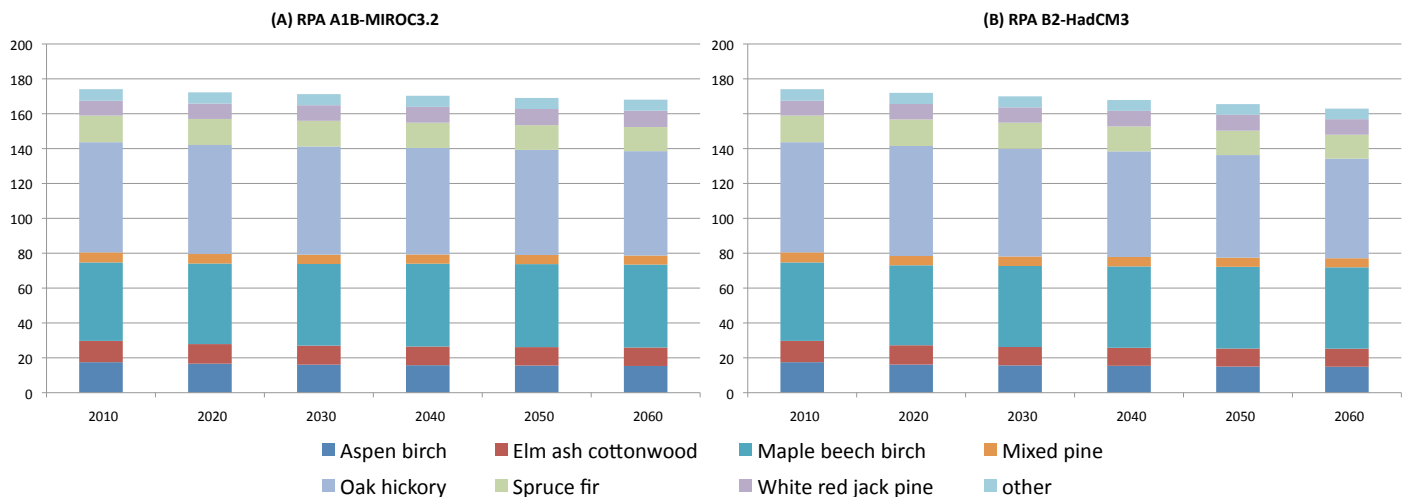


Figure 45—Current and forecasts of forest type distributions for A) Resources Planning Act (RPA) A1B-MIROC3.2 and B) RPA B2-HadCM3 scenario-climate combinations.

(7.7 percent) and maximum losses are 3.0 million acres (16.9 percent) (fig. 46D). For aspen-birch, the three market forecasts lead to the lowest amount of loss.

The two dominant softwood types show very different patterns of change across the scenario-climate combinations. Spruce-fir area decreases for all scenarios. While forecasts for the nine RPA scenario-climate combinations clump together and amount to 8–10 percent of area, the three market scenarios result in losses of 12–17 percent (fig. 46F). In contrast, the area of white-red-jackpine increases by 5–10 percent for the nine combinations but declines by between 3 and 16 percent for the three market forecasts (fig. 46E).

Standing Biomass

Of the various metrics available for measuring biomass changes for a site in a forest inventory, we opted to focus on the volume of growing stock because it is a useful index both for timber analysis and for measuring other ecosystem services. Total growing stock volumes are forecasted to change in response to both land use changes and timber harvesting levels. Total growing stock volumes increase from a base of 263 billion cubic feet to between 277 billion cubic feet and 290 billion cubic feet in 2060 for the nine RPA scenario-climate combinations (fig. 47). These nine combinations reflect a continuation of harvest activity observed over the past decade. In contrast, the three market forecasts show a peaking of inventory between 2020 (for RPA A1B-CGCM3.1-BIO) to 2030 (for RPA A2-CGCM3.1-BIO and RPA B2-CGCM2-BIO) and then declines in total inventories. In 2060, total growing stock inventories would be 1 percent lower than 2010 levels for RPA B2, 8 percent lower for RPA A2, and 20 percent lower for RPA A1B. Because hardwoods account for about 80 percent of total growing stock volumes, the pattern

of change for hardwoods is nearly identical to the pattern for the total (fig. 48). The pattern for softwoods is similar though the percentage declines for the market scenarios are somewhat higher: softwood inventories would be 2 percent lower than 2010 levels for RPA B2, 13 percent lower for RPA A2, and 24 percent lower for RPA A1B (fig. 49).

All these changes in growing stock volumes depart from historical patterns of volume accumulation in the North. Over the past 50 years, total growing stock volumes roughly doubled from 128 billion cubic feet in 1962 to 263 billion cubic feet in 2010 (fig. 50). Between 2010 and 2060, growing stock volume would either level off at around 285 billion cubic feet under the nine RPA scenario-climate combinations or peak and then decline somewhat under the three market scenarios. Under the RPA A1B scenario, the scenario with the highest rate of timber harvests, growing stock volumes would decline to levels observed in the 1990s by 2060.

Forest Carbon

Carbon contained in the forests of the North amounts to about 14.3 billion tons at the beginning of forecasts (fig. 51) with a majority of the carbon in soil organic matter and living trees (fig. 52). Accordingly, forecasts of forest carbon would be affected by changes in the area of forests and in the amount of biomass as described above. Figure 51 shows forecasts of future forest carbon in the North and generally shows a peaking of forest carbon in either 2020 or 2040 followed by a downward trajectory and reveals three clusters of the nine RPA scenario-climate combinations. The greatest loss of forest carbon is recorded for high urbanization (RPA A1B) scenarios with the least area of forest land in the future. The least loss of forest carbon is recorded for the scenarios with the least

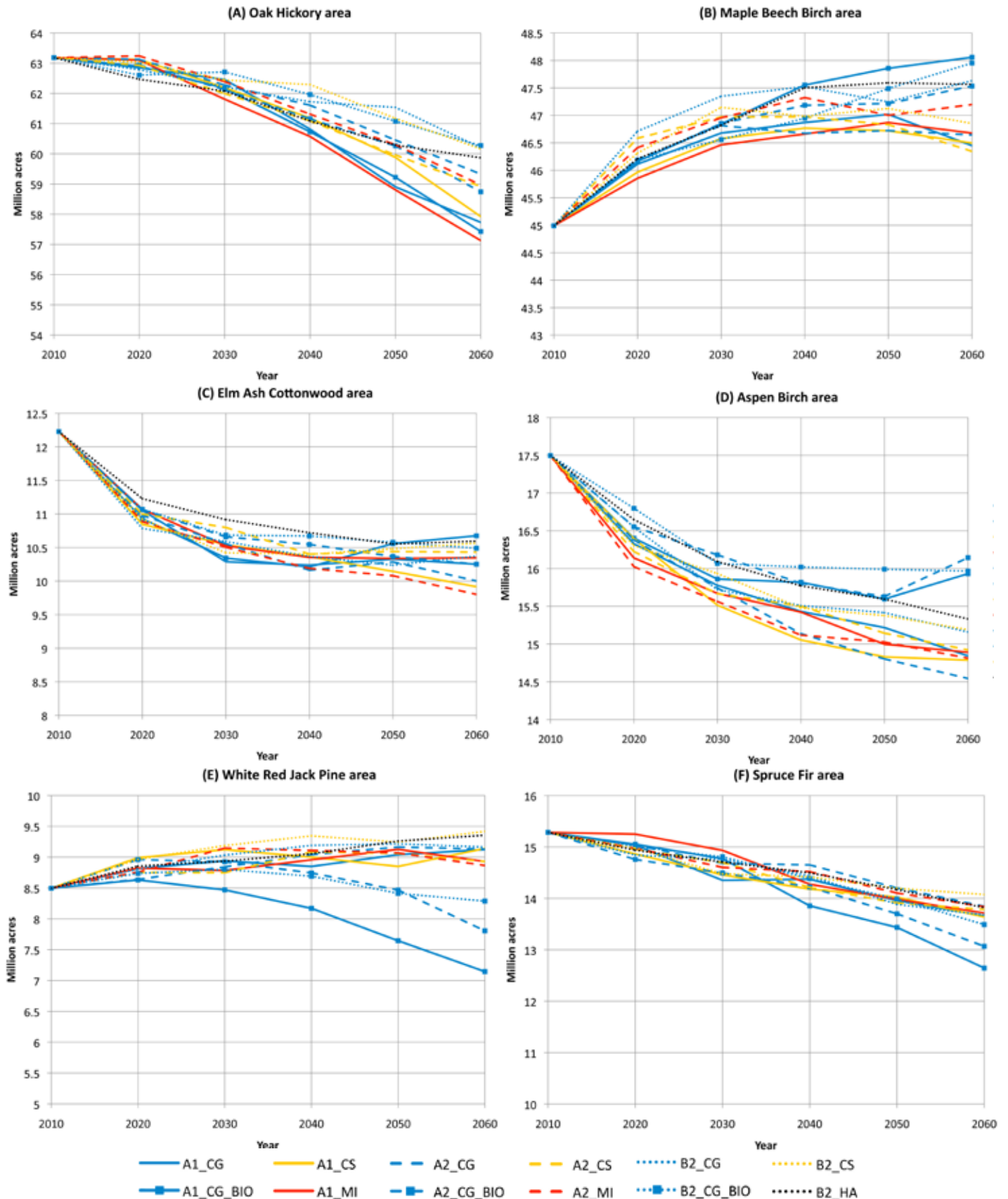


Figure 46—Forecasts of the area of forest type groups in the North Region for nine Resources Planning Act (RPA) scenario-climate combinations, with harvesting based on historical behavior and three RPA scenario-climate combinations, with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

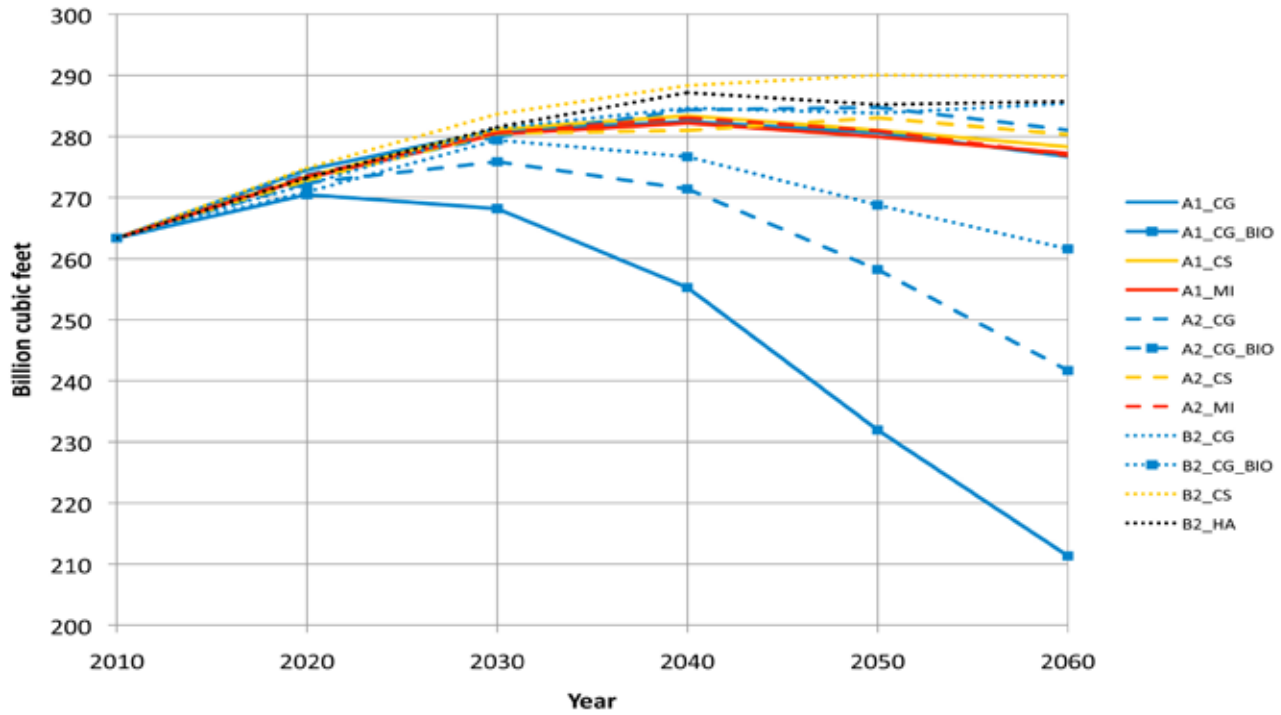


Figure 47—Forecasted total biomass measured as growing stock inventory of forests in the North Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

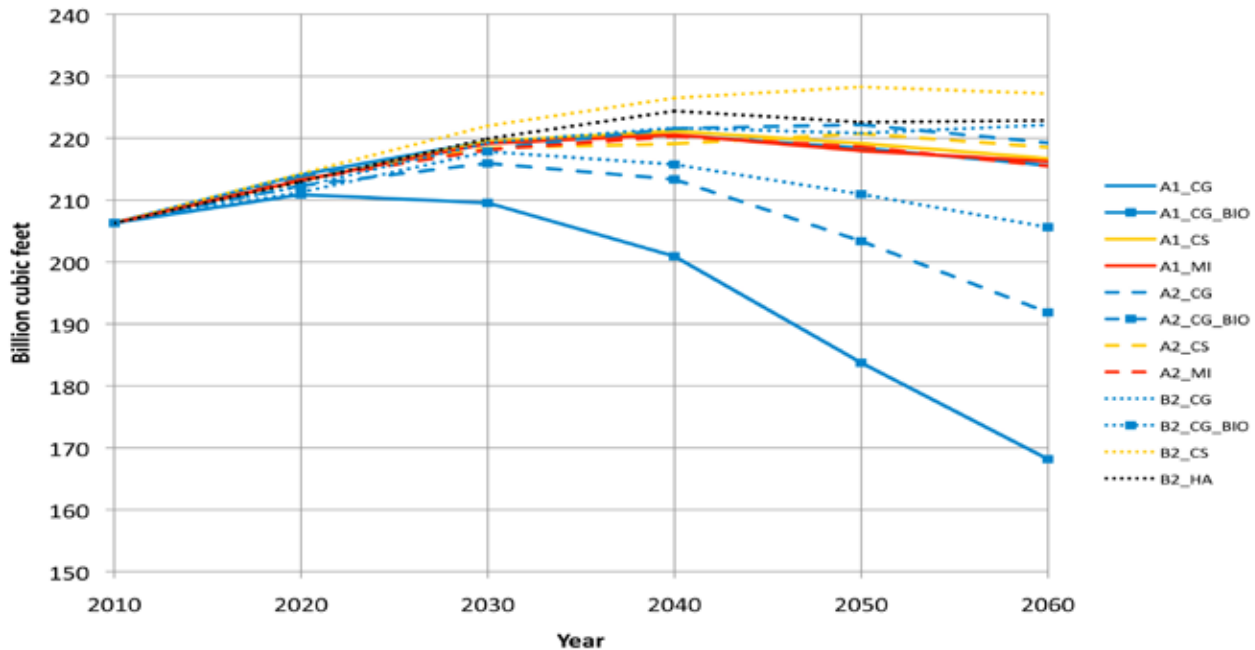


Figure 48—Forecasted hardwood biomass measured as growing stock inventory of forests in the North Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

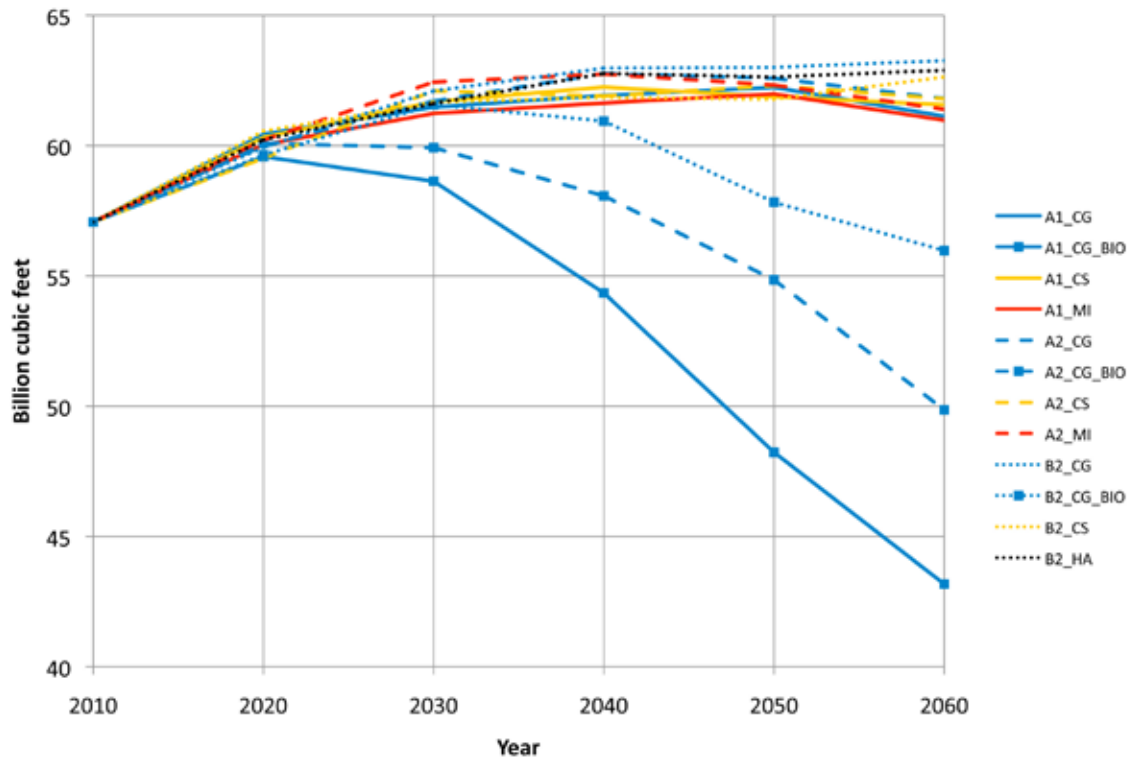


Figure 49—Forecasted softwood biomass measured as growing stock inventory of forests in the North Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

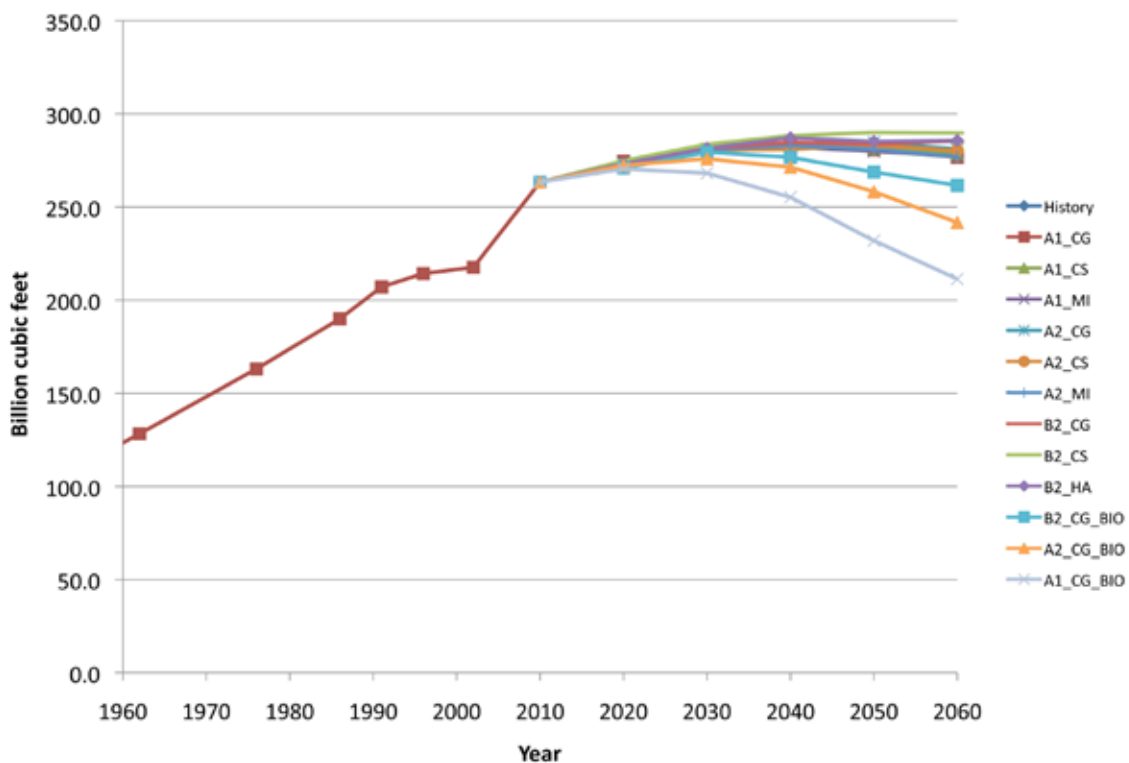


Figure 50—Softwood and hardwood growing stock inventories for the North Region, 1962–2060. Forecasts (2010–60) bracket the range of future inventories shown in figures 48 and 49.

urbanization (RPA B2). The middle cluster of scenarios is occupied by middle urbanization (RPA A2) scenarios.

The three market scenarios generate higher levels of carbon losses from the forests of the North (fig. 51). Under the RPA B2 market scenario, with the lowest increase in harvesting, carbon trajectories are similar to those forecast for the high urbanization (RPA A1B) scenarios with a loss of 3 percent of the stored carbon by 2060. For the RPA A2 market scenario (intermediate forest harvesting), stored carbon in 2060 would be about 7 percent lower than 2010 values and for the RPA A1B market scenario (highest levels of forest harvesting), carbon stocks in 2060 would be 11 percent lower than 2010 values.

Estimates of the total carbon stored in forests derive from summing estimates of the carbon stored in eight different compartments or pools in forested ecosystems. Aboveground pools include live trees, understory plants, down and standing dead trees, and litter. Belowground pools include root material for live trees, understory plants, and soil organic matter. The sum of soil organic matter, aboveground live trees, and belowground live trees comprises nearly 80 percent of the total, and forecasts of these three pools are shown in fig. 52. The pattern of change for soil organic carbon (fig. 52A) mirrors forest area changes shown in figure 43. The forecasts are organized by scenario with low urbanization (RPA B2) combinations having higher carbon than high urbanization combinations (RPA A1B). Live tree above- and belowground carbon pools (figs. 52B and 52C respectively) have patterns of change that are very similar to forecasts for growing stock inventories.

Removals

Removals from growing stock show very little variation across the nine RPA scenario-climate combinations reflecting the structure of the harvest choice model. Recalling that harvest probability estimates are associated with forest conditions on each plot (i.e., growth, site attributes, and diversity), and are not directly connected to market scenarios, these forecasts show harvest responses resulting only from the evolution of the inventory and assuming an unchanged market condition. For these nine combinations, removals move upward slightly for both hardwoods and softwoods between 2010 and 2060 (figs. 53 and 55). Hardwood removals grow by about 2 percent and softwood removals grow by about 10 percent between 2010 and 2060.

The three market scenarios generate removal patterns that are substantially different from the nine RPA scenario-climate combinations. Implemented by adjusting harvest probabilities to reflect the harvests predicted by the U.S. Forest Products Model, these scenarios show substantial growth in harvesting reflecting the expansion in demands for forest biomass in

bioenergy production associated with each scenario. For RPA B2 (lowest harvest increases) harvests depart from the nine combinations beginning in 2030 and are nearly double their 2010 levels in 2060. For RPA A2 (intermediate harvests) harvests expand beginning in 2020, double by 2050, and are roughly 2.5 times 2010 harvest levels by 2060. For RPA A1B (highest harvest growth) total harvest also begins to grow substantially after 2020, but doubles by 2040 and is roughly three times 2010 levels by 2060. The percentage changes in removals are comparable for softwoods and hardwoods; rates of growth in hardwood removals are only slightly higher than those for hardwoods.

Figure 54 compares the North's timber harvest forecasts from the Forest Products Model with the implied harvests from the Forest Dynamics Model, and shows that harvest forecasts are largely consistent between the models for the specific scenarios. Forest Dynamics Model harvest removals are within 10 percent of harvest removals from the Forest Products Model for all periods and scenarios with two exceptions. For the last two decades, the RPA A1B Forest Products Model projection is roughly 28 percent higher than the Forest Dynamics Model projections. As discussed previously, this scenario generates harvest demands unlikely to be met by traditional forest production techniques, implying structural changes beyond the scope of the model. The other exception is the last decade for RPA A2, where Forest Dynamics Model harvests fall 18 percent below Forest Products Model forecasts. Overall, the Forest Dynamics Model generates total harvests that are 79, 93, and 100 percent of Forest Products Model forecasts for A1B, A2, and B2 scenarios, respectively.

Age Structure/Habitat

Age class distributions are affected by the starting distributions and by disturbance regimes forecast for forests in the future. Simulated inventories can be used to evaluate various aspects of future forest conditions. One aspect of significance to wildlife habitat conditions in the North is the distribution of forests by age class, and the implications for the provision of early, middle, and late age forest conditions. We evaluate changes in the age class distributions of softwood and hardwood forest types using two charts. One displays the aerial age class distribution by decade for the most recent inventories of the northern States. We then summarize changes in age class resulting from the nine RPA scenario-climate combinations between 2010 and 2060 using box plots. Figure 56 shows the current age class distribution for hardwood forests in the North by 10-year age classes. Each box plot describes the distributions of changes in age classes. The bottom of the box represents the 25th percentile of the predicted changes, the top of the box represents the 75th percentile of the predicted changes, the line in the box indicates the median forecast, and the plus in the box

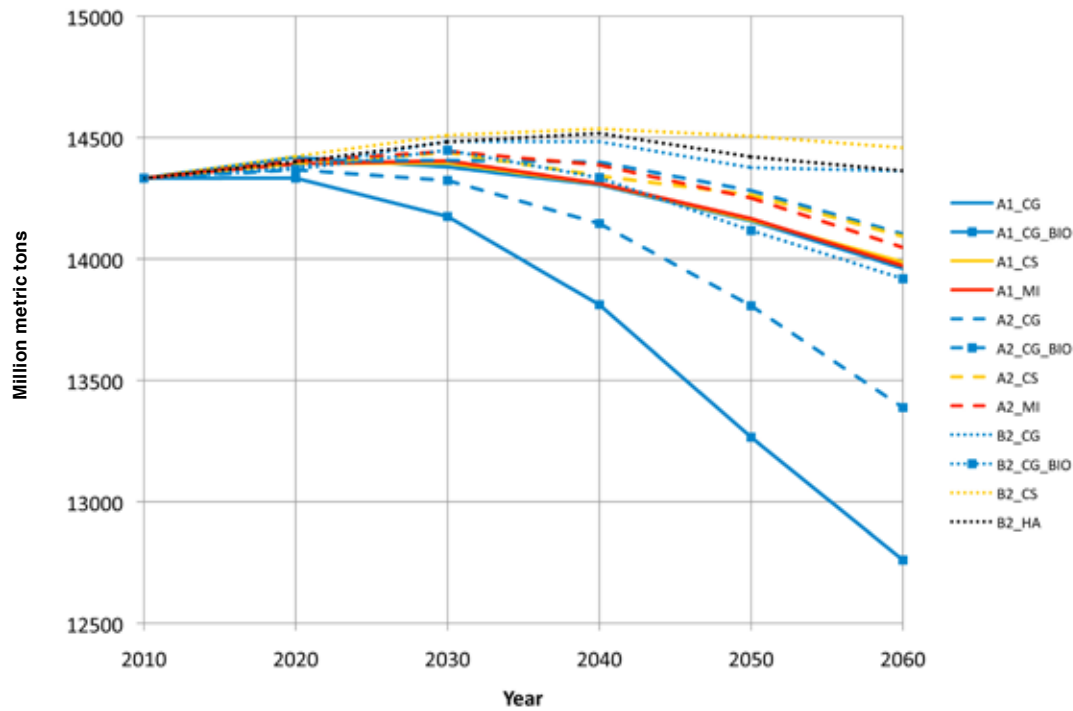


Figure 51—Forecasts of total carbon stored in forests in the North Region, 2010–60, for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

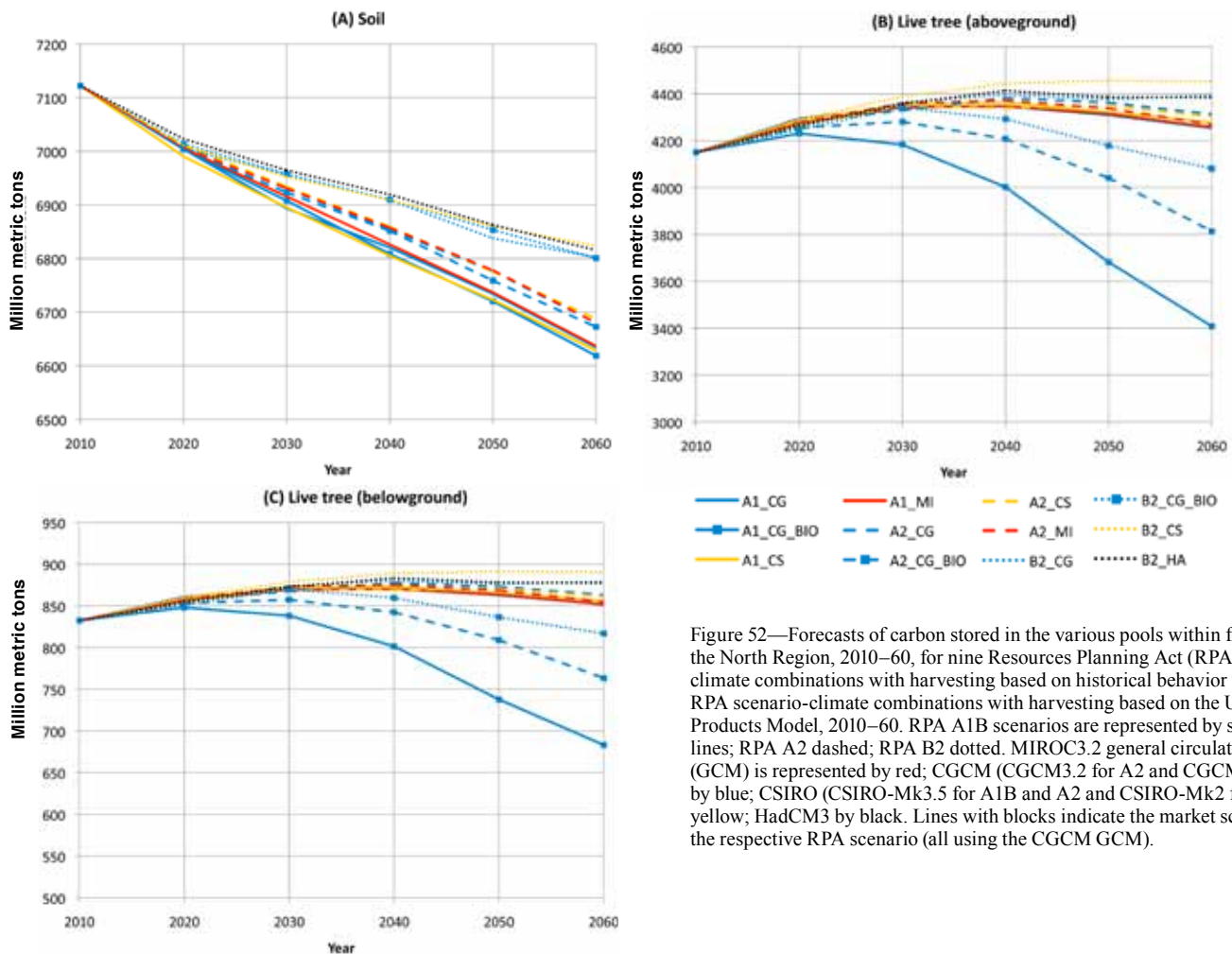


Figure 52—Forecasts of carbon stored in the various pools within forests in the North Region, 2010–60, for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

indicates the mean forecast. The “whiskers” of the box show the extreme values of the forecasts. Figure 57 contains the same results for softwood forest types in the North.

Figure 56 implies two overall results for hardwood forests in the North. The pattern of disturbances causes an overall flattening of the age classes between ages of 0 and 70. The area of the youngest ages (0–10, 11–20, and 21–30 years old) remains relatively constant at 5–7 million acres each from 2010 to 2060, while the area of the middle age classes (31–40, 41–50, and 51–60 years old) declines substantially and approaches the same level by 2060. In contrast, the area of older forests (> 80 years old) more than doubles by 2060. A similar pattern, relatively stable disturbance patterns leading to a flattening of the age distribution and a strong increase in older forest conditions, applies to softwood forests as well (fig. 57).

Discussion

The 12 futures modeled for the North provide a range of plausible futures for forests. The nine RPA scenario-climate combinations define an evolution of forest inventory with harvests at levels observed over the present past but also affected by projected changes in climate and changes in land use driven by population and income changes. The three

market scenarios examine how these futures might be altered by increased demands for woody biomass to provide various forms of bioenergy.

Climate projections affect changes in forest conditions through the imputation module which determines the subpopulation of forest plots that represent future inventories. The nine climate realizations used here project increasing temperatures throughout the region. As measured here, widespread significant changes in temperature distributions do not arise until late in the projection period (2050–60). The exception is the RPA A1B-MIROC3.2 combination where significant changes arise in 2040. Precipitation projections vary substantially—in some cases wetter, in others drier. In general, models suggest drier conditions in the New England States.

In the nine combinations, land use plays a dominant role in determining future forest area. Driven by a strong urbanization dynamic along the eastern seaboard and around some cities in the North Central States, forest losses amount to between 6 million and 11 million acres. While the pattern of forest losses remains constant, the amount varies across the three RPA scenarios based on both forecasted population and forecasted personal income. Urbanization affects dominate climate effects across the nine combinations.

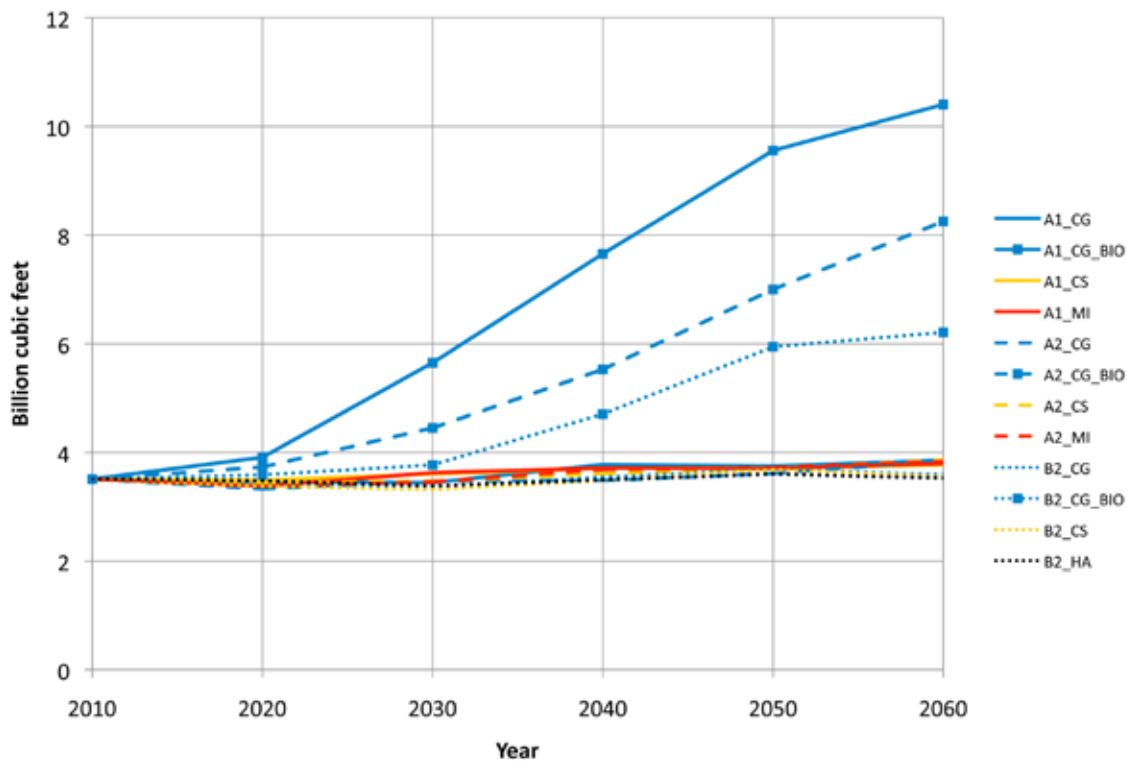


Figure 53—Total removals from inventory in the North Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

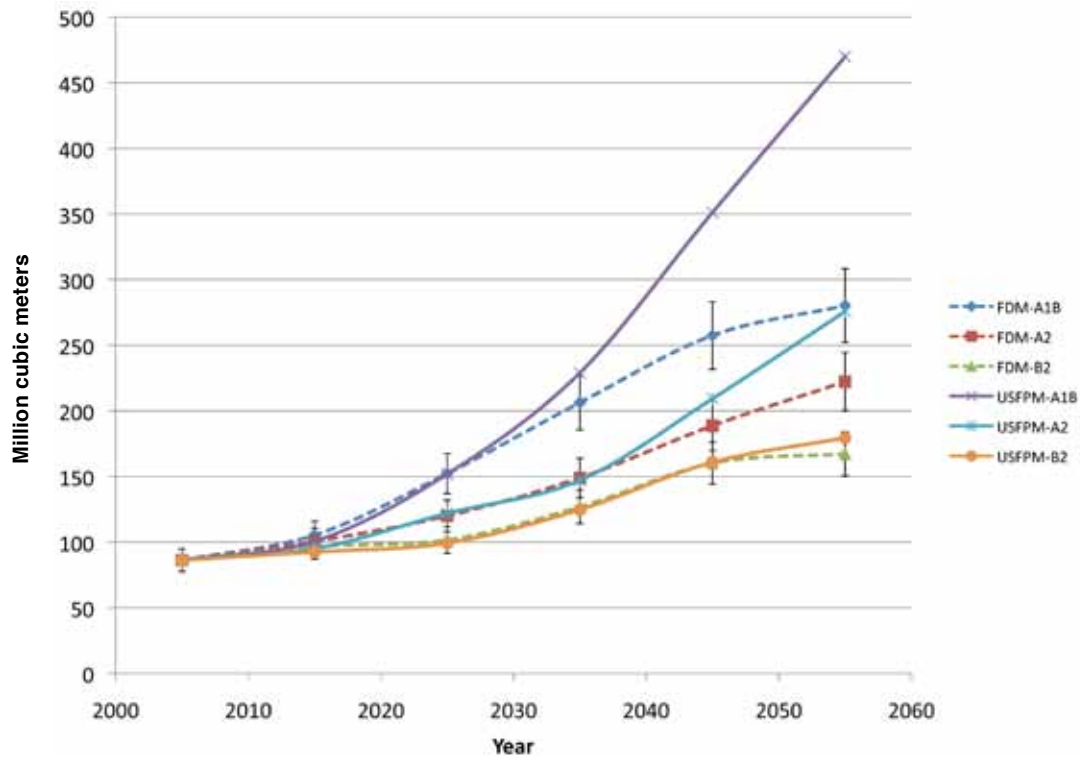


Figure 54—Comparison of harvests predicted by the U.S. Forest Products Model and the Forest Dynamics Model scenario associated with the U.S. Forest Products Model scenario for the North Region.

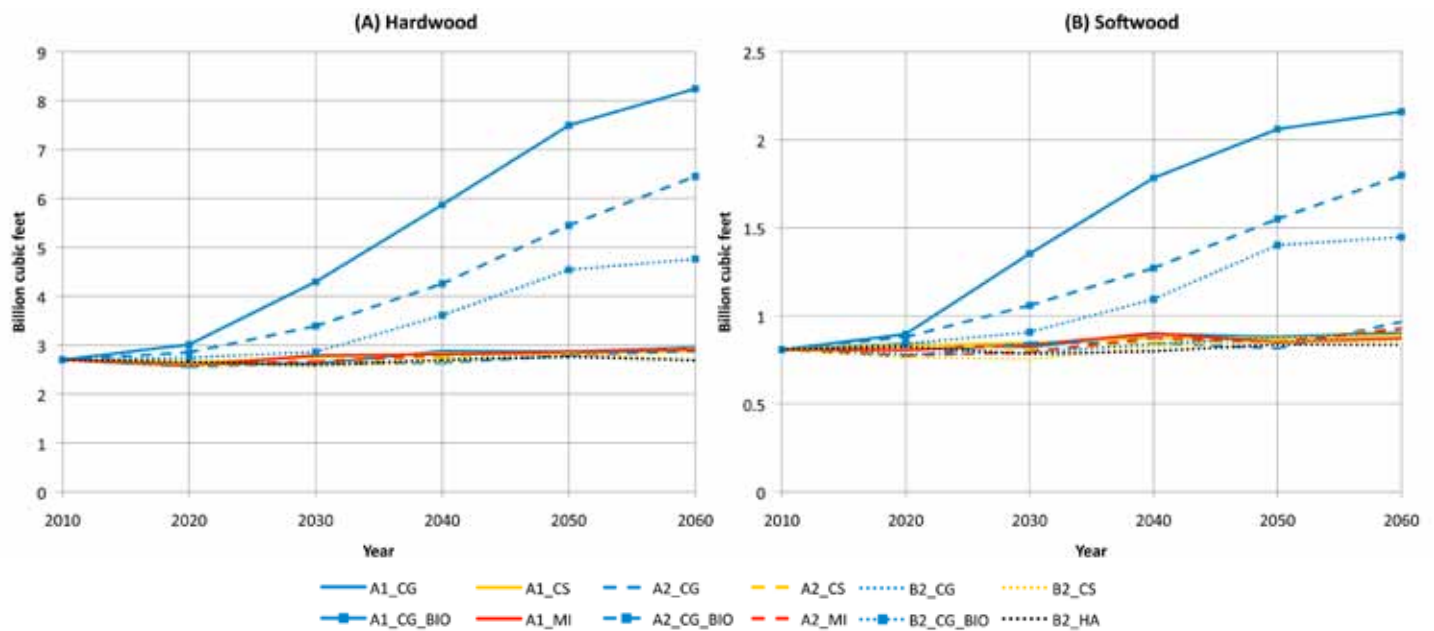


Figure 55—Removals from inventory by forest type in the North Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

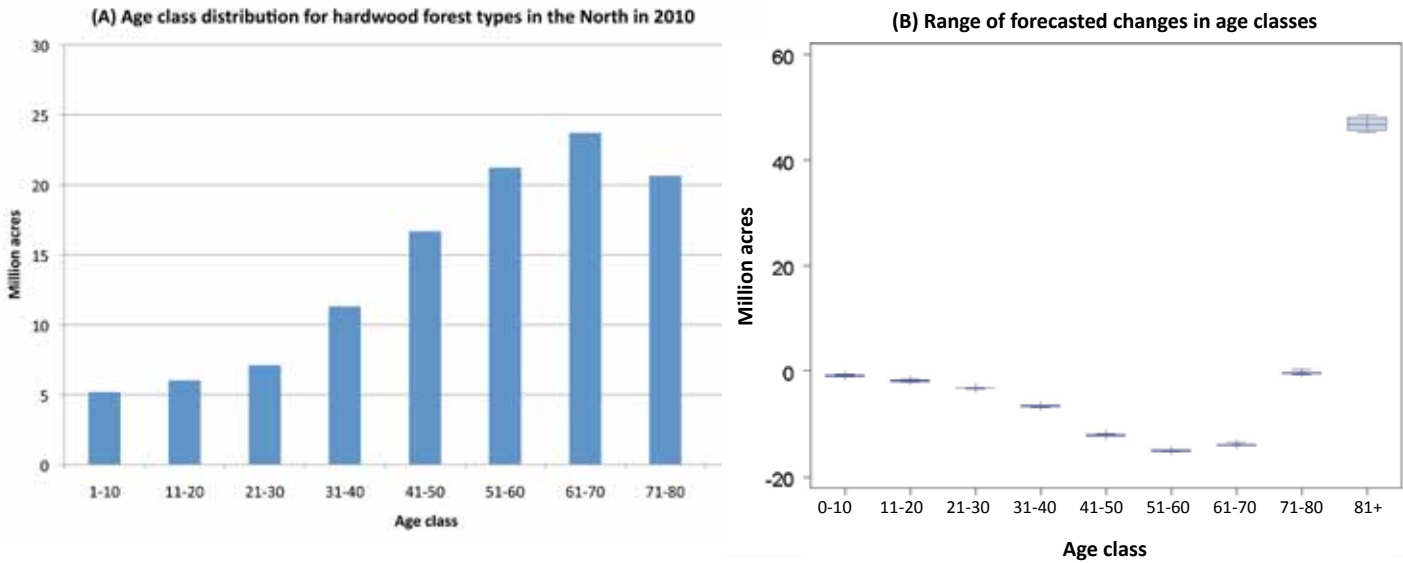


Figure 56—(A) Age class distribution for hardwood forest types in the North Region in 2010 and (B) the range of forecasted changes in age classes, 2010–60, for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60.

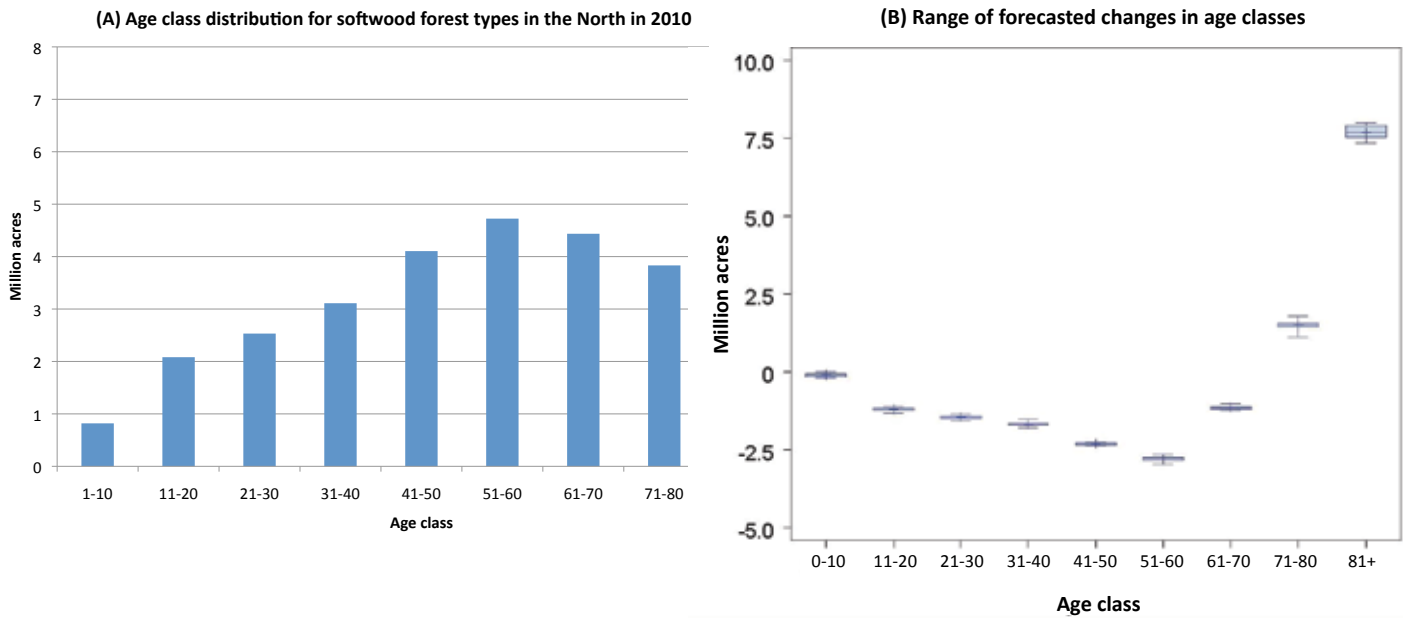


Figure 57—(A) Age class distribution for softwood forest types in the North Region, in 2010 and (B) the range of forecasted changes in age classes, 2010–60, for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60.

The areas of forest types change in response to land use changes but also in response to timber market futures. Forest type changes reflect a successional dynamic revealed by recent forest inventories and are not directly affected by climate changes. Within forest types, species compositions can shift in response to shifts in the donor pools used to populate future inventories. While the distribution between hardwood and softwood types holds relatively constant over the forecast period, changes within these large groups arise. For hardwoods, oak-hickory and elm-ash-cottonwood areas decline while maple-beech-birch area increases. For softwoods, spruce-fir area declines while white-red-jack pine area increases. As harvesting increases across the three market scenarios, so does the area of maple-beech-birch and aspen-birch while the area of softwood types declines.

The area of the elm-ash-cottonwood forest type declines by the greatest percentage across scenarios (13–20 percent) between 2010 and 2060. While these scenarios do not explicitly address the spread of emerald ash borer and resulting mortality of ash in northern forests, the forest type observations used to forecast changes in types may reflect the early impacts of this epidemic, i.e., a retying of forest plots influenced by ash mortality. While capturing some of this “signal” in the inventory data, the forecasts do not explicitly account for any anticipated changes in pest or epidemic dynamics.

The nine RPA scenario-climate combinations show a leveling of standing biomass volumes in the North. This approach

to an asymptotic biomass reflects the aging of forests in the region coupled with a fairly constant amount of future timber harvests for these scenarios. With the three market scenarios which reflect substantial expansion in harvests, growing stock inventories reach a peak between 2020 and 2030 and then decline. By 2060, these scenarios show a net drop from 2010 inventory levels (3 percent for RPA B2, 7 percent for RPA A2, and 11 percent for RPA A1B), reflecting the persistence of carbon in forest soils as aboveground biomass is removed.

The forecasted declines of standing biomass and carbon stocks in the North for the three market scenarios need to be considered in light of some modeling assumptions. Most importantly, the model takes no account of the potential for shifts in management strategies associated with increased market demands in the North. Because these scenarios represent what could be viewed as unprecedented market conditions, they could also affect structural changes in forest management practices, including increased planting, shifts in tree species, and even land use changes out of agriculture and into actively managed forests. We should expect some type of management response under these conditions, but our data are limited for incorporating these types of impacts within the inventory forecasts. The forecasts do provide insights into the circumstances under which management changes should be anticipated, namely under production scenarios comparable to RPA A1B and RPA A2.

CHAPTER 6
FOREST FORECASTS FOR THE ROCKY MOUNTAINS REGION

For the Rocky Mountains Region, forest forecasts were generated for each of the nine Resources Planning Act (RPA) scenario-climate combinations. For these nine combinations, we apply disturbance models that reflect historical harvest and other disturbance relationships—that is, we model the probability of mortality forest-replacing disturbance as a function of plot attributes recorded for each plot. Forest replacing disturbance includes timber harvesting but harvest records are so infrequent for inventory plots in the Rocky Mountain States as to preclude direct modeling of timber harvests. Because paired inventories were not available, future forest types could not be modeled using transition models and so instead were addressed using a forest type classification algorithm linked to climate projections and site attributes. This region spans a great variety of conditions between the northern and southern Rocky Mountains and also includes the Great Plain States of North and South Dakota, Nebraska, and Kansas. Table 3 defines labels used to describe the futures evaluated in this section.

Climate

To frame a discussion of the forest forecasts, we compare climate projections from the nine RPA scenario-climate combinations with historical conditions for the Rocky Mountains Region. Distributions of monthly values for a projected decade (2010 refers to the monthly values between 2001 and 2010, 2020 refers to monthly values between 2011 and 2020, and so on) are compared with a historical decade (2000 for the monthly values between 1991 and 2000). We start by plotting the cumulative distributions of temperatures/precipitation for a graphical view of change across time. We then map where significant differences arise between projected and historical distributions for counties in the region.

Figure 58 compares cumulative temperature distributions between the historical decade and the 2060 decade for the nine RPA scenario-climate combinations. For all projections, the distributions shift outward over time as temperature increases.

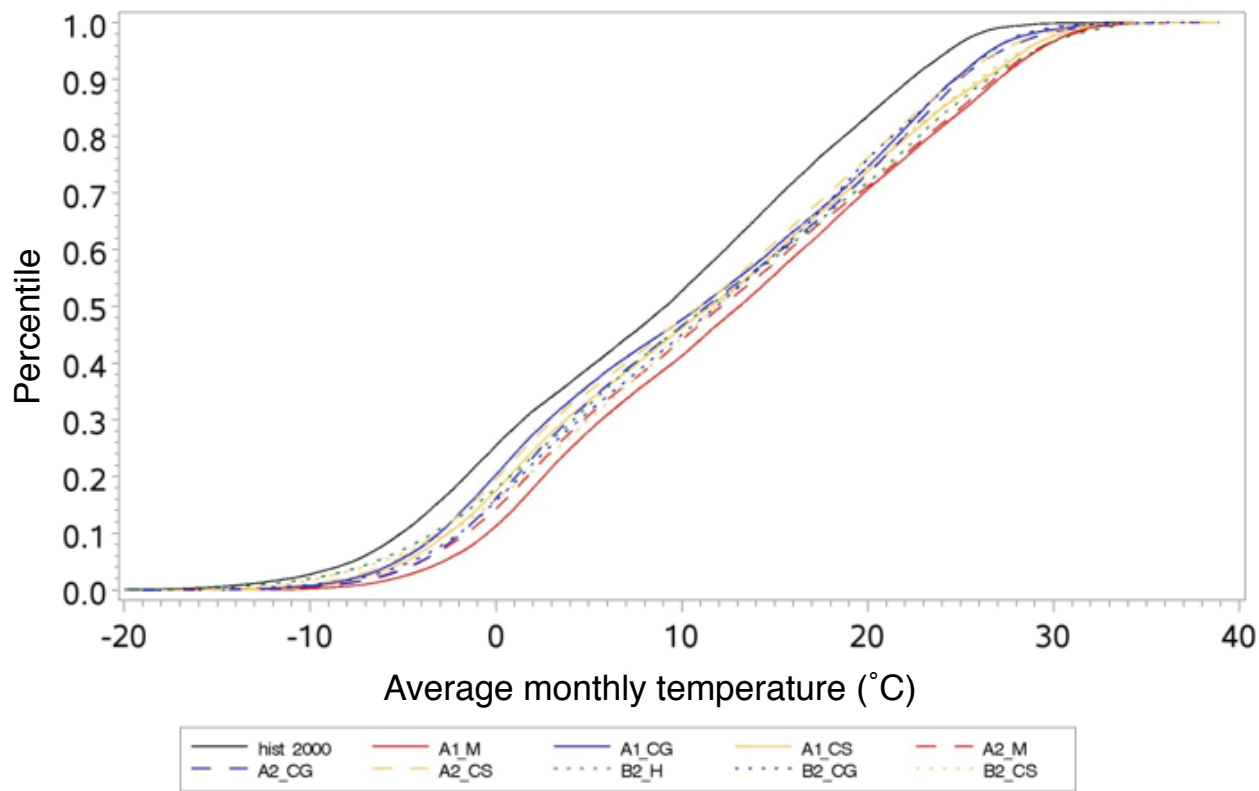


Figure 58—Empirical distributions of monthly temperatures for the Rocky Mountains Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–60).

The RPA A1B-MIROC3.2 combination shows the greatest overall increase in temperatures between 2010 and 2060; with a 4 °C increase in temperature at the 50th percentile of the distribution and a 5 °C increase at the 90th percentile (the RPA A2-MIROC3.2 combination has the second largest increases). The other scenario-climate combinations also show outward shifts in temperature distributions between 2000 and 2060 but with roughly half the temperature increase shown for RPA A1B-MIROC3.2 (about a 2 °C increase at the 50th percentile).

Comparing projections by decade shows that under RPA A1B-MIROC3.2 (the warmest combination), temperatures increase in every decade (fig. 59A).¹ A similar pattern holds for RPA B2-CSIRO-Mk2 (fig. 59B) and for the other seven combinations not shown here.

Spatial patterns of change vary across the scenario-climate combinations and across time and space. Figure 60 shows spatial patterns of change based on the Kolmogorov-Smirnov comparison of 2060 and 2000 distributions ($p=0.05$) for the temperature distributions for RPA A1B-MIROC3.2. The black areas indicate counties where there is distributional disagreement between historical and projected data for the specified decade. Figure 61 provides the same set of maps for RPA A1B-CSIRO-Mk3.5. For RPA A1B-MIROC3.2 (fig. 60), discernible temperature differences appear beginning in 2030 in eastern and southern Colorado, southwestern Arizona, and central and western Montana. By 2040, temperature increases consolidate across much of Arizona, Nevada, New Mexico, and Colorado. By 2050, nearly all of the Rocky Mountains Region shows significant shifts in temperature (the exception is

eastern Montana). By 2060, the entire map is black indicating a significant increase in temperature distributions beyond 2000 levels for all counties for RPA A1B-MIROC3.2.

The change pattern is different for RPA A1B-CSIRO-Mk3.5 (fig. 61) where significant temperature increases arise only after 2040. In 2050, a small number of counties show significant differences, especially in southern Arizona and New Mexico. In 2060, temperature increases are found west of the Rocky Mountain front from New Mexico to Montana and throughout southern Arizona and New Mexico.

Figure 62 maps the proportion of the nine climate realizations leading to rejection of equivalent temperature distributions in 2000 and 2060 (KS test, $p=0.05$). By 2060, four or more of the nine RPA scenario-climate combinations show significantly different temperature distributions across nearly the entire Rocky Mountains Region. Counties in most of New Mexico and a majority of Arizona, along with counties in the Colorado Rocky Mountains region, western Wyoming, western Montana, and northern Idaho demonstrate the greatest degree of model concurrence with significantly different temperatures in seven or more of the nine climate scenarios. A large part of the Great Plains sub-region, including all of Kansas, and portions of Nebraska and South Dakota, shows less convergence across the temperature forecasts.

Projections of precipitation are more variable than temperature projections across the RPA scenario-climate combinations and across the region (Joyce and others, in press). Under some projections, the precipitation distribution shifts inward between 2000 and 2060; under others precipitation increases by 2060. Cumulative distributions of monthly precipitation values for the historical decade (2000) and for the nine climate projections

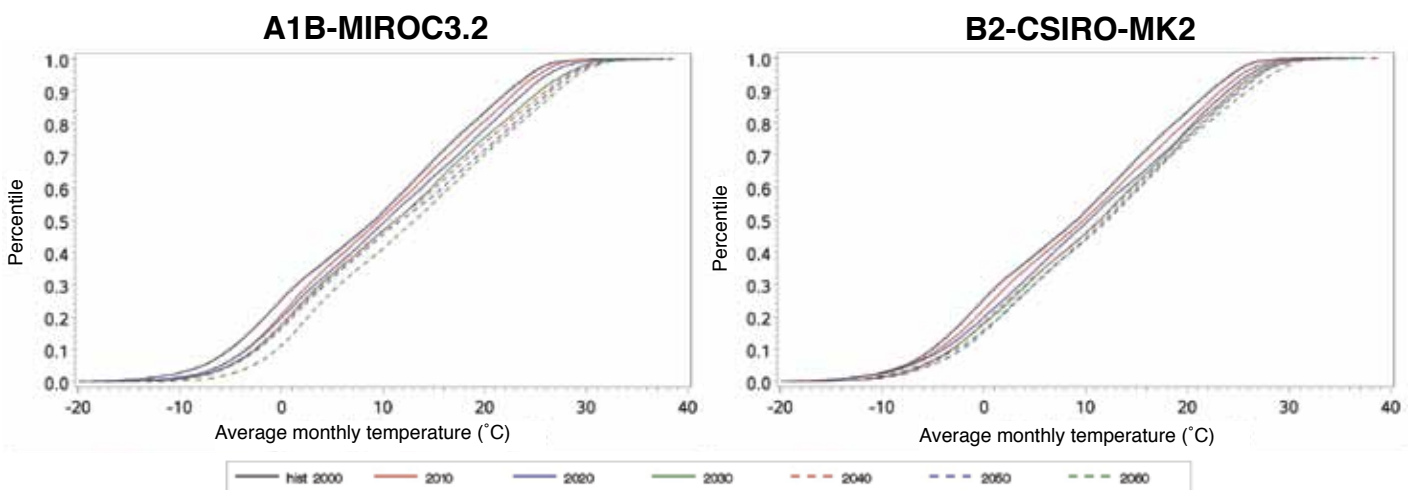


Figure 59—Empirical distributions of monthly temperatures for the Rocky Mountains Region for a historical decade (1991–2000) and for 6 successive decades of climate projections (A) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination and (B) for the RPA B2-CSIRO-Mk2 combination.

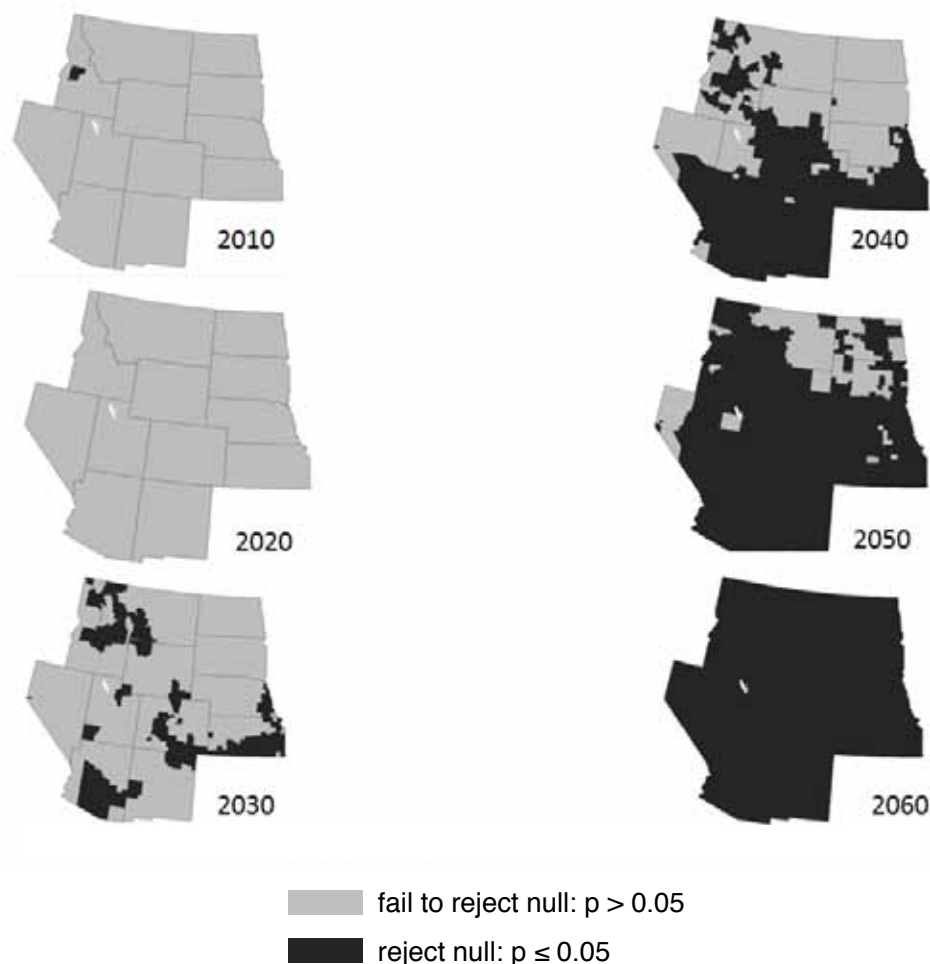


Figure 60—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

in 2060 show an inward shifting of precipitation (drying) for RPA A1B-MIROC3.2 and RPA A2 MIROC3.2-A1B and a strong outward shift (increase) in precipitation for RPA A2-CSIRO-Mk3.5 (fig. 63). For the other climate projections, the distributions pivot, indicating that some areas become wetter while others become drier. For the various combinations (including RPA A1B-MIROC3.2, which is drier in 2060), the precipitation projections vary across time steps, in some cases alternating between wetter and drier decades (fig. 64).

The spatial pattern of precipitation change is highly variable. For RPA A1B-MIROC3.2 (fig. 65) the greatest number of significant differences in precipitation distributions are shown for the 2010 decade. In subsequent decades, the effects shrink and shift around the region, and only northern Montana shows a consistent drying across the decades. A similar pattern of change is shown for RPA B2-HadCM3 (not shown)—drying generally focused on north central Montana. RPA A1B-CSIRO-Mk3.5 (fig. 66) gives rise to much less significant change in precipitation patterns across the decades.

Figure 67 maps the proportion of the nine climate realizations leading to rejection of equivalent monthly precipitation distributions between the 1991–2000 decade and the 2051–60 decade (KS test, $p=0.05$). The nine climate projections generate no significantly different precipitation projections between 2000 and 2060 for much of the plains (most of the Dakotas, much of Nebraska and nearly all of Wyoming). For most of Nevada, Utah, and Arizona, one to three of the nine climate projections generate significantly different precipitation forecasts. North central Montana is the only large area with seven to nine significantly different precipitation projections reflecting the projections of drying for this area in figures 65 and 66.

Maps of significant shifts in mean temperature and total precipitation highlight areas with emphatic change in these two variables (i.e., these are conservative tests). Other climate variables may also have important influence on future forest conditions but are not examined here.

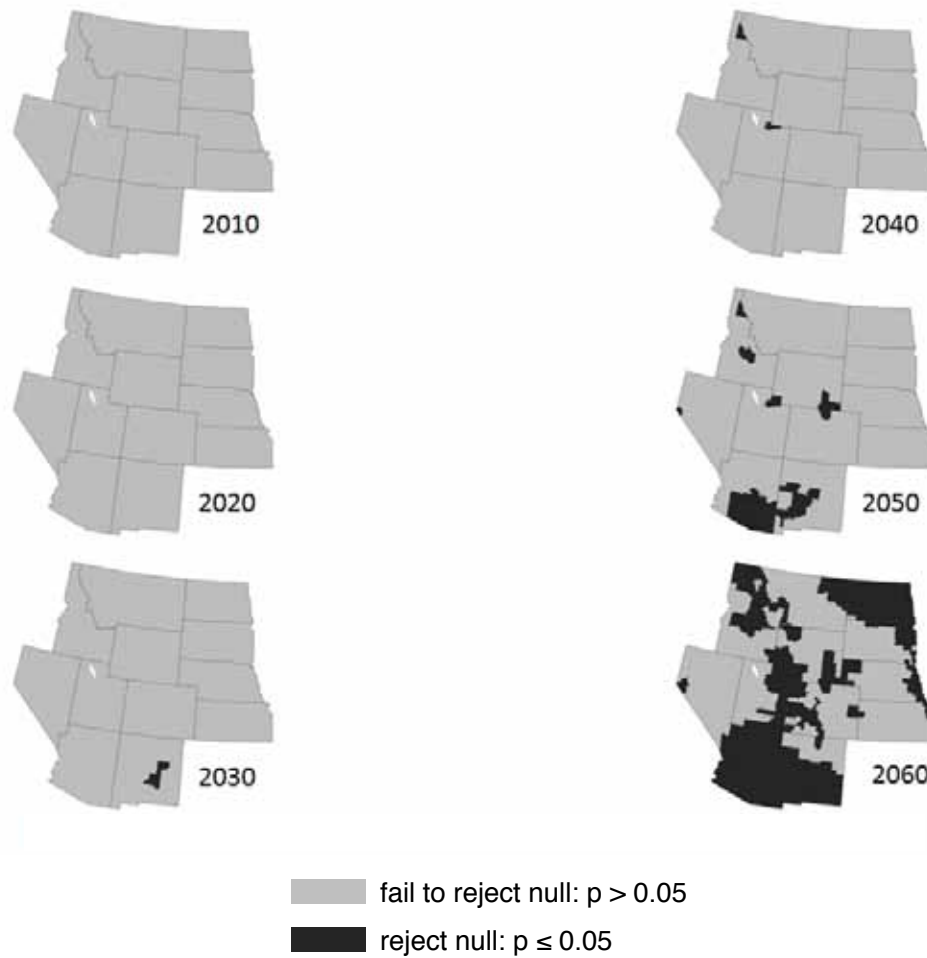


Figure 61—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-CSIRO-Mk3.5 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

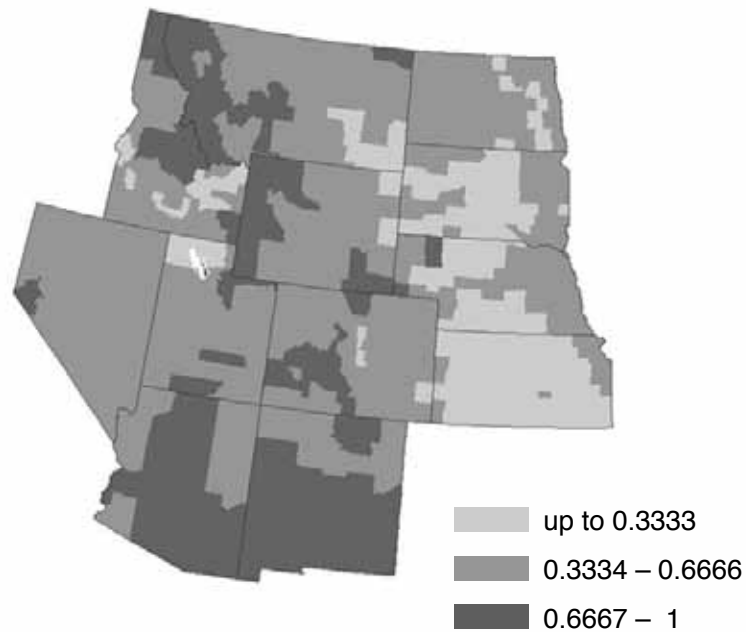


Figure 62—Proportion of the nine scenario-climate combinations yielding significant differences in decadal temperature distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the Rocky Mountains Region.

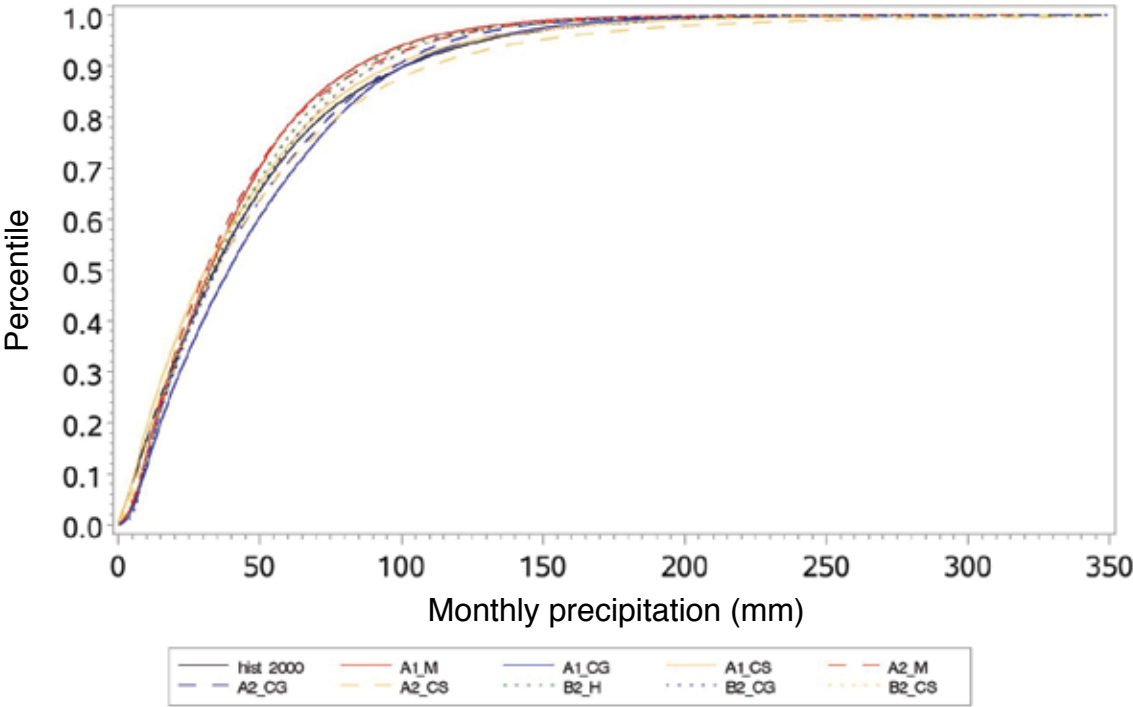


Figure 63—Empirical distributions of monthly precipitation values for the Rocky Mountains Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–2060).

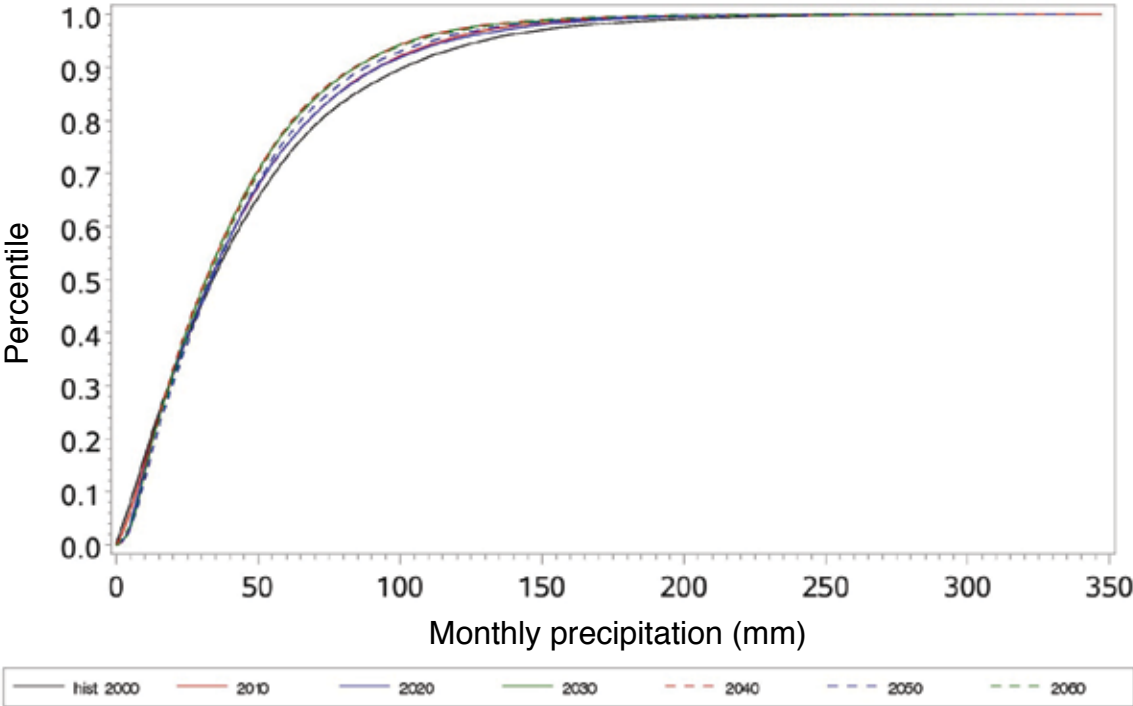


Figure 64—Empirical distributions of monthly precipitation for the Rocky Mountains Region for a historical decade (1991–2000) and 6 successive decades (2010–60) of climate projections for the Resources Planning Act (RPA) A1B- MIROC3.2 combination.

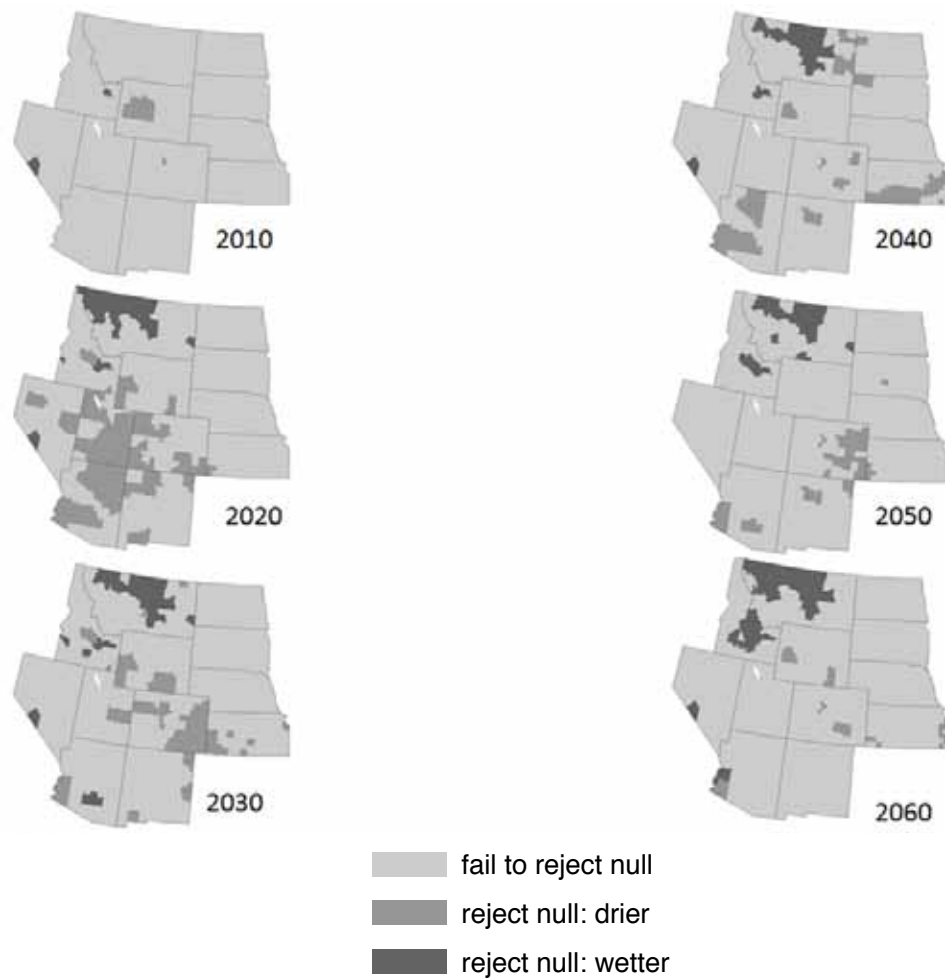


Figure 65—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value < 0.05) and indicate drier and wetter conditions, respectively.

Forest Area

Forecasts of forest area change derive from the land use analysis contained in Wear (2011).² Unlike forecasts for the North, South, and the Pacific Coast regions, forecasts of forest losses are very small in absolute and percentage terms for the Rocky Mountains Region. The preponderance of public forests and the concentration of forests in a small portion of the region largely explain this result. All three RPA scenarios, driven by population and income forecasts, predict increased developed area on the private lands of the region. However, because a large portion of forests are held in public ownership [approximately 75 percent, according to Smith and others (2007)], development is generally concentrated on other types

of lands. Of the 7–10 million acres forecast to be developed between 1997 and 2060 in the Rocky Mountains Region, most involve conversion from an agricultural or rangeland use. About 1–1.5 million acres of forest is forecast to be developed in this region between 2010 and 2060 (fig. 68).

Forest losses are concentrated in only a few counties in the Rocky Mountains Region (fig. 69). The largest areas of loss are found in Colorado, along the Interstate 25 corridor between Fort Collins and Colorado Springs, and extending west of Denver along Interstate 70. Losses of forest land are also concentrated in a few counties in southwestern Colorado and around Albuquerque and Santa Fe, NM, and St. George and Salt Lake City, UT. Northwestern Montana and northern Idaho also show some losses of non-Federal forests.

² The total forest area changes reported in this report differ from those in Wear (2011) because: (1) the analysis in Wear (2011) is based on National Resource Inventory (NRI) data benchmarked in 1997, while this chapter translates those projections into FIA data benchmarked in 2010; and, (2) while the NRI measures only non-Federal land uses the FIA data address all ownerships.

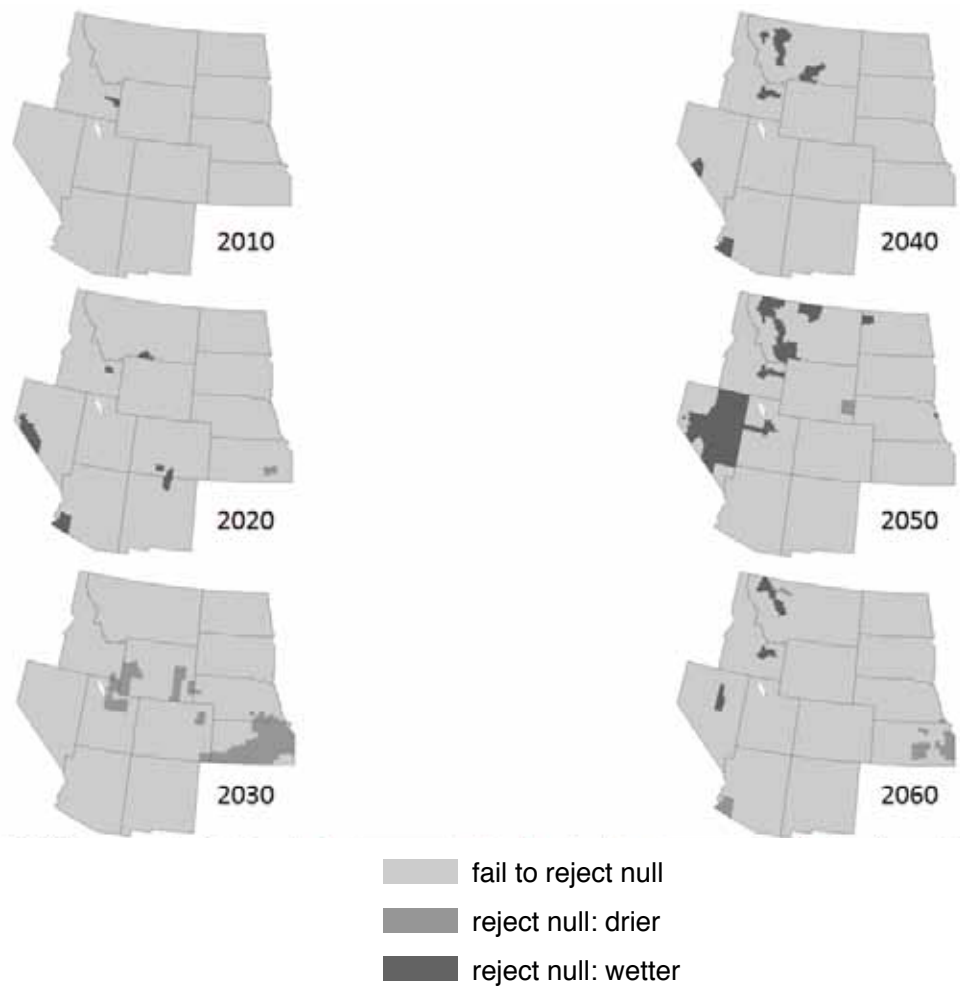


Figure 66—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-CSIRO-Mk3.5 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value < 0.05) and indicate drier and wetter conditions respectively.

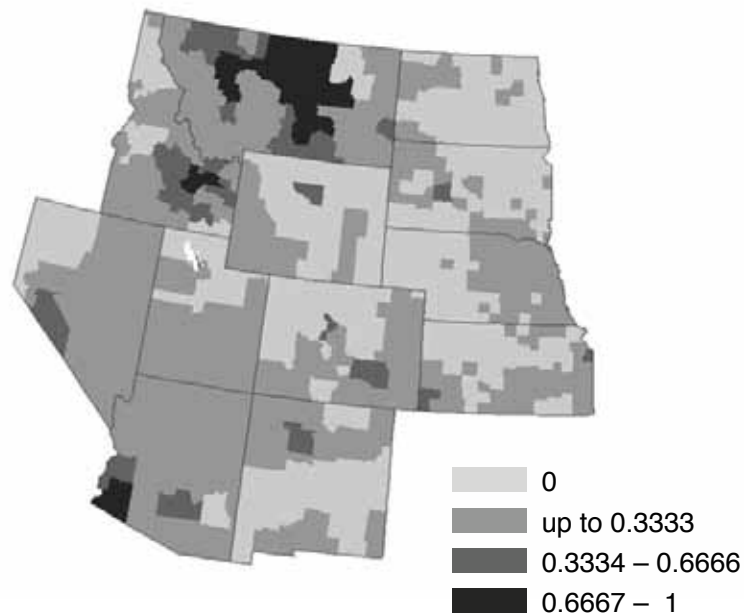


Figure 67—Proportion of the nine scenario-climate combinations yielding significant differences in decadal precipitation distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the Rocky Mountains Region.

Forest Types

While the total area of forests varies little across the 50-year forecasts by scenarios, the areas of individual forest types do change in response to shifts in projected climates associated with the scenarios. Recall that western models of forest type transitions derive from a single cross-sectional dataset and focus on predicting forest type probabilities as functions of site and climate variables. General circulation model (GCM) projections for a given time period and scenario defines the set of forest type probabilities and random draws are used to select forest type for each plot in the inventory. In this way, shifts in climate give rise to predicted changes in forest type distributions.

The Rocky Mountains Region contains numerous forest type groupings, but six types comprise about 85 percent of total forest area in 2010 (fig. 70): pinyon juniper (34 percent), fir-spruce-hemlock (15 percent), Douglas fir (13 percent), lodgepole pine (8 percent), ponderosa pine (9 percent), and aspen-birch (5 percent). Pinyon juniper is a woodland type that occupies arid sites. The remaining six forest types occupy a wide range of conditions and generally contain overlapping mixes of tree species, e.g., fir-spruce-hemlock types may contain Douglas fir trees and Douglas fir types may contain grand fir trees. The classification algorithm therefore projects

a shift in the dominance of certain tree species in response to climate and other variables.

Forecasts show changes in forest type distributions over time. The largest forest type group in the Rocky Mountains Region is pinyon juniper (combined here with other western softwoods). Starting at a little more than 50 million acres in 2010, across the nine RPA scenario-climate combinations, forecasts range from a loss of about 4 million acres (8 percent) for RPA B2-HadCM to a very slight gain in acreage (about 1 million acres or 2 percent) for RPA A1B-CGCM3.1 (fig. 71A). There is no clear separation of pinyon juniper forecasts across the scenarios or climate projections.

At 23 million acres, the fir-spruce-hemlock forest type group is the second largest in the region. The area of this forest type is forecasted to increase across all nine combinations, though it dips for the first 2 decades under RPA B2-CSIRO-Mk2 (fig. 71B). Area expands between 2010 and 2060 by half a million acres to 3 million acres (up to about 15 percent of 2010 area). The greatest increase occurs for RPA A1B MIROC3.2 and RPA A2-MIROC3.2; the smallest increase is for RPA B2 CSIRO-Mk2.

In contrast, the area of the Douglas fir forest type group falls the most in percentage terms between the nine combinations

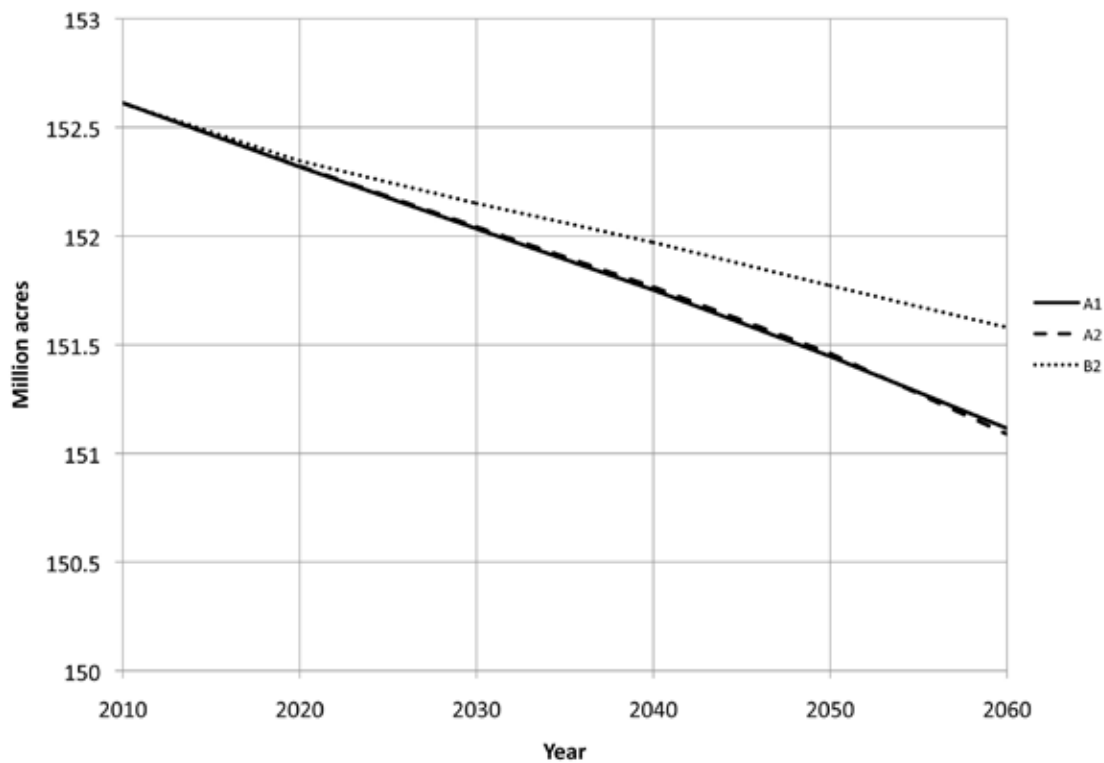


Figure 68—Total forest area for three scenarios for the Rocky Mountains Region. By model construction, forest area in the Rocky Mountains Region varies only by storyline (not by general circulation model).

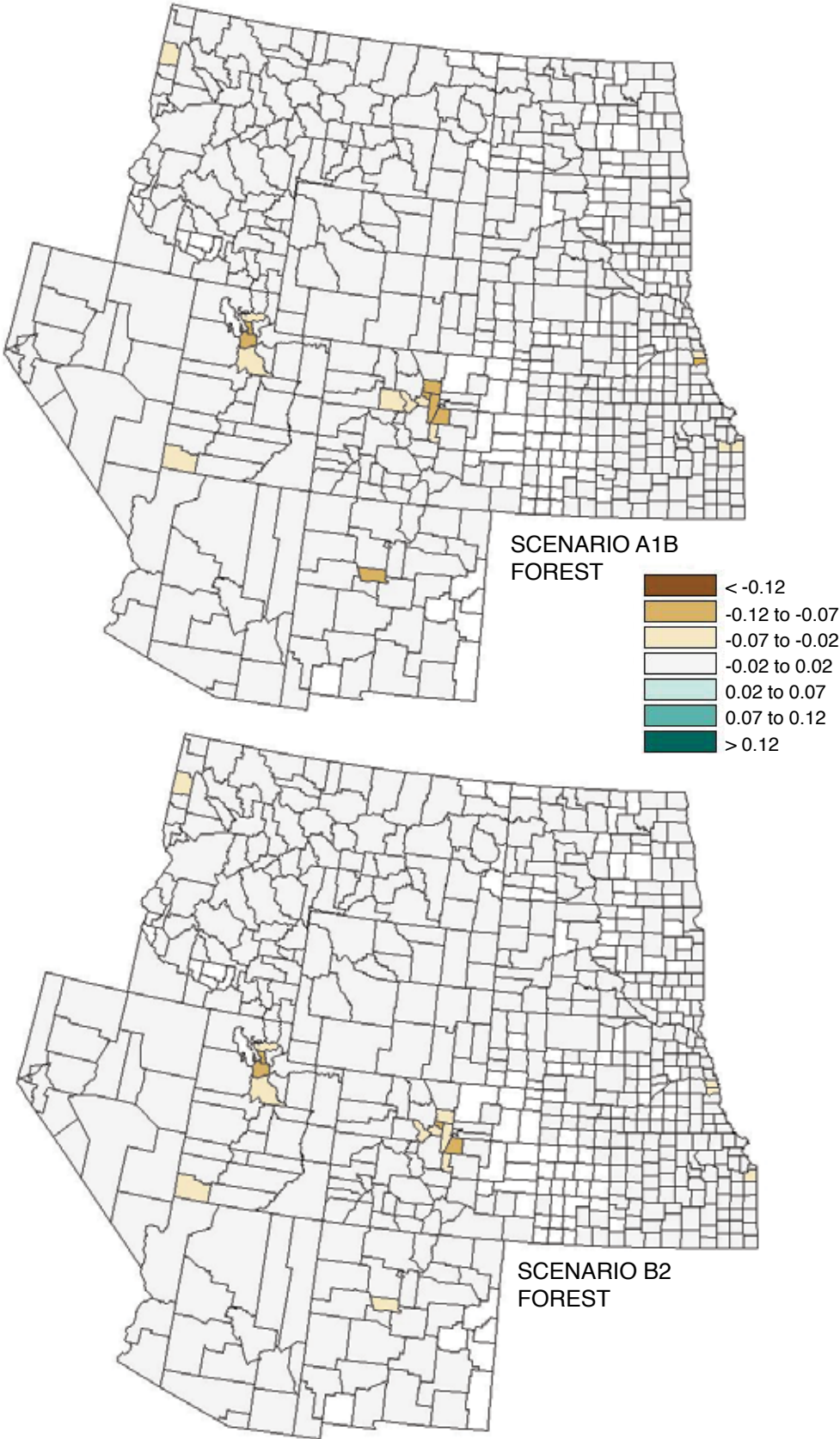


Figure 69—Forecasted changes in the proportion of non-Federal land within a county in forest, 1997–2060, for the A1B and B2 storylines.

(fig. 71C). Declines range from 3 million to 6 million acres (16–33 percent), with unclear separation among forecasts for the three scenarios, but clearly evident separation between the GCMs applied to the scenarios. Scenarios paired with MIROC3.2 and HadCM3 GCMs yield the greatest declines while scenarios paired with the CGCM3.1 and CGCM2 GCMs yield the lowest declines. Scenarios paired with the CSIRO-Mk3.5 and CSIRO-Mk2 GCMs yield intermediate results. The area of the lodgepole pine forest type group also declines across all RPA scenario-climate combinations with the ranking of forecasts across the combinations similar to that for the Douglas fir group (fig. 71E). Declines in the area of this forest type group are also large and range from 1 million to 3.5 million acres (8–32 percent).

All combinations yield increases in the area of ponderosa pine forest type group—between 0.5 million and 4 million acres. Increases in the Ponderosa pine type group mirror the decline in the Douglas fir and lodgepole pine type groups across scenarios (fig. 71D). The greatest increases in ponderosa pine occur with the MIROC3.2 and HadCM3 GCMs and the smallest increases occur with the CGCM3.1 and CGCM2 GCMs. The dominant net shifts in forest types for the Rocky Mountains Region are from Douglas fir and lodgepole forest type groups to ponderosa pine and fir-spruce-hemlock forest type groups. In contrast, the area of aspen-birch forests changes relatively little between 2010 and 2060, ranging from slight increase to a slight decrease over the forecast period (fig. 71F).

Standing Biomass

Projections of growing stock inventories (figs. 72A and 72B) show that future biomass varies little over current levels across the nine RPA scenario-climate combinations. Softwood growing stock inventory (roughly 90 percent of biomass) stands at about 125 billion cubic feet in 2010 and is forecasted to be between 123 billion cubic feet and 128 billion cubic feet in 2060—maximum growth of 3 percent over this 50-year

period. Hardwood inventory (about 10 percent of biomass) stands at about 12 billion cubic feet in 2010 and would remain at this level through 2060. These forecasts suggest that mortality and removals from inventory would be just offset by inventory growth. This type of balance occurred during the 1960s and 1970s followed by strong increases in growing stock inventories in the 1980s and 1990s (fig. 73). Inventory data since the 1990s have indicated a slowing of inventory expansion and the forecasts show a continuation of these trends, i.e., further slowing.

Forest Carbon

Carbon contained in the forests of the Rocky Mountains Region amounts to about 7.2 billion metric tons at the beginning of forecasts (fig. 74) with a majority of the carbon in soil organic matter and living trees (fig. 75). Accordingly, forecasts of forest carbon would be affected by changes in the area of forests and in the amount of biomass as described above. Figure 74 shows forecasts of future forest carbon totals for the Rocky Mountains Region and shows an essentially constant level of carbon in forest pools between 2010 and 2060.

Estimates of the total carbon stored in forests derive from summing estimates of the carbon stored in eight different compartments or pools within forested ecosystems. Aboveground pools include live trees, understory plants, down and standing dead trees, and litter. Belowground pools include root material for live trees, understory plants, and soil organic matter. The sum of soil organic matter, aboveground live trees, and belowground live trees comprises nearly 80 percent of the total and forecasts of these three pools are shown in figure 74. The pattern of change for soil organic carbon (fig. 75A) mirrors forest area changes shown in figure 68. The forecasts reflect the slight downward trend in total forest area in the region. Live tree above- and belowground carbon pools (figs. 75B and 75C, respectively) have patterns of change that are very similar to forecasts for growing stock inventories and reflect a very slight

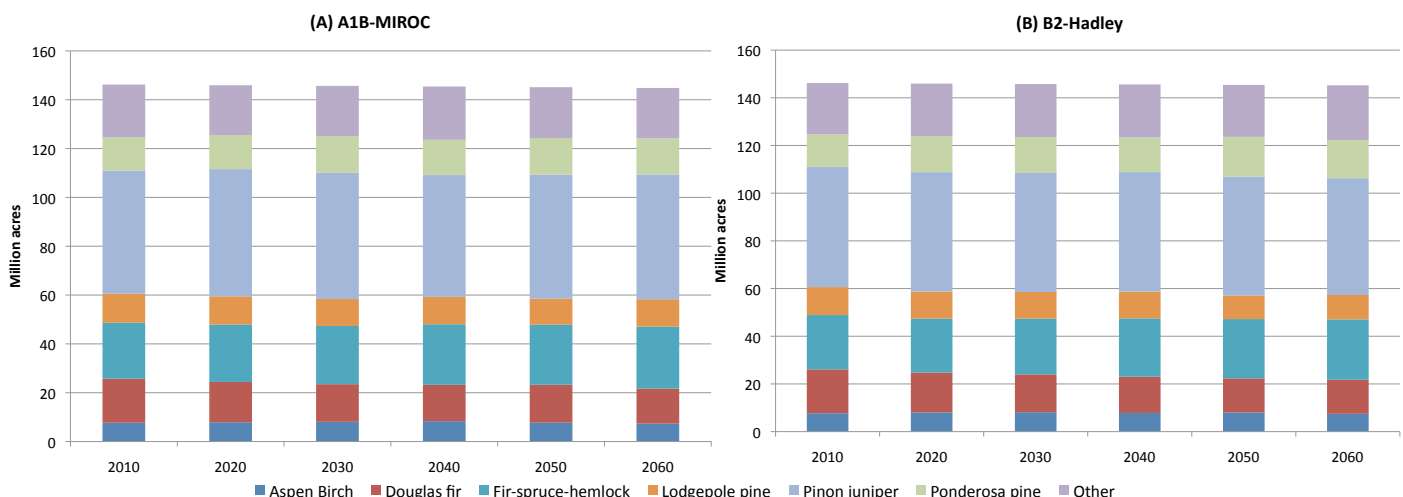


Figure 70—Current and forecasts of forest type distributions for A) A1B-MIROC and B) B2-Hadley scenarios (this chart does not include forest area in the Great Plains States of North Dakota, South Dakota, Nebraska, and Kansas).

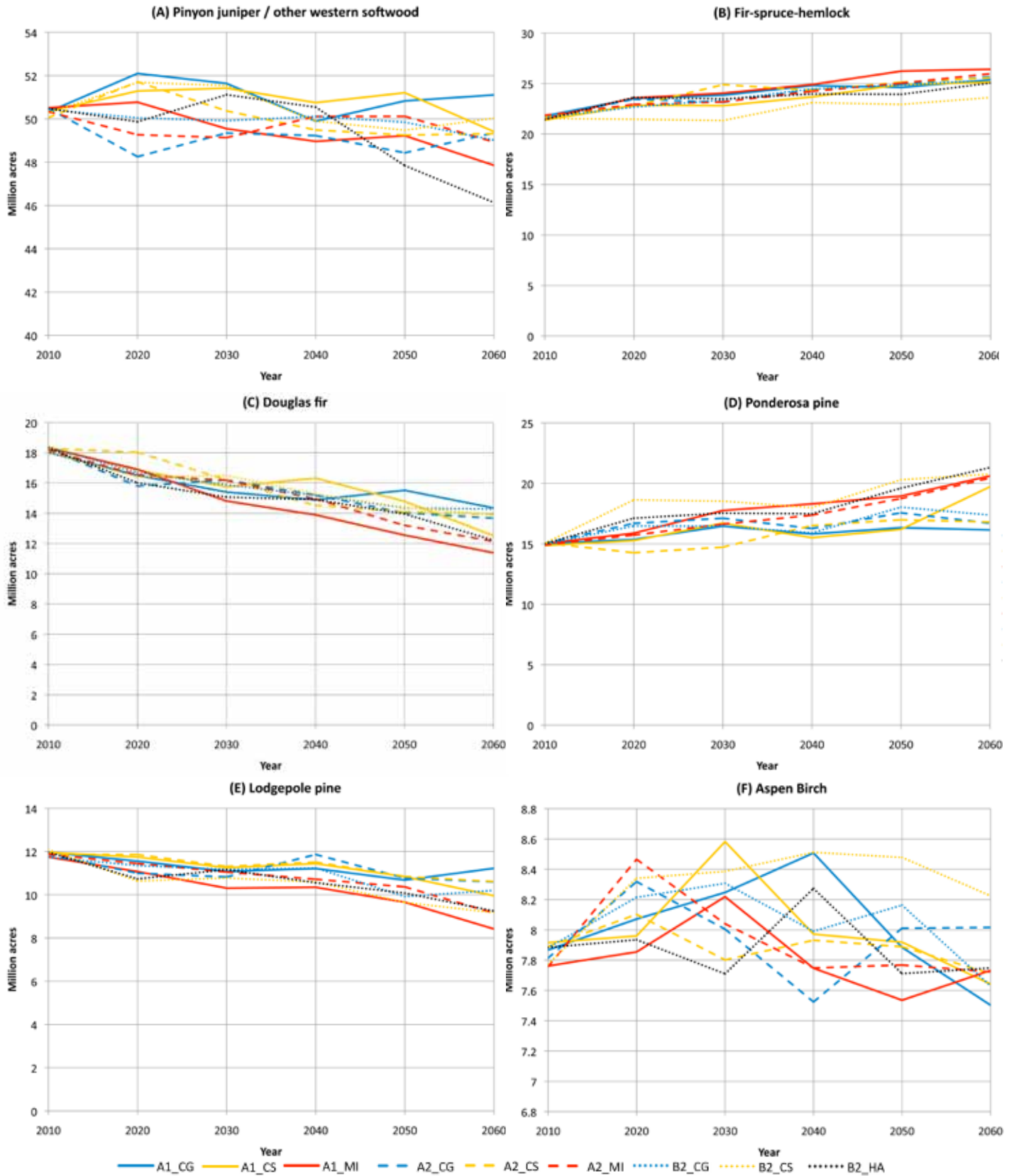


Figure 71—Forecasts of the area of forest types in the Rocky Mountains Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

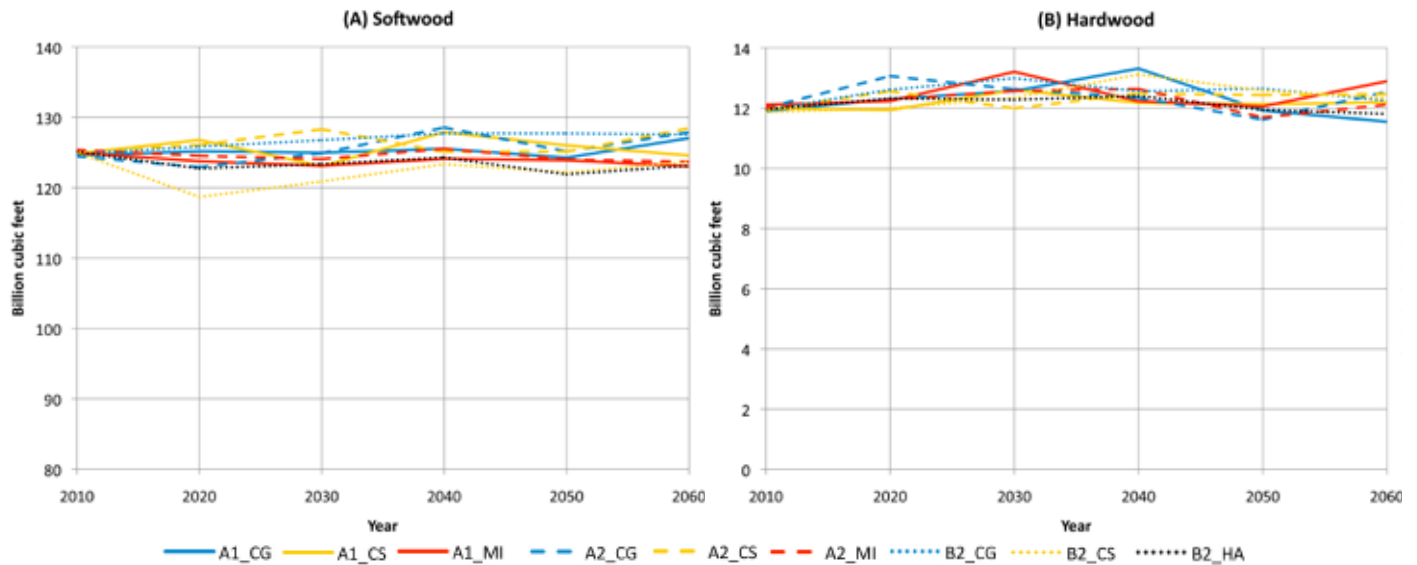


Figure 72—Forecasted biomass measured as growing stock inventory by forest type in the Rocky Mountains Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

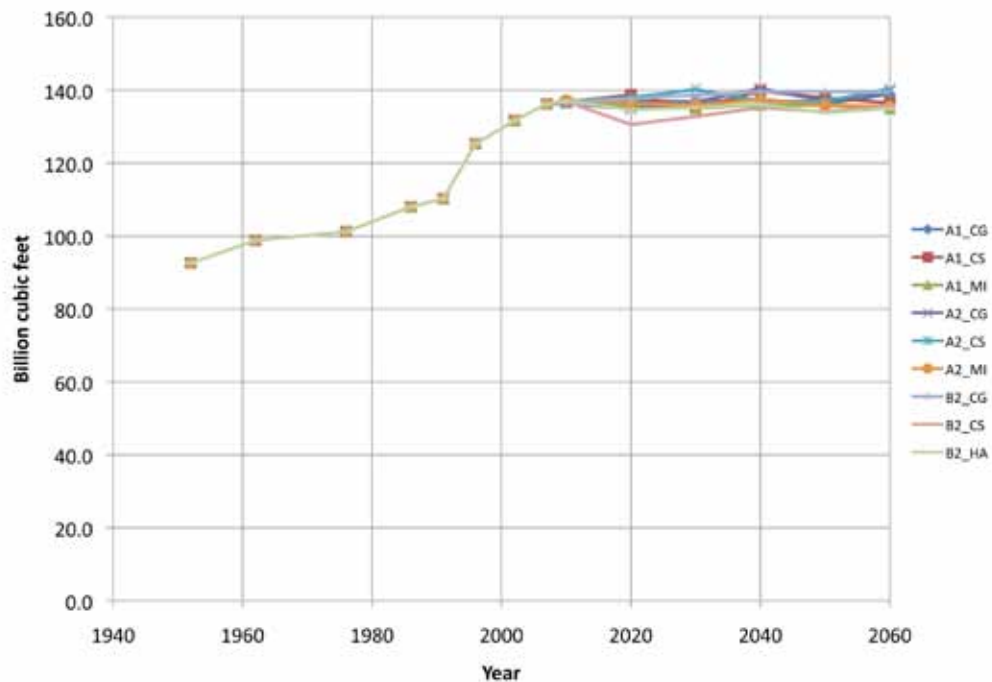


Figure 73—Softwood and hardwood growing stock inventories for the Rocky Mountains Region, 1952–2060. Forecasts (2010–60) bracket the range of future inventories shown in figures 62 and 63.

upward trend in these pools. Slight decreases in soil carbon just offset by increases in carbon in overstory and understory pools yield stable carbon pools through time.

Removals

Due to limited data, harvests are not directly modeled for the Rocky Mountains Region. Harvests are infrequent when compared to the area or volume of forests in this region—about 0.5 percent of growing stock inventory per year (Smith and others 2007)—so harvested plots are observed very rarely in data from the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture, making the direct modeling of harvest activities implausible. Instead we focus on modeling stand replacing events generally. Accordingly there is no direct estimate of removals available from the model. We can infer from age class projections that the rate of removals is roughly consistent with the average values observed between the mid-1990s and the mid-2000s plus or minus the FIA sampling error for removals. We discuss total removals forecasts for the West in the section of this report on the Pacific Coast Region.

Age Structure/Habitat

Age class distributions are affected by the starting distributions and by disturbance regimes forecast for forests in the future. Simulated inventories can be used to evaluate various aspects of future forest conditions. One aspect of significance to wildlife habitat conditions in the Rocky Mountains Region is the distribution of forests by age class, and the implications for the provision of early, middle, and late age forest conditions. We evaluate changes in the age class distributions of softwood forest types using two charts. One displays the aerial age class distribution by decade for the most recent inventories of the Rocky Mountains Region. We then summarize changes

in age class resulting from the nine RPA scenario-climate combinations between 2010 and 2060 using box plots. Figure 76 shows the current age class distribution for hardwood forests in the Rocky Mountains Region by 20-year age classes. Each box plot describes the distributions of changes in age classes. The bottom of the box represents the 25th percentile of the predicted changes, the top of the box represents the 75th percentile of the predicted changes, the line in the box indicates

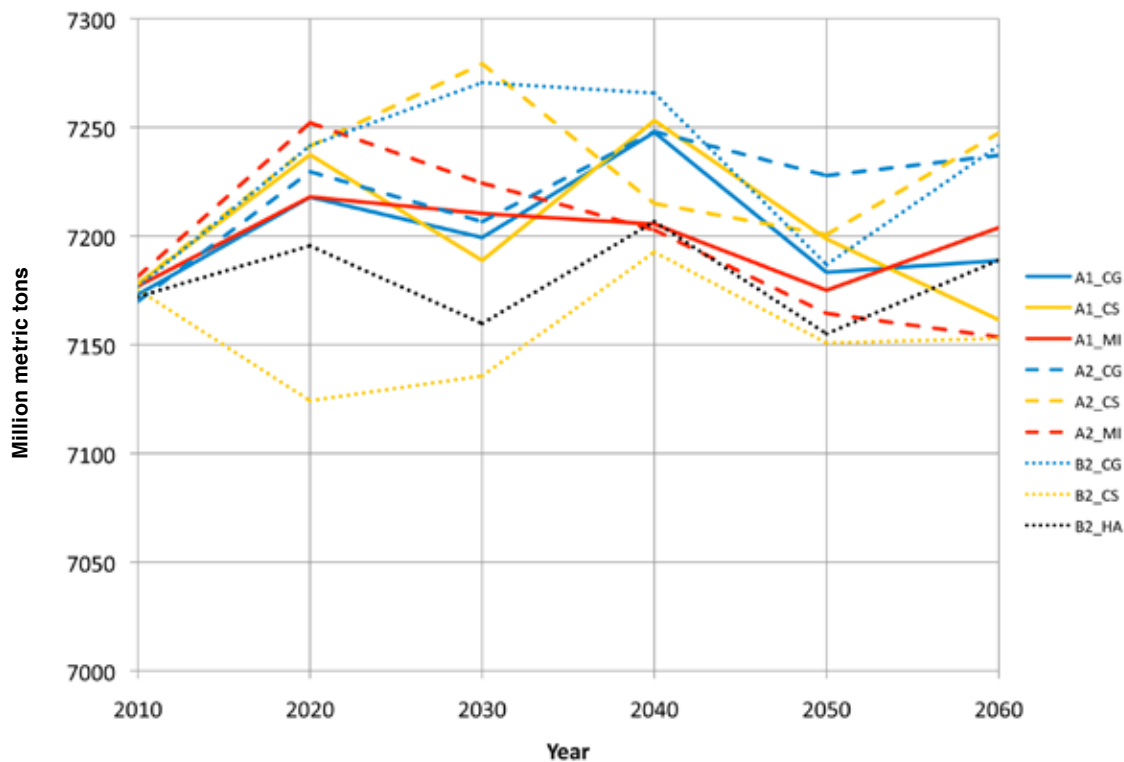


Figure 74—Forecasts of total carbon stored within forests in the Rocky Mountains Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

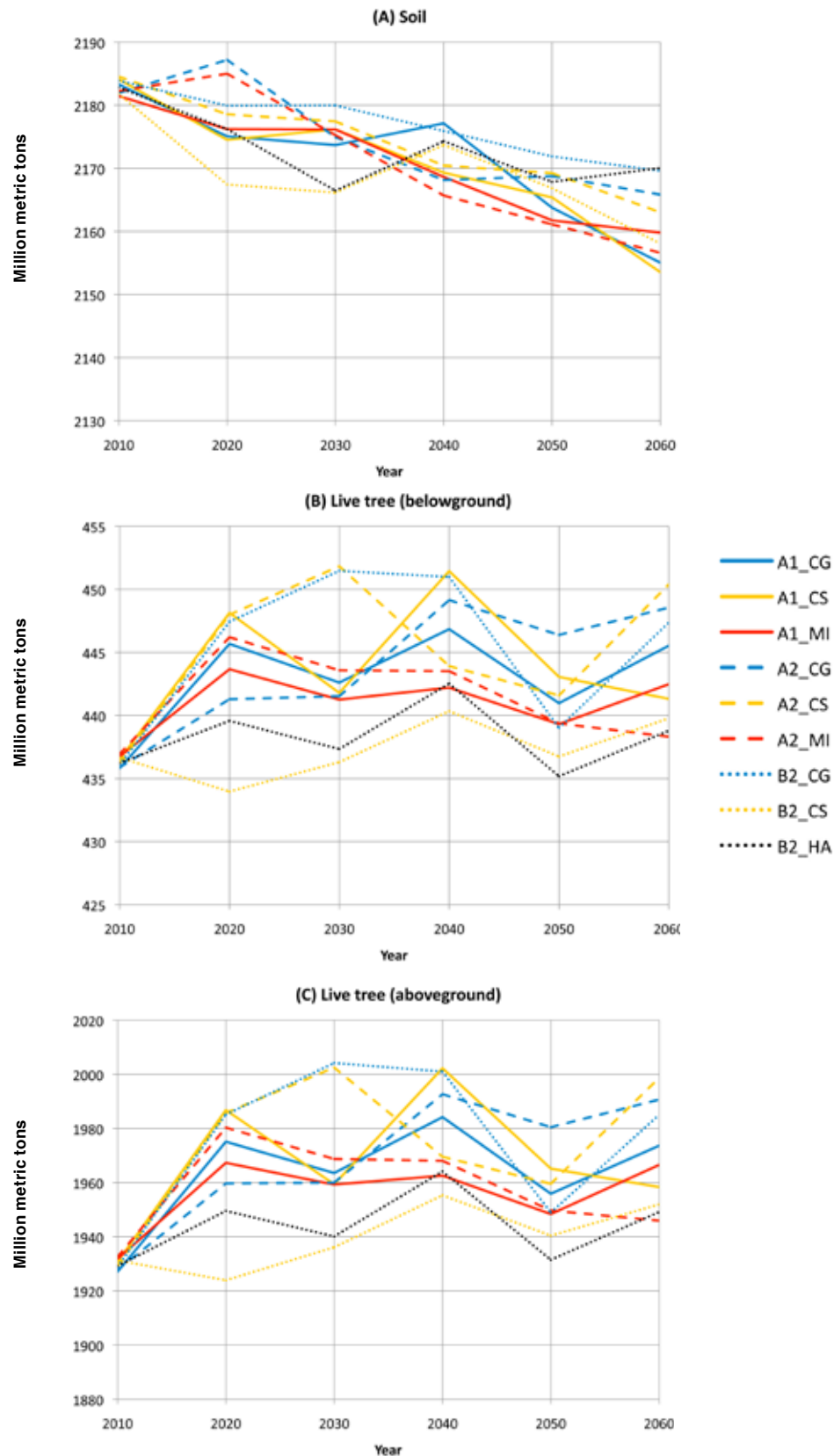


Figure 75—Forecasts of carbon stored in various pools within forests in the Rocky Mountains Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

the median forecast, and the plus in the box indicates the mean forecast. The “whiskers” of the box show the extreme values of the forecasts.

The age class distribution in 2010 is peaked in the 81–100 and 101–120 age class groupings, reflecting disturbance history including early logging and fires (fig. 76). Forecasts emphasize an aging of this cohort and an expansion in the area of forests in the 201+ age classes. Stand replacement models yield a steady level of the youngest aged forests and models indicate a substantial reduction in the area of the middle age classes, especially for the 81–100 and 101–120 classes.

Discussion

The nine RPA scenario-climate combinations considered for the Rocky Mountains Region provide a range of plausible futures affecting forests in the region. Population and income changes affect an increase in developed land, but the effects on forest area in the Rocky Mountains Region is small in terms of area and proportion—a loss of 1–1.5 million acres amounting to < 1 percent of total forest area. More of the forecasted development is focused on agricultural and rangelands in this region.

Inventories of forest biomass are forecast to remain relatively constant in the region as forests age and stand replacement rates are essentially constant. These forecasts imply that removals and mortality just offset forest growth and growth is expected to decline as forest aging progresses.

What is variable across the forecasts is change in forest types driven by projected changes in climate variables between 2010 and 2060. The direction of these changes is generally consistent across RPA scenario-climate combinations but the magnitude of change is variable. The greatest changes arise for lodgepole pine, ponderosa pine, and Douglas fir forest types. Across all combinations, both lodgepole pine and Douglas fir types are forecasted to decline in area (8–32 percent and 16–33 percent, respectively) while the area of the ponderosa pine type is forecasted to increase (up to 29 percent). A moderate increase in spruce-fir forests type area is also projected. Two studies addressing the potential influence of climate change on forest species distributions in the Rocky Mountains Region, while not congruent with our approach to modeling forest type associations, provide points of comparison. Our forecasts of increasing ponderosa pine types are generally consistent with increased *P. ponderosa* distributions predicted by Shafer (2001) and by Rehfeldt and others (2006). Increases in spruce-fir types conflicts with the prediction by Rehfeldt and others (2006) of decline but is consistent with Shafer’s prediction of an increase in *P. engelmannii* in the region.

Rates of forest type changes are generally ordered by the GCMs paired with the RPA scenarios. The greatest change in forest types occur under the MIROC3.2 (both A1B and A2 scenarios) and HadCM3 (B2) GCMs, the warmest and driest scenario-climate combinations. Conversely the least change is associated with the CGCM3.1 and CGCM2 GCMs. The RPA scenarios paired with the MIROC3.2 GCM (A1B and A2) produce the greatest increases in temperature between 2010

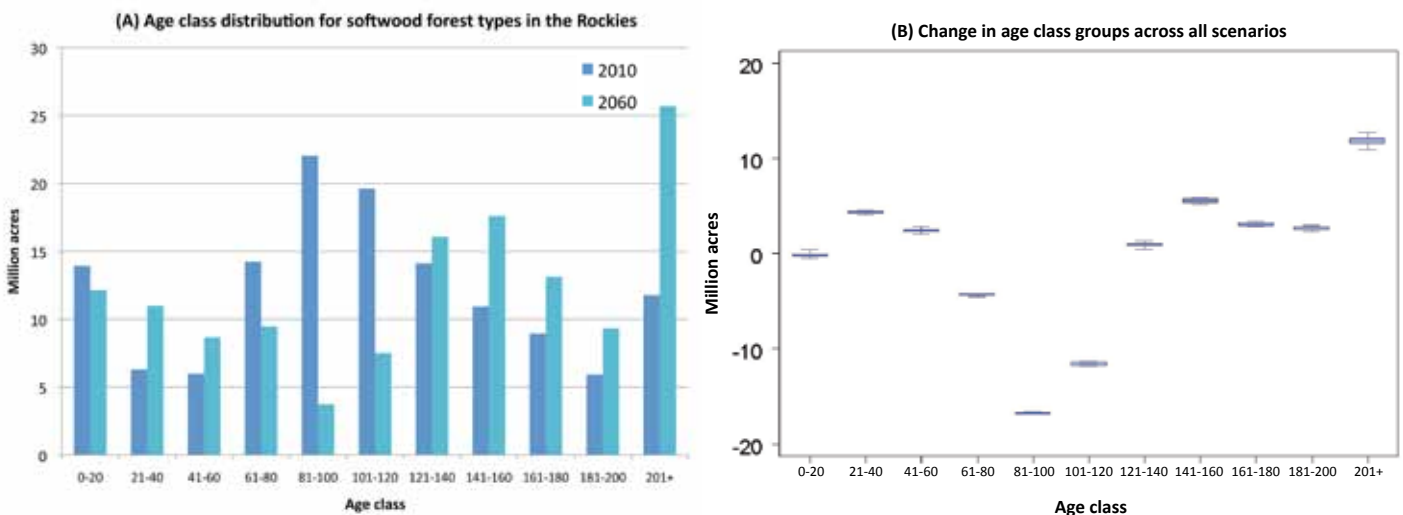


Figure 76—(A) Age class distributions for softwood forest types in the Rocky Mountains Region in 2010 and for the B2-Hadley scenario in 2060, and (B) change in age class groups across all scenarios.

and 2060 and by 2030, and temperature changes are largely coincident with the forested portions of the Rocky Mountains Region. HadCM3 temperatures are coincident with MIROC3.2 beyond the 75th percentile of the temperature distribution, i.e., in the warmest 25 percent of the region. MIROC3.2 and HadCM3 generate the greatest reductions in total precipitation between 2010 and 2060 among the GCMs evaluated. Forecast models for forests in the West (Rocky Mountains Region and Pacific Coast) differ from those developed for the eastern regions in some fundamental ways. Inventory data are relatively scarce in the West with survey intervals exceeding 10 years for most States and the transition to the newer annual inventory approach taking longer. In all cases, the inventory design changed substantially between the most recent two inventories, effectively precluding the use of matched plots to estimate change models. As a result, transition models could not be fit and models of forest type change relied on cross-sectional analysis (classification) of forest type occurrences relative to current conditions. While these models allow for a high degree of detail regarding the relationship between site variables, climate variables, and forest conditions, they cannot incorporate the relative inertia or the speed of change of type condition on forest plots. We might expect these types of models to overestimate the rates of resulting changes in forest conditions. This suggests placing most focus on the longer term projections where disturbance, mortality, and recruitment have time to play out in generating the changes.

CHAPTER 7
FOREST FORECASTS FOR THE PACIFIC COAST REGION

For the Pacific Coast Region, forest forecasts were generated for each of the nine Resources Planning Act (RPA) scenario-climate combinations with harvest models that reflect historical harvest relationships. In addition, we simulate inventory development under three futures (based on the RPA A1B-CGCM3.1, A2- CGCM3.1, and RPA B2-CGCM2 combinations); with adjusted harvest probabilities to simulate removals predicted by the U.S. Forest Products Model (Ince and others 2011) for the economic futures attached to the RPA scenarios. To match the harvests from the Forest Products Model, we adjust the scaling parameter in equation 4 to reflect Forest Product Model runs for the respective scenario. Because paired inventories are not available, future forest types could not be modeled using transition models but were modeled using a forest type classification algorithm linked to climate forecasts and site attributes. This region spans a great variety of conditions between the Eastside and Westside of the Cascades, so separate models were developed for these two sub-regions for both forest type transitions and for harvest probabilities by ownership class. Data for Oregon and Washington were pooled to estimate models and a separate set of California models were estimated. Table 3 defines the labels for the 12 futures evaluated in this section.

Climate

To frame a discussion of the forest forecasts, we compare climate projections from the nine RPA scenario-climate combinations with historical conditions for the Pacific Coast Region. Distributions of monthly values for a projected decade (2010 refers to the monthly values between 2001 and 2010, 2020 refers to monthly values between 2011 and 2020, and so on) are compared with a historical decade (2000 for the monthly values between 1991 and 2000). We start by plotting the cumulative distributions of temperatures/precipitation for a graphical view of change across time. We then map where significant differences in these distributions arise between projected and historical data for counties in the region.

Figure 77 shows a comparison of empirical temperature distributions between the historical decade and the 2060 decade for the nine climate projections. For all projections, the distributions shift outward over time as temperatures are projected to rise. The RPA A1B-MIROC3.2 combination generally shows the greatest increase in temperatures between 2010 and 2060, with a 3 °C increase in temperature at the 50th percentile of the distribution and a 4 °C increase at the 90th

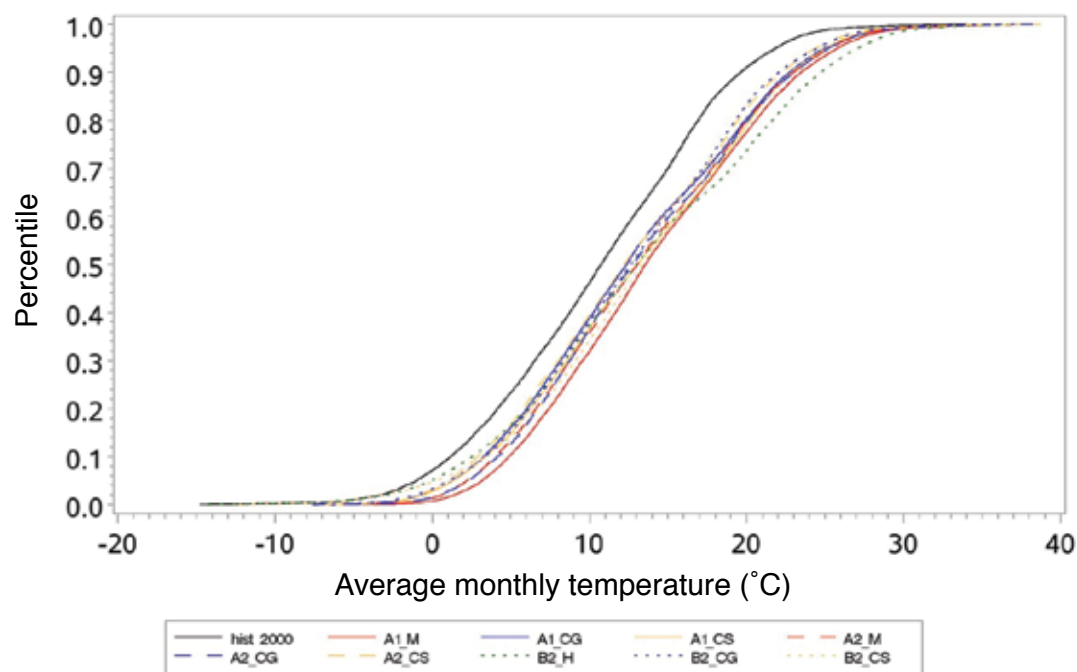


Figure 77—Empirical distributions of monthly temperatures for the Pacific Coast Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–60).

percentile. Through the 50th percentile, the other scenario-climate combinations yield outward shifts in temperature distributions of about 75 percent of the temperature increase shown for RPA A1B-MIROC3.2 (about a 2.5–3 °C increase at the 50th percentile). However, beyond the 65th percentile the RPA B2-HadCM3 combination yields larger temperature increases (+5 °C at the 90th percentile). This combination generates the greatest increase in temperature at the warm end of the distribution and the least increase at the cool end of the distribution. All scenario-climate combinations show a fairly regular outward shift in distributions over the decades (figs. 77 and 78).

Spatial patterns of change vary across the scenario-climate combinations. Figure 79 shows spatial patterns of change based on the Kolmogorov-Smirnov test ($p=0.05$) for monthly temperatures at the county level applied to the RPA A1B-MIROC3.2 combination (one of the two warmest scenario-climate combinations). The black areas indicate counties where there is distributional disagreement between historical and projected temperature data across the decades. Figure 80 provides the same set of maps for RPA A1B-CSIRO-Mk3.5. For RPA A1B-MIROC3.2 (fig. 79), discernible temperature differences appear beginning in 2030 largely along the coastal portions of the Pacific Coast Region. By 2050 temperature increases consolidate along the coast and include inland areas of southern and central California, and eastern Washington and Oregon. Beginning with the 2050 decade, many more inland counties show significant change. By 2060, the entire map is black for this combination, indicating a significant difference in temperature distributions over 2000 distributions for all counties.

For the Pacific Coast Region, the change pattern is similar for RPA A1B-MIRO3.2 and RPA A1B-CSIRO-Mk3.5 combination (fig. 80). Significant temperature increases start along the coastal areas of the Pacific Coast Region in 2030 and spread inland over the decades. By 2060, temperature distributions

are significantly different for most of the region (exceptions are eastern Washington and south central California). Figure 81 shows a strong degree of concurrence among the RPA scenario-climate combinations for temperature projections in the Pacific Coast Region. Along the coast, and for a strong majority of counties in the region, 7 to 9 of the 9 climate projections show significant differences in temperature (KS test, $p=0.05$). This region shows the greatest concurrence across climate projections among RPA regions.

Projections of precipitation are more variable than temperature projections across the RPA scenario-climate combinations and across the region (Joyce and others, in press). Under some combinations, overall precipitation is lower than historical values in the 2060 decade; under others precipitation is higher in the 2060 decade (fig. 82). Cumulative distributions of monthly precipitation values for the historical decade (2000) and for the nine climate projections in 2060 show an inward shifting of precipitation (drying) for RPA A2-MIROC3.2 and RPA B2-HadCM3 and a strong outward shift (increase) in precipitation for RPA A1B-CGCM3.1 and RPA B2-CGCM2 (figs. 82 and 83). For the other combinations, the distributions pivot, indicating that some areas become wetter while others become drier. For the various scenarios, the precipitation distribution shifts vary between time steps, in some cases alternating between wetter and drier decades (figs. 84 and 85). Figure 86 indicates very few counties with significantly different precipitation distributions in 2060 for four or more scenarios. These are focused in an area from the Bay area of California to the south.

Maps of significant shifts in mean temperature and total precipitation highlight areas with emphatic change in these two variables, i.e., these are conservative tests. Other climate variables may also have important influence on future forest conditions but are not examined here.

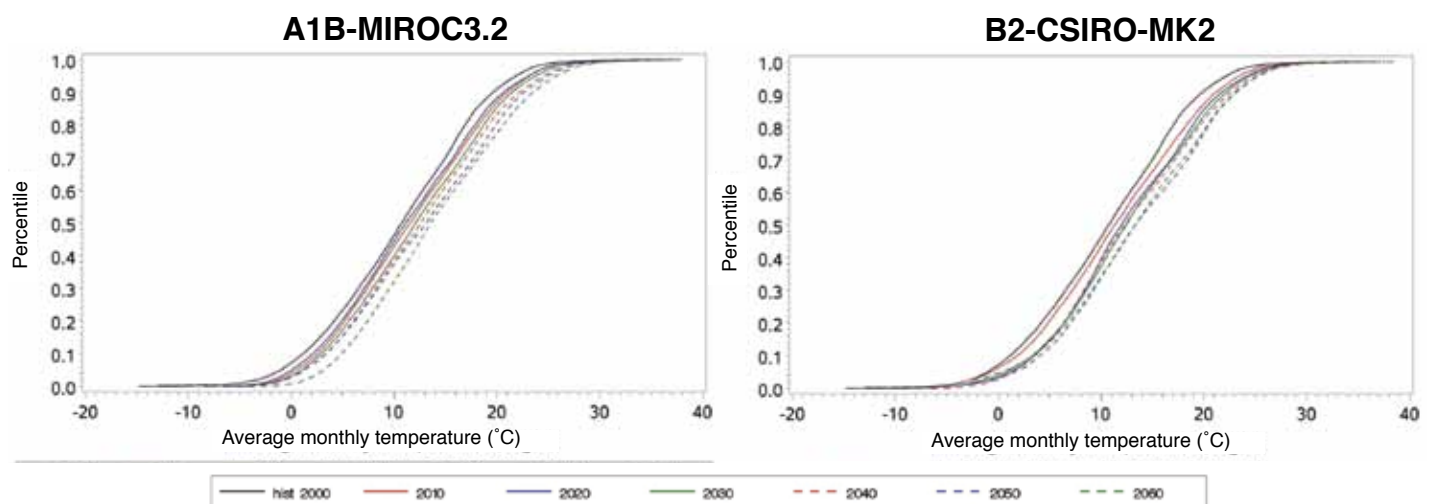


Figure 78—Empirical distributions of monthly temperatures for the Pacific Coast Region for a historical decade (1991–2000) and 6 successive decades of climate projections (A) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination and (B) for the RPA B2-CSIRO-Mk2 combination.

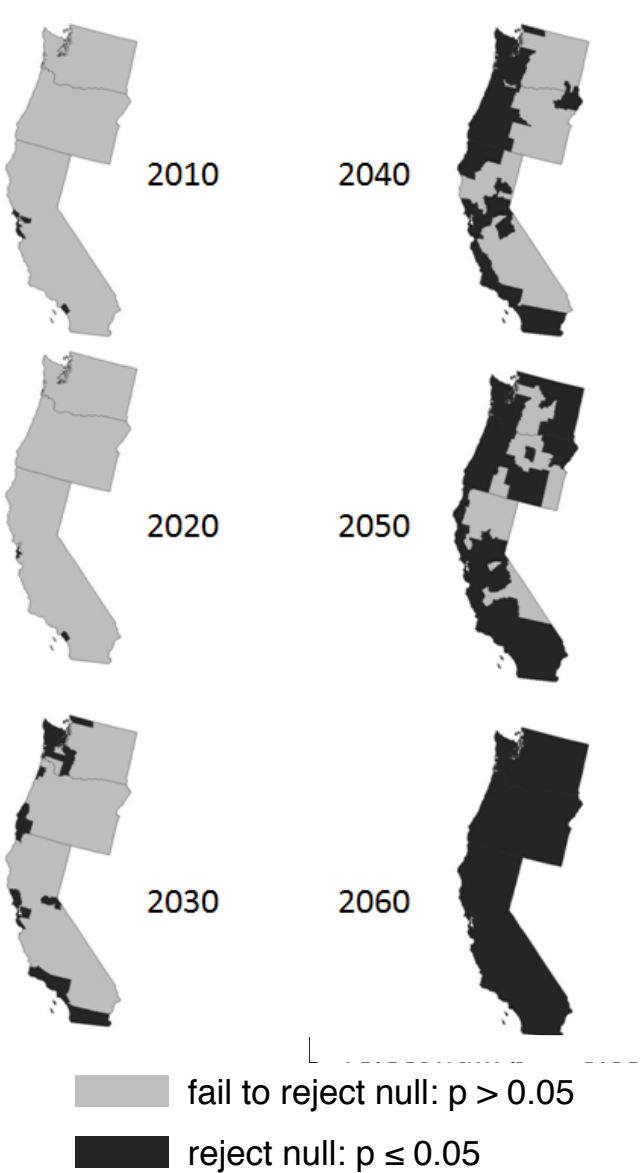


Figure 79—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

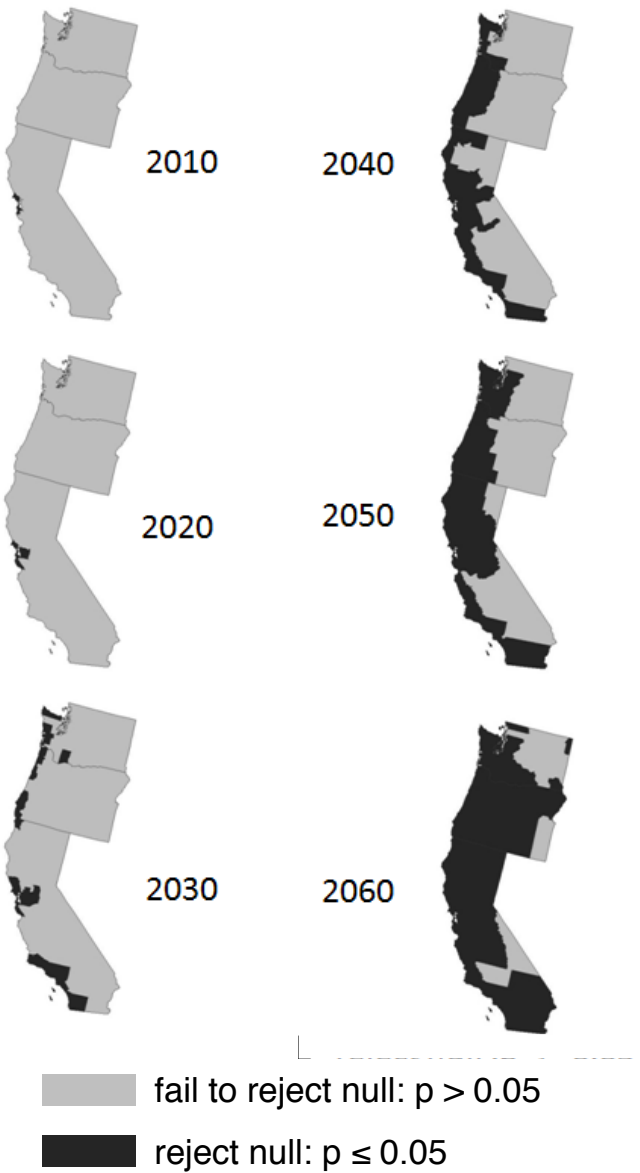


Figure 80—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-CSIRO-Mk3.5 combination. Black areas indicate distributional disagreement between historical and projected temperature distributions (p value < 0.05).

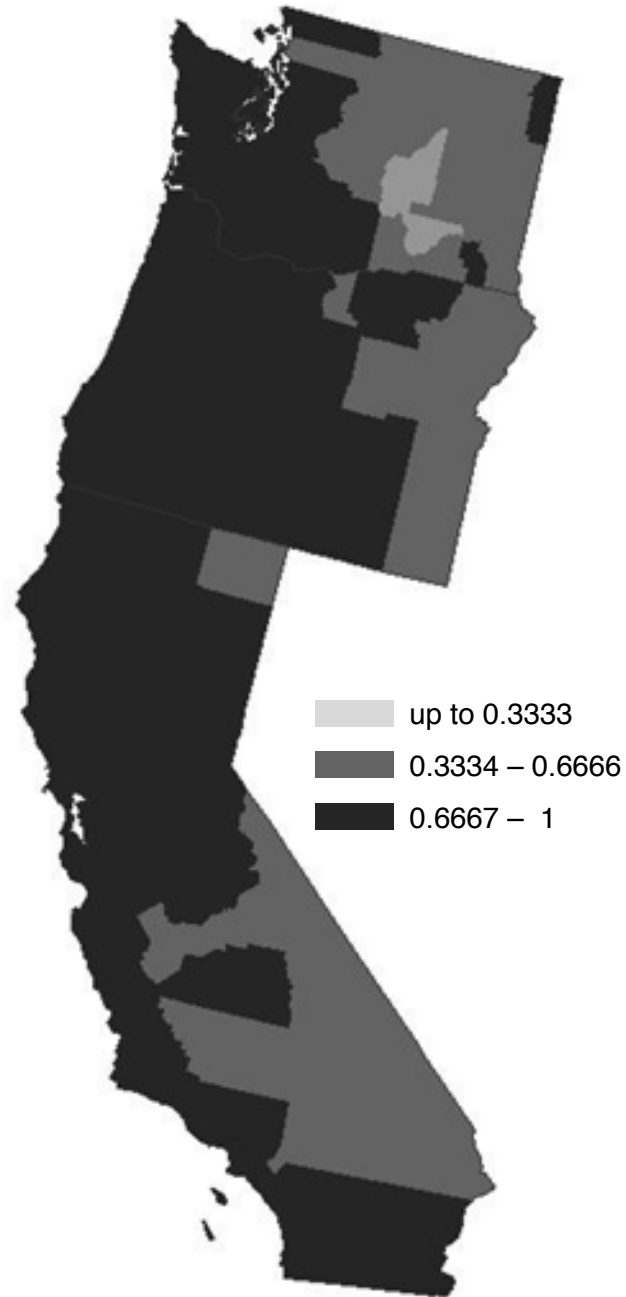


Figure 81—Proportion of the nine scenario-climate combinations yielding significant differences in decadal temperature distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the Pacific Coast Region.

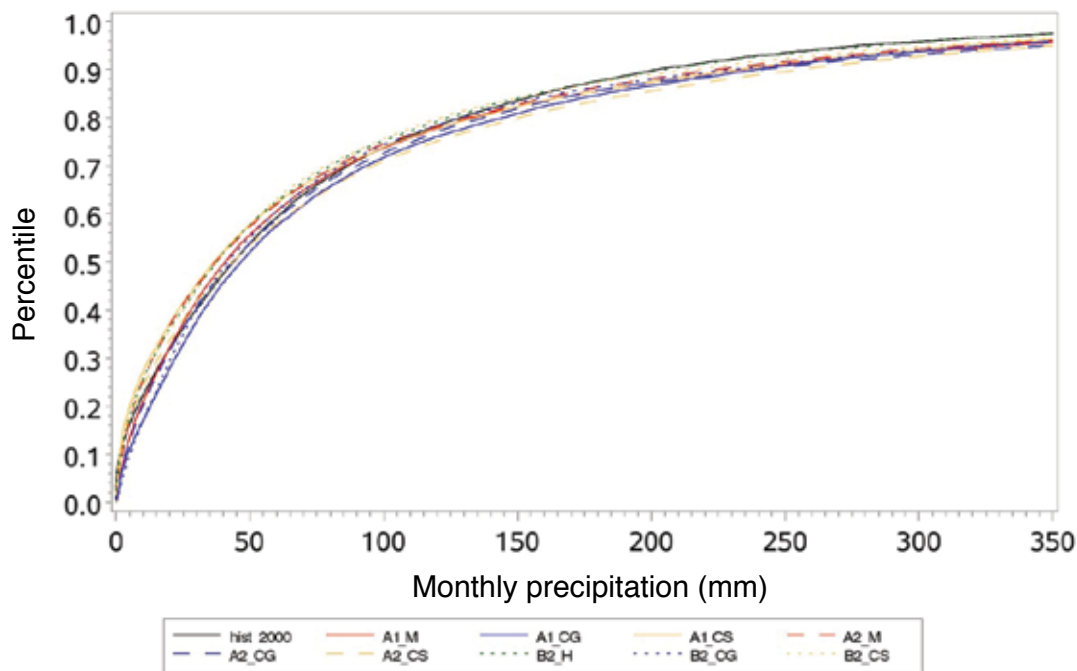


Figure 82—Empirical distributions of monthly precipitation values for the Pacific Coast Region for a historical decade (1991–2000) and projections of the nine Resources Planning Act (RPA) scenario-climate combinations in the 2060 decade (2051–60).

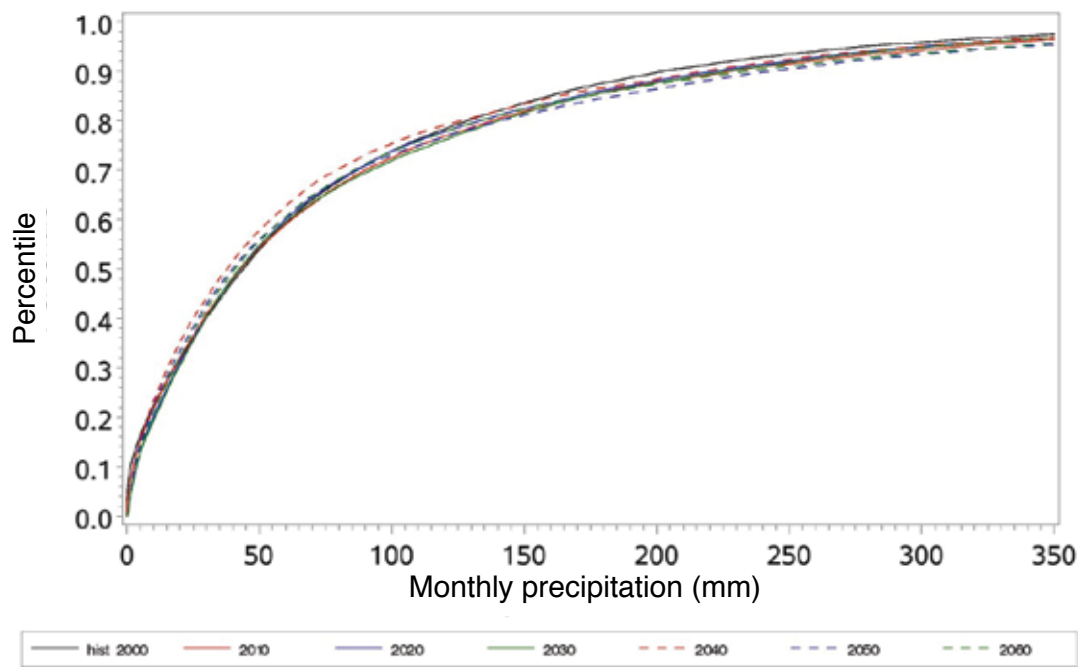


Figure 83—Empirical distributions of monthly precipitation for the Pacific Coast Region for a historical decade (1991–2000) and 6 successive decades (2010–60) of climate projections for the Resources Planning Act (RPA) A1B-MIROC3.2 combination.

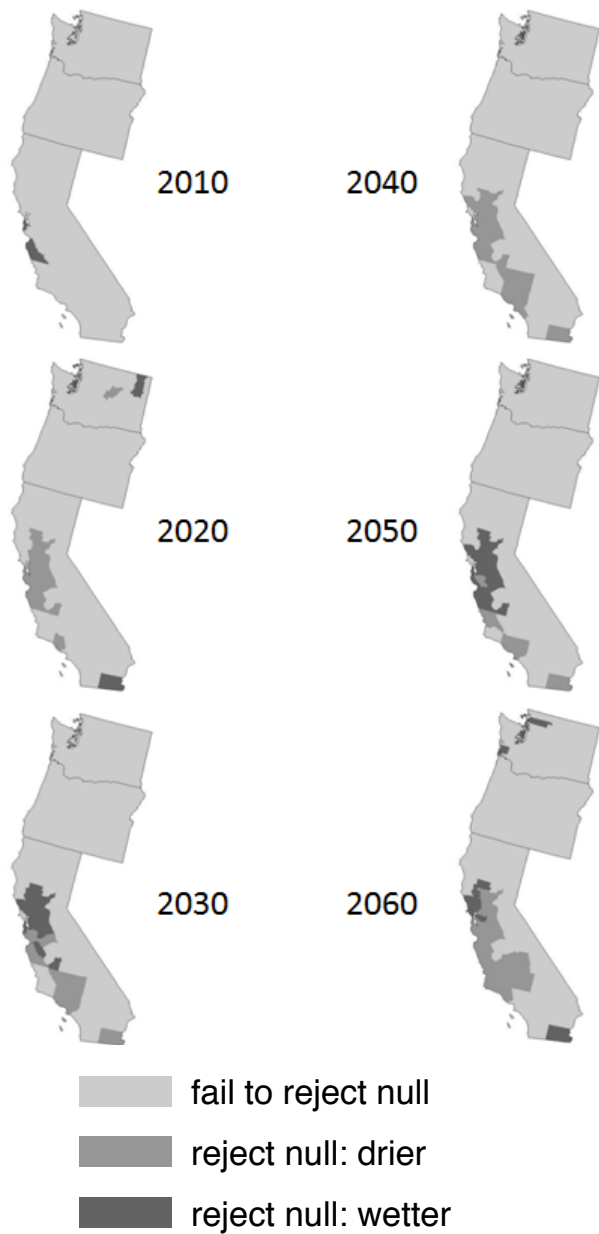


Figure 84—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-MIROC3.2 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value <0.05) and indicate drier and wetter conditions, respectively.

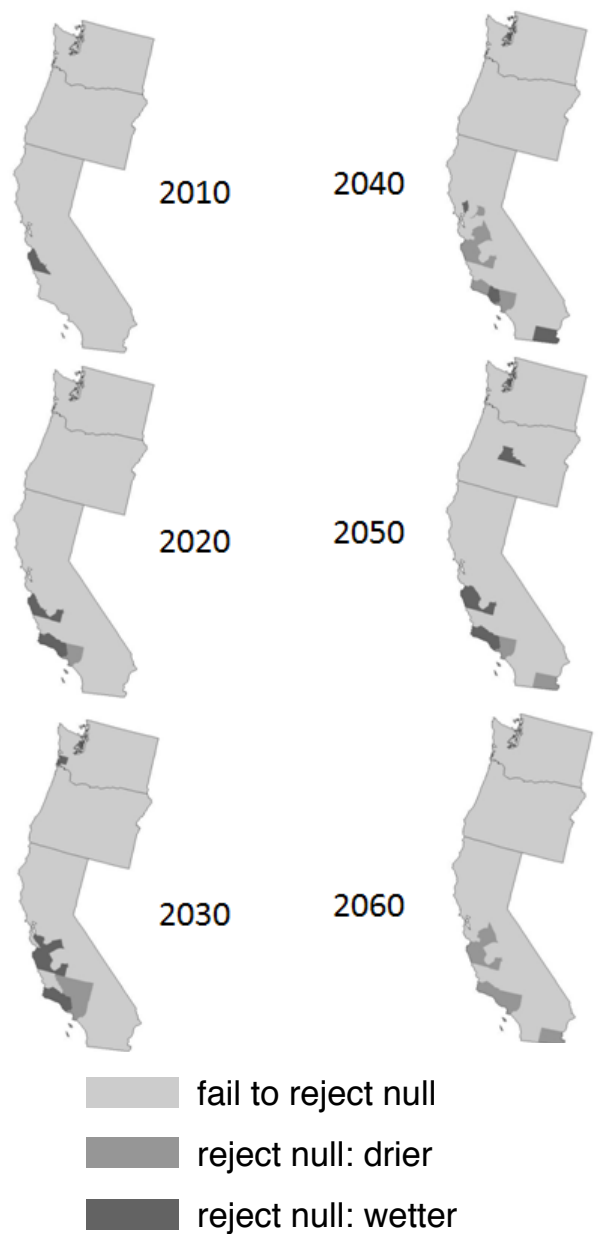


Figure 85—Results of county-level Kolmogorov-Smirnov tests comparing distributions of monthly temperatures for a historical decade (1991–2000) and 6 successive forecasted decades (2010–60) for the Resources Planning Act (RPA) A1B-CSIRO-Mk3.5 combination. Grey and black areas on the maps indicate distributional disagreement between historical and forecasted distributions (p value <0.05) and indicate drier and wetter conditions, respectively.

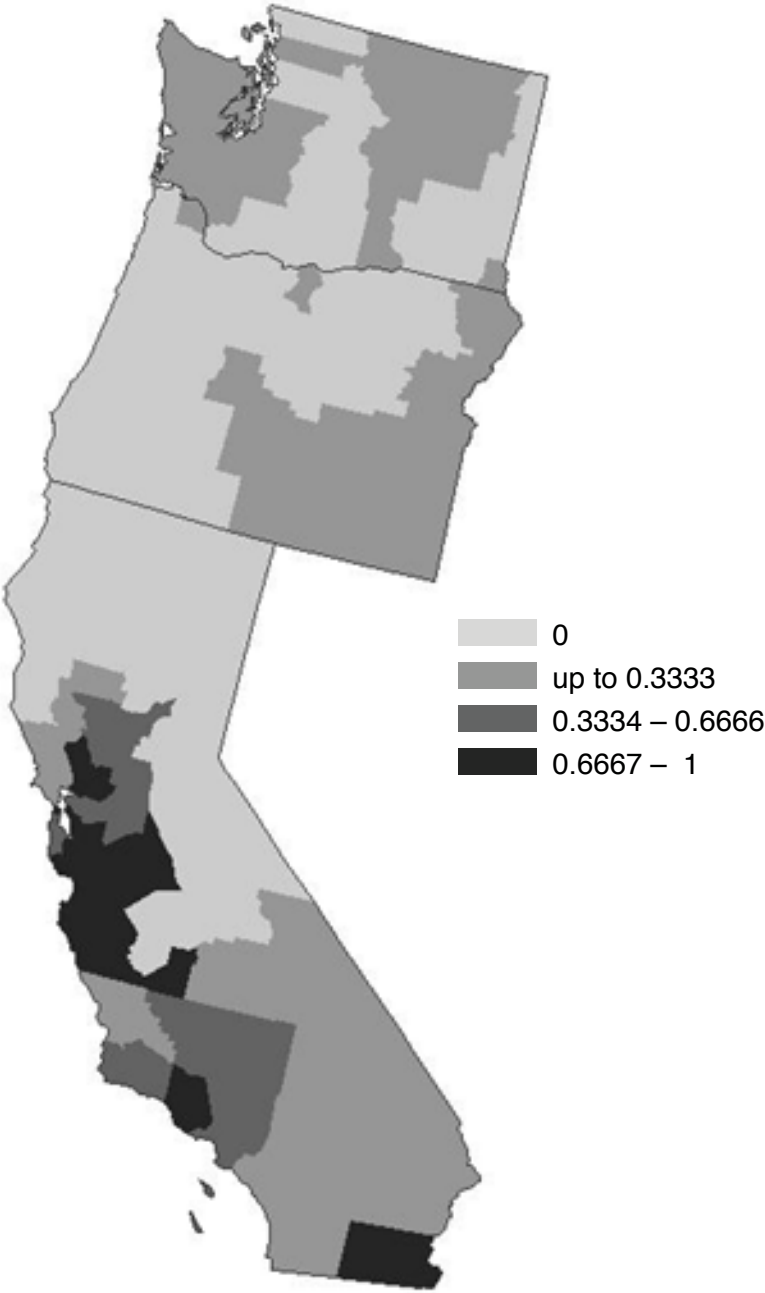


Figure 86—Proportion of the nine scenario-climate combinations yielding significant differences in decadal precipitation distributions between the historical decade (1991–2000) and the 2060 decade (2051–60) for counties in the Pacific Coast Region.

Forest Area

Across the three RPA scenarios, the Pacific Coast Region is forecast to lose between 1.7 million and 2.7 million acres of forest in response to ongoing population-fueled development between 2010 and 2060 (fig. 87). The highest loss is for the RPA A2 and A1B scenarios (unlike other regions, the Pacific has nearly identical forest loss trajectories for these two scenarios). The least area of loss accrues to the RPA B2 scenario. Due especially to patterns of land use in the region, land use changes and forest losses are not spread evenly across the Pacific Coast Region. Instead there are several large blocks of changes within the region (fig. 88). The largest area of projected forest losses is forecasted for the west side of the Cascade mountain range in Washington, in an area centered on Seattle but extending between the Canadian border and the Oregon border. In Oregon, forest losses concentrate in two areas, the northwestern corner centered on Portland and the southwest corner centered on Medford. In California, forest losses are forecasted for the San Francisco Bay area and along the Interstate 80 corridor to the Nevada border at Reno.

Forest Types

While the 50-year forecast of forest area varies little across the various three RPA scenarios, the area of individual forest types does change in response to shifts in projected climates associated with the scenario-climate combinations. Western models of forest transitions derive from a single cross-sectional dataset and focus on predicting forest type probabilities as a function of site and various climate variables. General circulation model projections for a given year and scenario define the set of forest type probabilities, and random draws are used to select forest type for each plot within the inventory. In this way, shifts in climate can give rise to changes in overall forest type distributions.

The broad diversity of forest types in the Pacific Northwest reflects the variety of growing conditions from the Coast to the Inland West. Six forest type groups—Douglas fir, fir-spruce-hemlock, ponderosa pine, hemlock-sitka spruce, white oak, and California mixed conifer (CMC)—combine to make up about 73 percent of forests in the region in 2010 (fig. 89). Douglas fir and

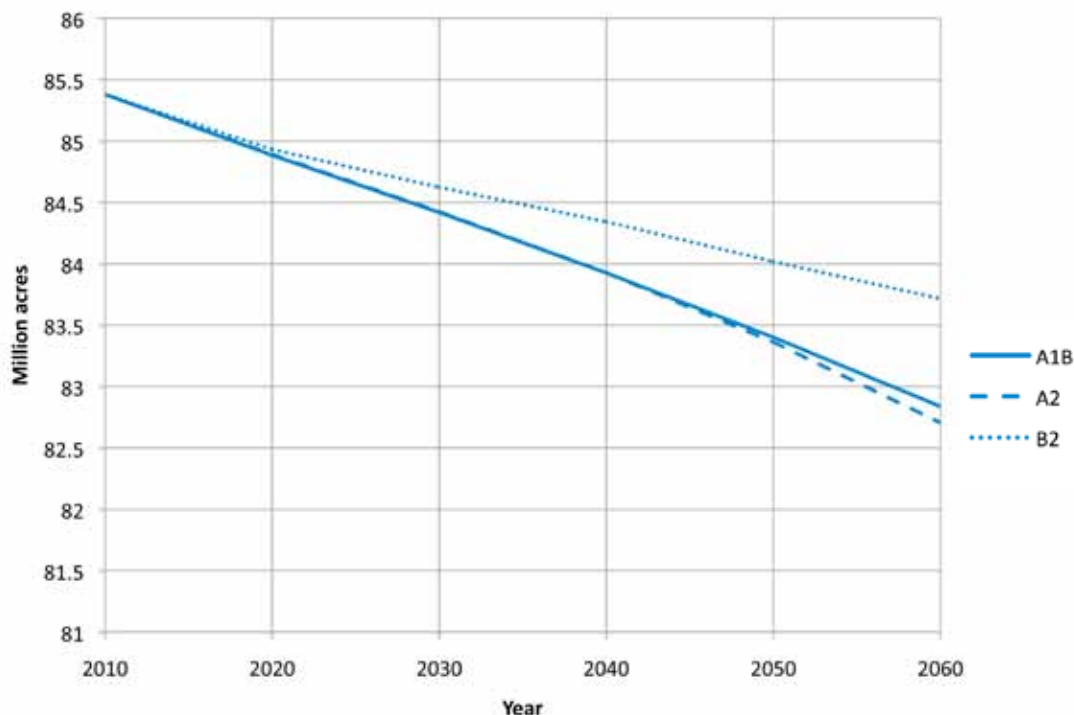


Figure 87—Total forest area for three RPA scenarios for the Pacific Coast Region. By model construction, forest area in the Pacific Coast Region varies only by Resources Planning Act (RPA) scenario (not by general circulation model).

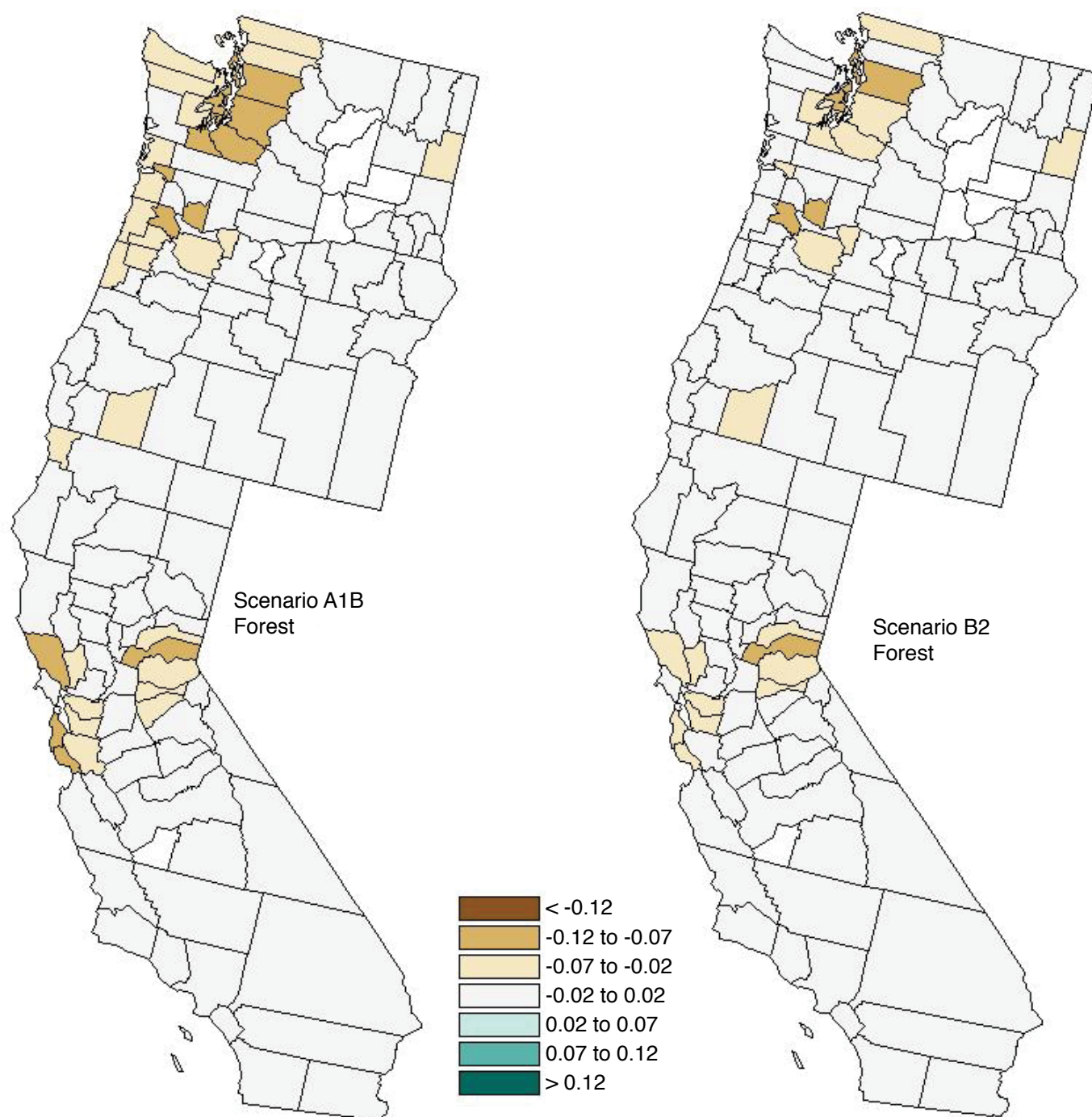


Figure 88—Forecasted changes in the proportion of non-Federal land within a county in forest, 1997–2060, for the A1B and B2 storylines

hemlock-Sitka spruce dominate the Westside forests, but Douglas fir is also a dominant type in the drier and less productive forests of the east side, reflecting its very broad ecological amplitude (Rehfeldt and others 2008). Forecasts suggest some changes in type composition over the next 50 years.

In 2060, the area of Douglas fir ranges from its 2010 value (20 million acres) to an increase of about 15 percent across the scenario-climate combinations (fig. 90A). The relative stability of Douglas fir in the Pacific Coast Region is the result of offsetting trends in Eastside and Westside forests. On the Westside,

Douglas fir increases and mirrors strong declines in hemlock-Sitka spruce (from 4 million acres in 2010 to between half a million and 2 million acres in 2060; fig. 90D). On the east side, Douglas fir declines and mirrors increases in ponderosa pine.

The area of fir-spruce-hemlock declines for all scenario-climate combinations (fig. 90B). Starting at roughly 9 million acres in 2010, this forest type group which is predominantly on the East side of the Cascades, falls to between 3.5 million and 7 million acres (a decline of 20–60 percent) by 2060. The ordering of combinations shows no clear differences between scenarios or GCMs and change in the area of fir-spruce-hemlock.

Ponderosa pine, in contrast, shows strong gains across all scenario-climate combinations (fig. 90C). By 2060, ponderosa pine area is forecasted to grow by substantial amounts from 9.2 million acres in 2010 to between 12 million and 18 million acres (gains of 30–96 percent). This gain in ponderosa pine forests in Eastside forests is qualitatively similar to forecasts of expanding ponderosa pine for the Rocky Mountains Region.

Hemlock-Sitka spruce has the greatest percentage loss of area among forest type groups across the forecasts (fig. 90D). Starting at 4.3 million acres in 2010 this forest type group is forecast to occupy between half a million and 2.3 million acres in 2060 (losses of between 55 and 88 percent).

The CMC forest type shows some variation over time but in 2060 all forecasts are very close to the 8 million acres observed in 2010 (fig. 90E). In contrast, the white oak forest type group is forecasted to expand across all scenarios from about 10

million acres in 2010 to between 12.4 million and 14.9 million acres (gains of 24–49 percent) in 2060 (fig. 90F). Most of this forest type and all the gains forecast for the type are found in California.

Standing Biomass

Of the various metrics available for measuring biomass changes for a site in a forest inventory, we opted to focus on the volume of growing stock because it is a useful index both for timber analysis and for measuring other ecosystem services. Total growing stock volumes are forecasted to change in response to both land use changes and timber harvesting levels. In the Pacific Coast Region, nearly 90 percent of total growing stock inventory is softwood. Standing at 204 billion cubic feet in 2010, softwood inventories are forecast to expand slightly between 2010 and 2030 and then decline gradually to 2060 (fig. 91A). In 2060, softwood inventories range between 175 billion and 197 billion cubic feet (net declines of 2–12 percent from 2010 values; fig. 91A). Hardwood inventories, about 10 percent of total inventory, would fall by about 20 percent for all nine of the scenarios (fig. 91B).

Figure 92 puts changes in softwood growing stock in the context of a longer history of changes. Peak values forecast for 2020–30 would be roughly equivalent to growing stock values estimated for the early 1950s. Relatively high harvest levels from the 1960s to the 1990s were accompanied by a decline in inventories. Harvest reductions beginning in the early 1990s were followed by a net accumulation of inventory in the region.

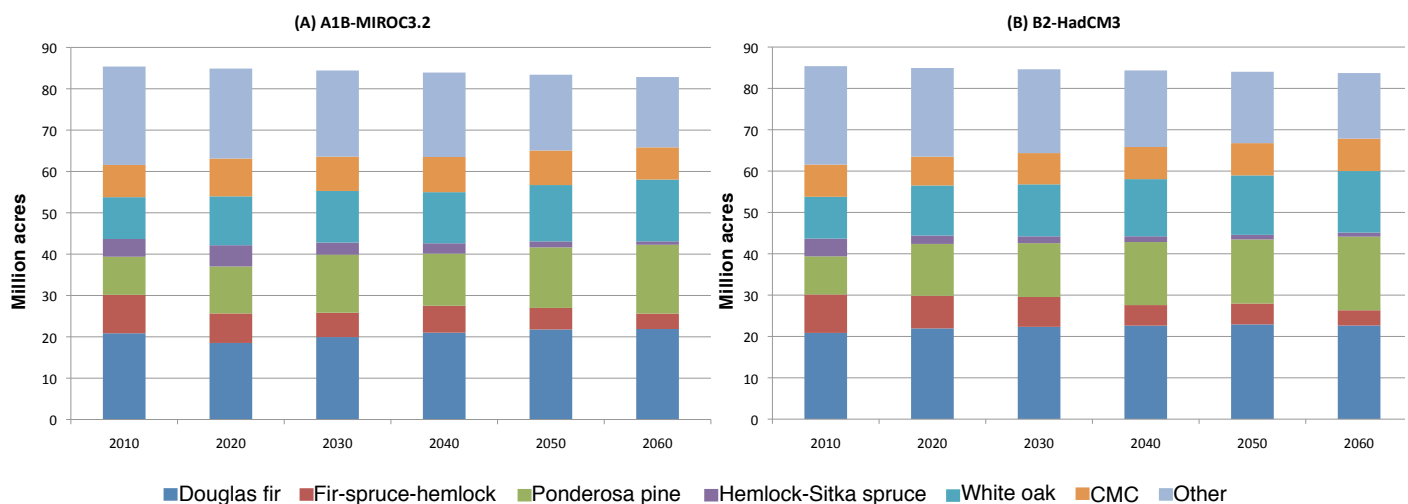


Figure 89—Current and forecasts of forest type distributions for A) A1B-MIROC3.2 and B) B2-HadCM3 scenarios.

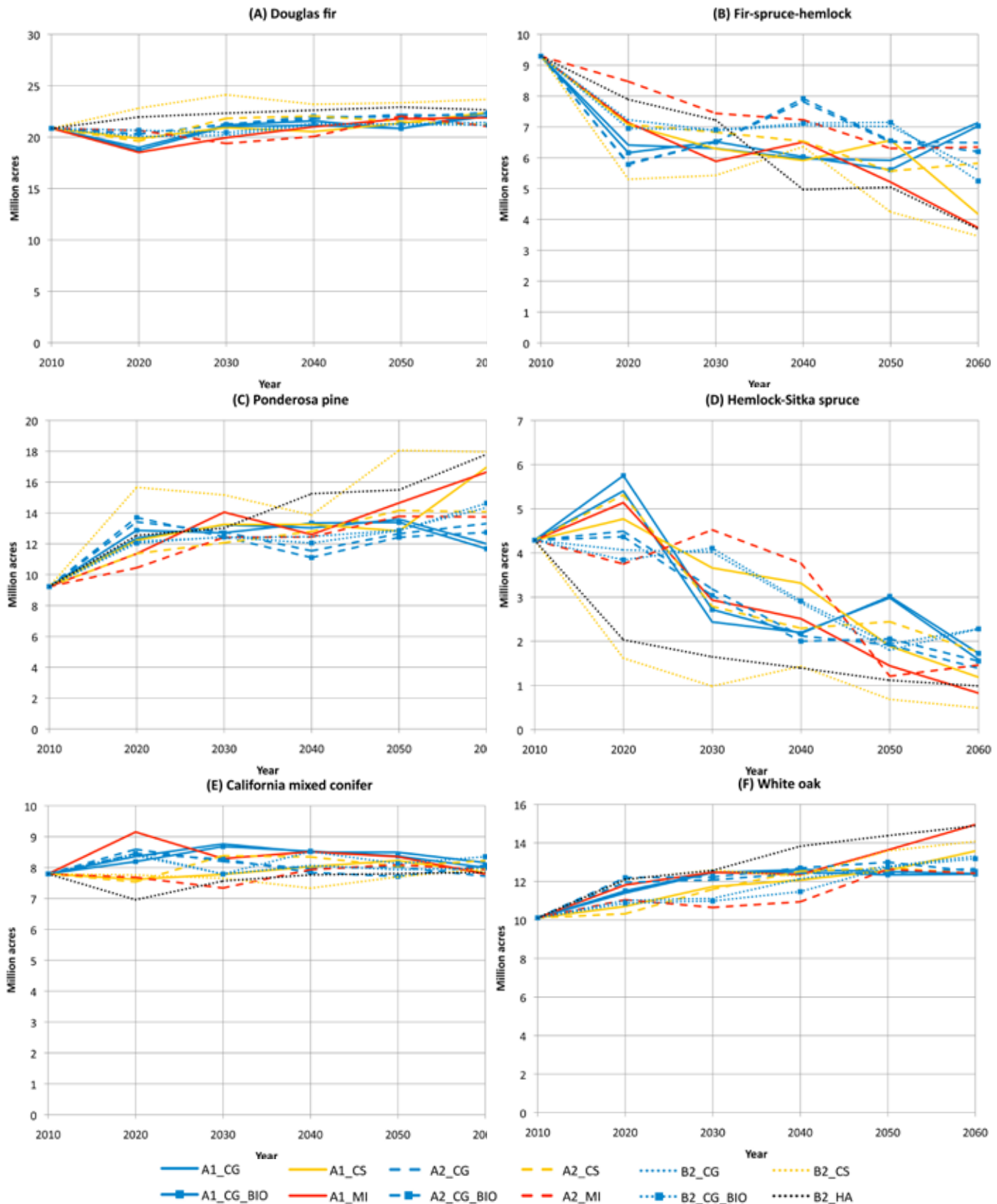


Figure 90—Forecasts of the area of forest types in the Pacific Coast Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

Softwood growing stock inventories in 2060 would be roughly equivalent to the range of values observed between the 1990s and the 2000s.

Forest Carbon

Carbon contained in the forests of the Pacific Coast Region amounts to about 7.8 billion metric tons at the beginning of the forecasts (fig. 93), with a majority of the carbon in soil organic matter and living trees (fig. 94A). Accordingly, forecasts of forest carbon would be affected by changes in the area of forests and in the amount of biomass as described earlier. Figure 93 shows forecasts of future forest carbon in the Pacific Coast Region and a gradual decline in the amount of carbon in forest pools between 2010 and 2060. Total forest carbon declines to between 7.1 billion and 7.5 billion tons (or a loss of between 4 and 9 percent) over this period. Patterns of loss are dominated by the change in growing stock volumes (forest area loss is relatively small in this region over the simulation period).

Estimates of the total carbon stored in forests derive from summing estimates of the carbon stored in eight different compartments or pools in forested ecosystems. Aboveground pools include live trees, understory plants, down and standing dead trees, and litter. Belowground pools include root material

for live trees, understory plants, and soil organic matter.

The sum of soil organic matter, aboveground live trees, and belowground live trees comprises nearly 80 percent of the total and forecasts for these three pools are shown in figs. 94A through C. Losses of soil organic carbon are greater than the slight downward trend in total forest area in the region (5–8 percent versus 1–3 percent). We posit that they also reflect changes in forest types associated with the climate futures. Live tree above- and belowground carbon pools show patterns of change that are very similar to forecasts for growing stock inventories, e.g., a decline of 6–13 percent for live tree aboveground pools.

Removals

Forecasts of removals for the nine scenario-climate combinations without links to the Forest Product Model outputs are driven by harvest probabilities assigned to plots based on ownership types, forest type, and age class and adjusted to reflect recent historical regional removal patterns. Applying these probabilities to forecasted forest inventories (i.e., accounting for climate, forest type shifts, and aging), yields a set of removals forecasts that extends historical patterns to future conditions. For eight of the nine combinations, forecasted softwood removals (about 83 percent of total removals) increase over the first 20 years

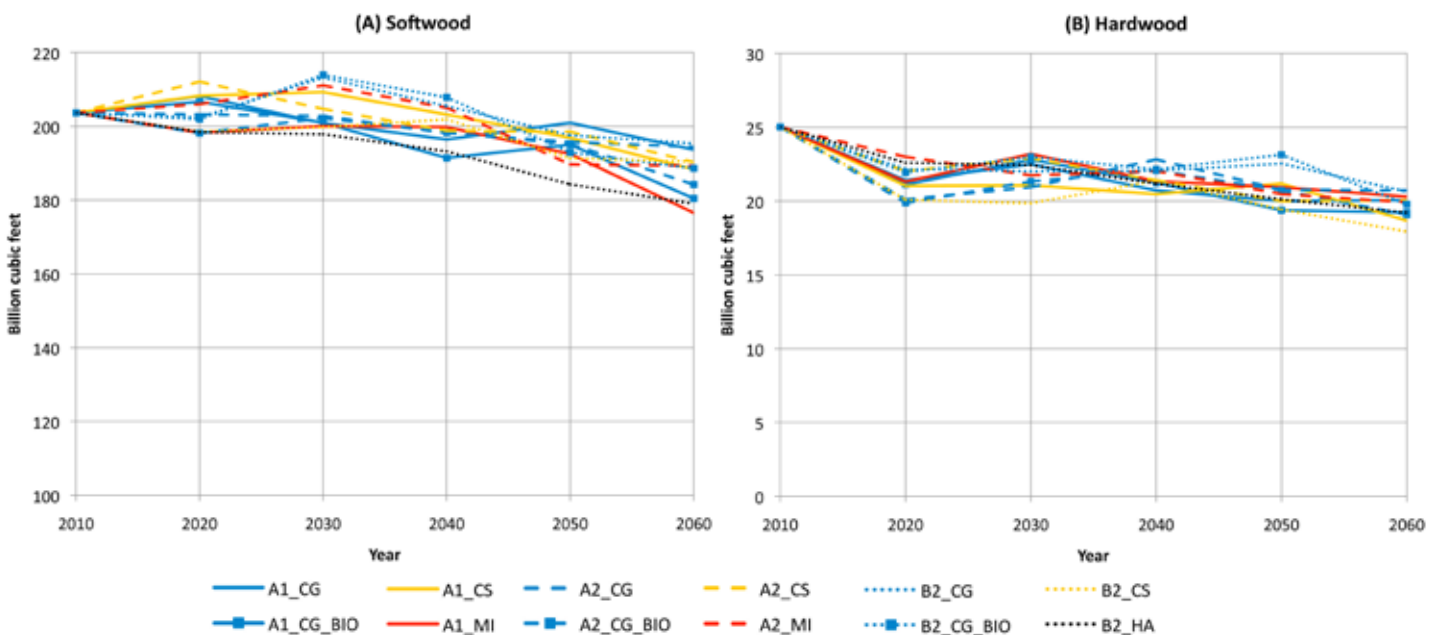


Figure 91—Forecasted biomass measured as growing stock inventory of forests in the Pacific Coast Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010-2060. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

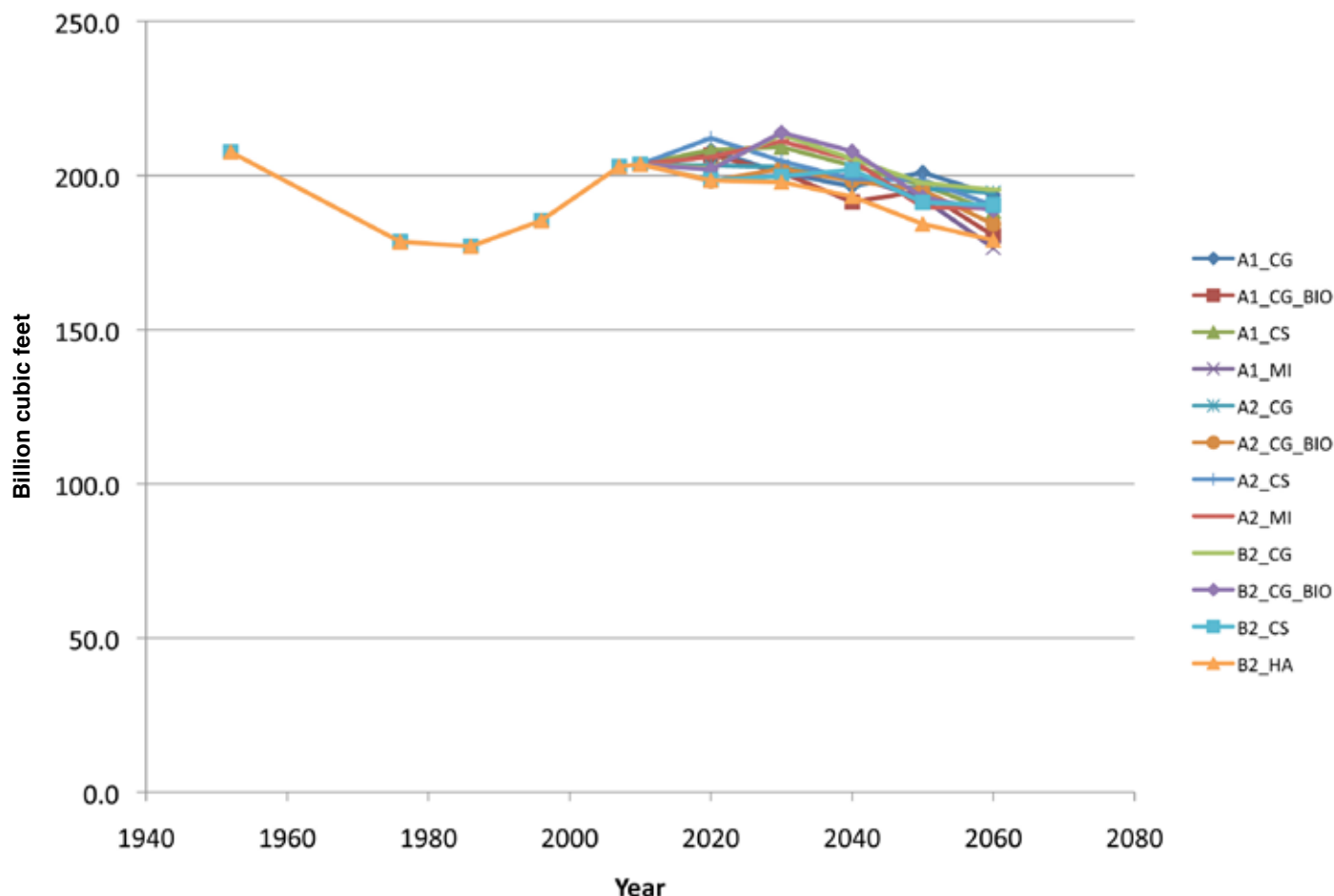


Figure 92—Softwood growing stock in the Pacific Coast Region, 1953–2060.

and then decline slightly (fig. 95A). In 2060, softwood removals would be between 77 and 97 percent of 2010 values.

Softwood removals forecast for the three market scenarios are based on the CGCM3.1 GCM for scenarios RPA A1B and RPA A2 and the CGCM2 GCM for scenario RPA B2. The 2060 removals reflect increases over the 2010 removals level by roughly 3, 29, and 40 percent for the RPA B2, A2, and A1B scenarios, respectively and A1B and A2 removals are substantially larger than forecasts for the nine RPA scenario-climate combinations (fig. 95A). Hardwood removals, which are a very small portion of total removals in the Pacific Coast Region, do not differ substantially between the market scenarios nor among the nine RPA scenario-climate combinations (fig. 95B). Hardwood removals, which comprised a small portion of harvests in 2010 (17 percent), decline throughout the forecasts. All nine combinations yield substantial declines in hardwood removals—2060 removals

levels amount to about 50 percent of their 2010 values. A comparison of forecasted harvest removals under even the A1B market scenario would not begin to approach peak harvest levels achieved in the early 1990s (fig. 96).

Figure 97 compares the West's (Rocky Mountain plus Pacific Coast regions) timber harvest forecasts from the Forest Products Model with the implied harvests from the Forest Dynamics Model, and shows that harvest forecasts are largely consistent between the models for the specific scenarios. Forest Dynamics Model harvest removals are within 10 percent of harvest removals from the Forest Products Model for all periods and scenarios, with one exception. As is the case in the other regions, the RPA A1B Forest Products Model projection is higher than the Forest Dynamics Model projections in the last 2 decades of the simulation—by roughly 20 percent in the West. Total removals match fairly closely for the entire simulation period. The Forest Dynamics Model projects 94,

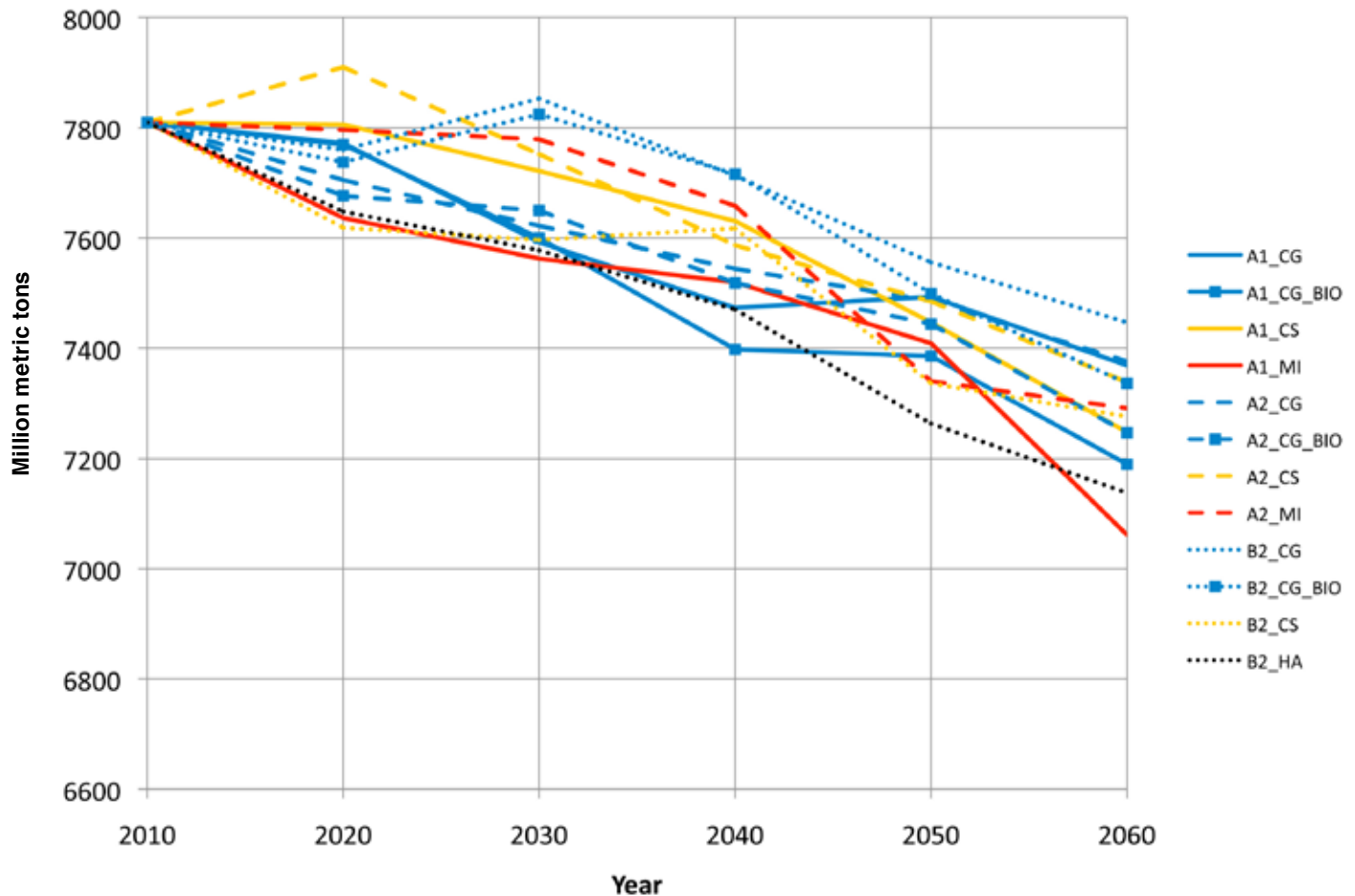


Figure 93—Forecasts of total carbon stored within forests in the Pacific Coast Region, 2010–60, for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

101, and 101 percent of total removals forecast by RPA A1B, A2, and B2 scenarios, respectively.

Age Structure/Habitat

Age class distributions are affected by the starting distributions and by disturbance regimes forecast for forests in the future. Simulated inventories can be used to evaluate various aspects of future forest conditions. One aspect of significance to wildlife habitat conditions in the Pacific Coast Region is the distribution of forests by age class, and the implications for the provision of early, middle, and late age forest conditions. We evaluate changes in the age class distributions of softwood forest types using two charts. One displays the aerial age class distribution by decade for the most recent inventories of the Pacific Coast Region. We then summarize changes in age class resulting from the nine RPA scenario-climate combinations between 2010 and 2060 using box plots. Figure 98 shows the

current age class distribution for hardwood forests in the Pacific Coast Region by 20-year age classes. Each box plot describes the distributions of changes in age classes. The bottom of the box represents the 25th percentile of the predicted changes, the top of the box represents the 75th percentile of the predicted changes, the line in the box indicates the median forecast, and the plus in the box indicates the mean forecast. The “whiskers” of the box show the extreme values of the forecasts.

The 2010 age class distribution of forests in the Pacific Coast Region is strongly peaked in the 61–80 age category, reflecting harvest history in the region (fig. 98). As harvests and other disturbances are applied, 50-year forecasts shift this peak out and flatten the age class distribution. The oldest age class remains relatively constant in this area, reflecting an offsetting of mortality and recruitment and the area of the youngest age classes (0–20 and 21–40) remains relatively constant between 2010 and 2060 across the scenarios.

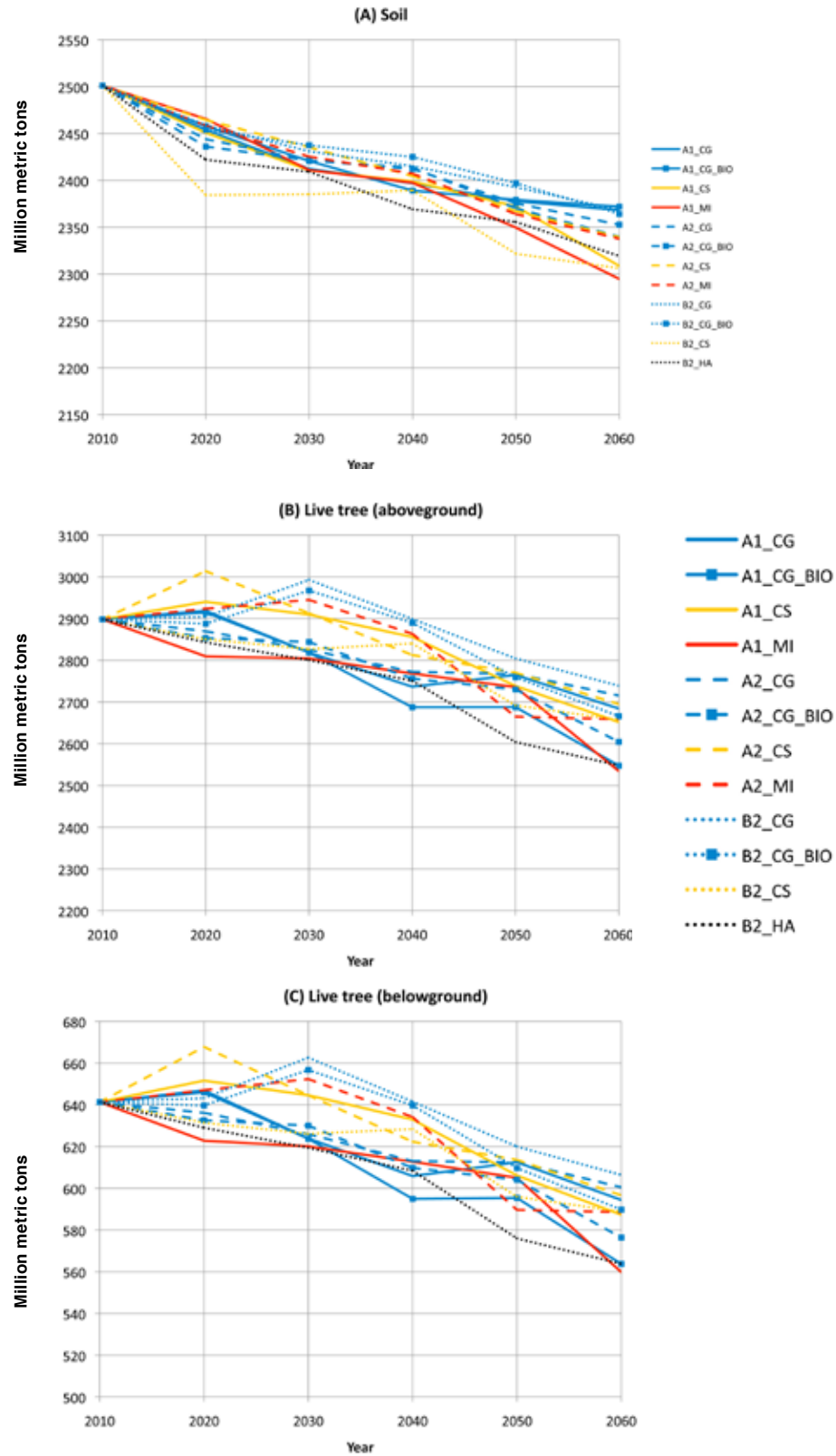


Figure 94—Forecasts of carbon stored in various pools within forests in the Pacific Coast Region, 2010–60, for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

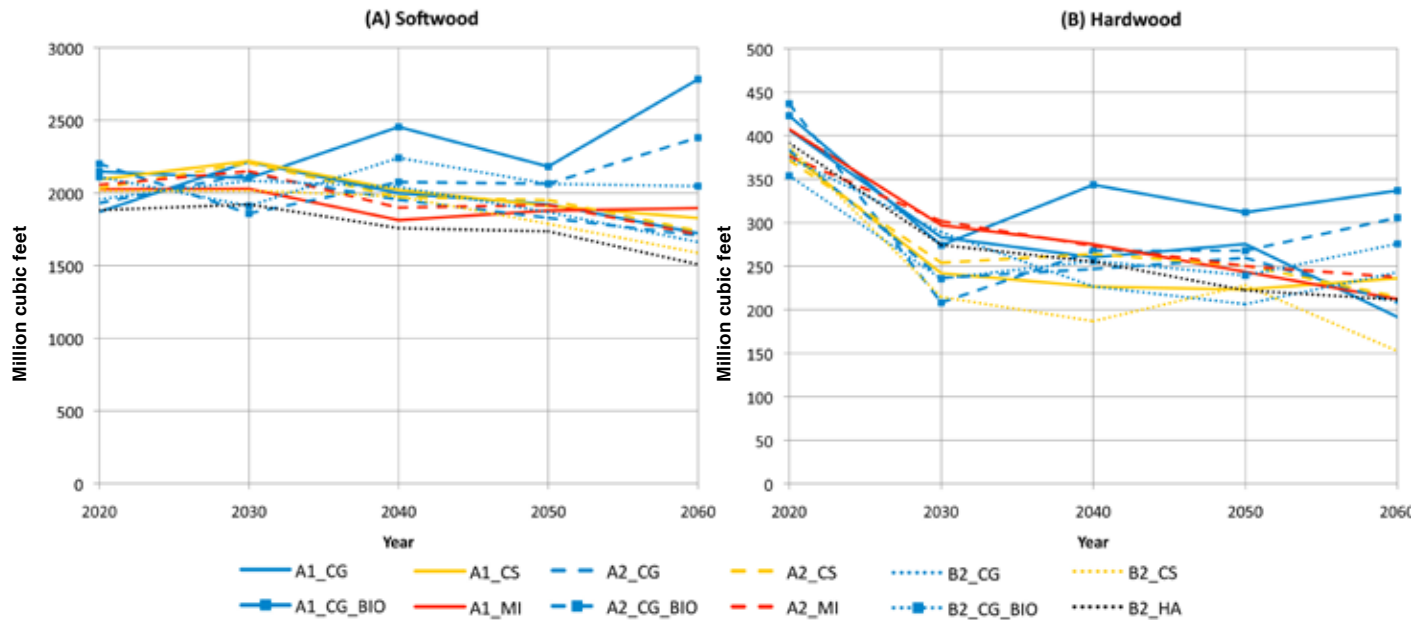


Figure 95—Removals from inventory in the Pacific Coast Region for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

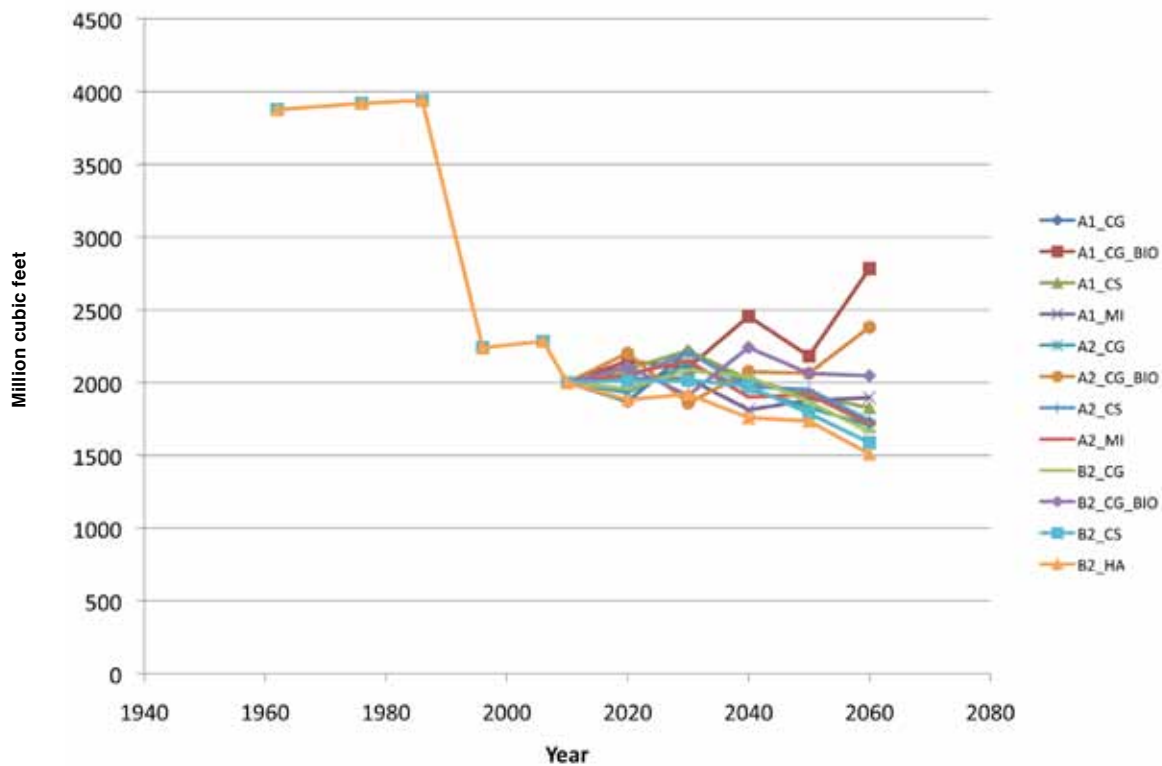


Figure 96—Softwood removals from growing stock for nine Resources Planning Act (RPA) scenario-climate combinations with harvesting based on historical behavior and three RPA scenario-climate combinations with harvesting based on the U.S. Forest Products Model, 2010–60. RPA A1B scenarios are represented by solid lines; RPA A2 dashed; RPA B2 dotted. MIROC3.2 general circulation model (GCM) is represented by red; CGCM (CGCM3.2 for A2 and CGCM2 for B2) by blue; CSIRO (CSIRO-Mk3.5 for A1B and A2 and CSIRO-Mk2 for B2) by yellow; HadCM3 by black. Lines with blocks indicate the market scenario for the respective RPA scenario (all using the CGCM GCM).

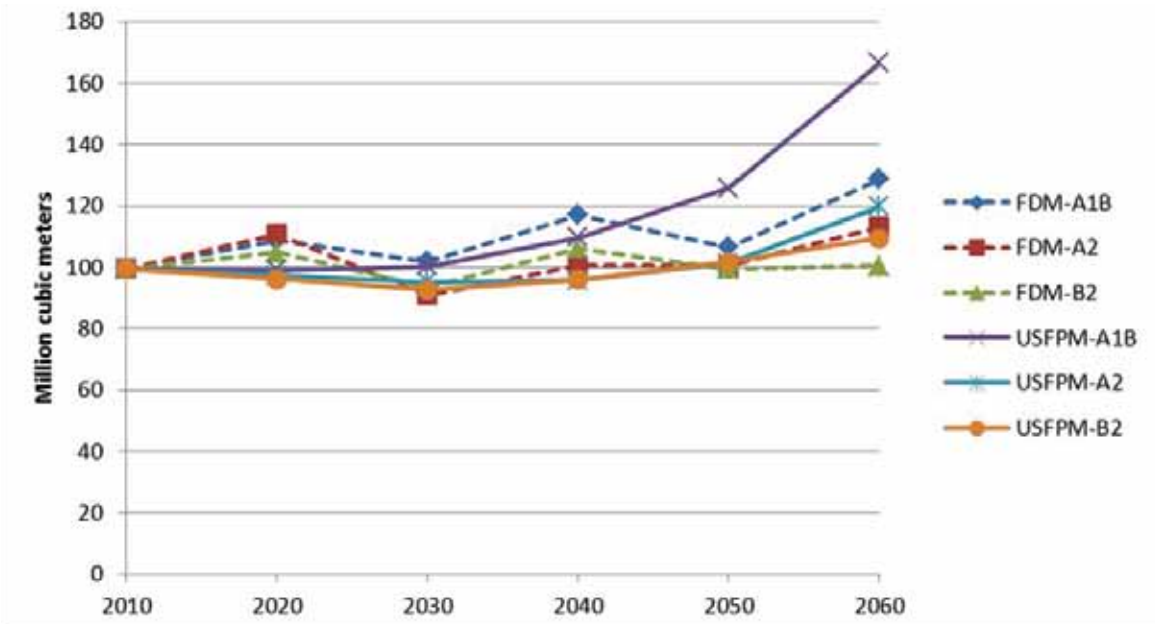


Figure 97—Comparison of harvests predicted by U.S. Forest Products Model and the Forest Dynamics Model scenario associated with the U.S. Forest Products Model scenario for the Western United States (defined as the combination of the Rocky Mountain and Pacific Coast regions).

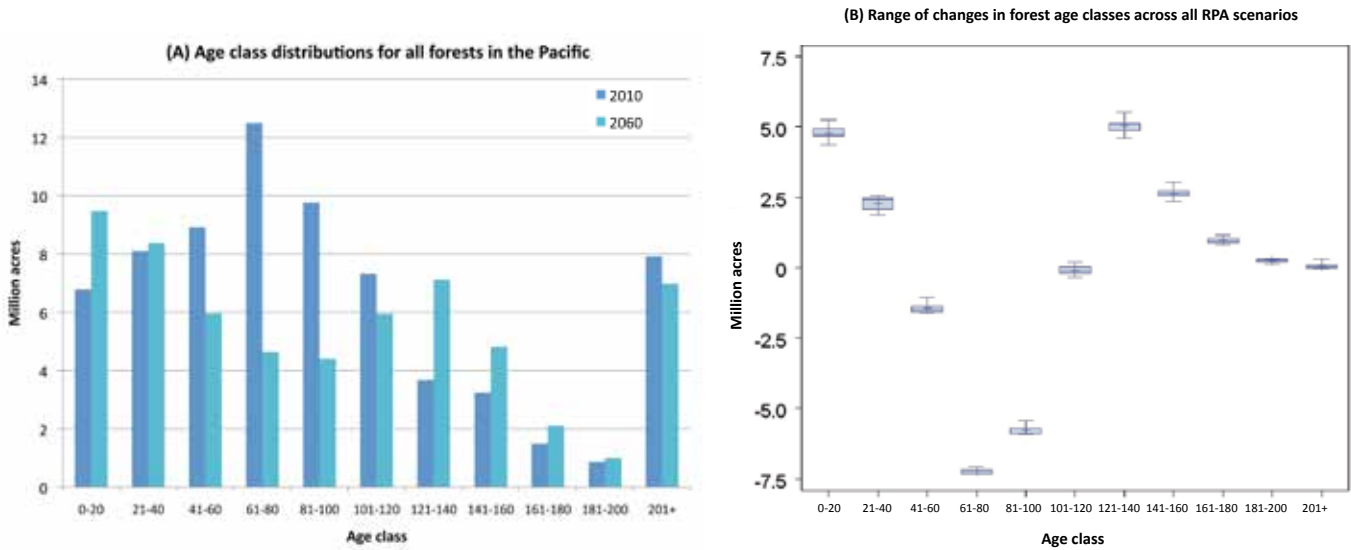


Figure 98—(A) Age class distributions for all forests in the Pacific Coast Region, 2010 and 2060, for the B2-HadCM3 scenario and (B) the range of changes in forest age classes across all Resources Planning Act (RPA) scenarios.

Discussion

Forecasts of forest conditions in the Pacific Coast Region indicate a loss of 2–3 percent of forest area, amounting to 1.7–2.7 million acres between 2010 and 2060, with most of this loss concentrated in the highly productive Westside forests of Oregon and Washington. This forest loss has implications for the standing biomass in the region with a decline in softwood and hardwood growing stock volumes between 2010 and 2060. Due to land area and growing stock declines overall, the total amount of carbon stored in Pacific Coast Region forest is also forecast to decline, falling between 4 and 9 percent between 2010 and 2060.

While forecasts of overall forest area, biomass, and carbon attributes change gradually over time, change in forest types is more substantial. For the Westside of the Cascades, the area of the hemlock-Sitka spruce forest type group is forecast to decline substantially (50–85 percent) while the Douglas fir forest type group increases. While we caution against over-interpreting forecasts for small forest area (at 4 million acres hemlock-Sitka spruce represents about 5 percent of forest area in 2010) our forecasts indicate especially important shifts in the habitat suitability for this forest type over all the climate scenarios considered here. This is consistent with Hansen and

others' (2001) finding that habitats for rainforest conifers in the Pacific Northwest are likely to decline in area as a response to anticipated climate changes.

The dominant forest type dynamic for inland forests in the Pacific Coast Region are declines in the subalpine spruce-fir-hemlock forest type group (20–60 percent) and a strong increase in ponderosa pine forest type group (30–96 percent) between 2010 and 2060. Similar patterns of change have been forecast by Rehfeldt and others (2006), who simulate loss of suitable habitat for *Picea engelmannii* (47 percent across the Rocky Mountain and Pacific Coast regions by 2060), and gains in suitable habitat for *Pinus ponderosa* (11 percent by 2060). Both are consistent with overall declines in subalpine vegetation simulated by Rehfeldt and others (2008) and by Bachelet and others (2001) under various climate futures.

While the trends are generally consistent across scenarios, the broad range of the forecasts for forest type areas indicates that these forecasts are sensitive to climate futures. Futures generated using the CGCM3.2 and CGCM2 produced the least change across most variables; the HadCM3 and MIROC3.2 GCMs, with the warmest and driest futures, generally produced the most change in key variables from forest type areas to carbon storage.

CONCLUSIONS

In this report, we describe 50-year forecasts of forest conditions for several scenarios regarding future demographic, economic, and climate conditions. Forecasts define a range of plausible futures for forests reflecting the breadth of the Resources Planning Act (RPA) scenarios, as interpreted by a set of models and the design of the U.S. Forest Assessment System. The Forest Dynamics Model defines forecasts that directly simulate change in the forest inventories conducted by the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture. Forecast variables therefore correspond directly to the measures used to monitor the Nation's forest conditions, and establish a means of evaluating the performance of forecasts using subsequent inventories. In a sense, this defines the Forest Assessment System as a "hypothesis generator" regarding the future of forest inventories in the United States, with hypotheses defined using metrics consistent with the ongoing monitoring system.

The Forest Dynamics Model attempts to draw maximum information from the data contained in the FIA system to forecast future inventories. Future measured inventories should provide additional information for improving the various component elements of the model and for validating/invalidating forecast performance. Additional panels of data for the Western United States, where it is not yet possible to match plots between successive inventories, should prove especially useful, but new inventories will allow the refinement of models in all regions, e.g., in the South where data are already relatively plentiful but where harvesting is the most frequent and land use dynamics are the most rapid in the United States.

Any modeling approach has strengths and weaknesses. In the case of the Forest Dynamics Model, use of historical plot imputations allows for forecasts of forest conditions that preserve the joint distributions of the many plot measures contained within the FIA system (Reams and McCullum 2000). This coherence depends on the assumption that the constituent elements of the future inventory (plots) will be consistent with the universe of historical plot observations—for example, that a forest plot of forest type X at age Y with average temperature Z in the future can be represented by a historical forest plot with X, Y, and Z attributes. In effect we assume that "novel" or "no-analog" conditions are unlikely to arise over the 50-year timeframe evaluated with these models.

Several potential sources of novelty might be anticipated. Climate novelty (Williams and Jackson 2007) occurs where future climate conditions are unprecedented within a region. While the extent of novelty may be much greater over a

100-year forecast period, our analysis indicates relatively low occurrences of significant shifts in temperature and precipitation distributions in the first three decades of the five decade period considered by the RPA Assessment. Novelty could also occur where the intersection of climate and site variables give rise to favorable conditions for an unprecedented combination of tree species (Iverson and others 2008, Rehfeldt and others 2006). Atmospheric composition defines another potential source of novelty, e.g., CO₂ fertilization has enhanced tree growth in controlled experiments (Norby and others 2005).

Our approach to imputing future forest plots by resampling from plots of forest type groups allows for shifts in species composition both within and between type groups. For example, while a plot might retain its assignment to the oak/hickory type group (500), its resampled type could shift from yellow poplar/white oak (506) to white oak/red oak/hickory (503) in response to climate changes and forest aging. Still all species combinations are restricted to those observed within the universe of measured FIA plots contained in the donor pool. Iverson and others (2008) in the East and Rehfeldt and others (2006) in the West indicate a potential for structural shifts in species mixes over a 100-year timeframe with the extent of change depending on the severity of the projected climate changes. Our decision to retain historical forest type associations is fundamental to the use of the imputation approach—without it, the species structure of novel plots would need to be constructed introducing new sources of forecast error—and might be justified based on the 50-year timeframe of the forecasts and the inertia of forest ecosystems. The degree to which this assumption could be violated is expected to be directly proportional to the timeframe of the forecasts. Uncertainty regarding the plausibility of predicted forest composition increases over time.

The inertia of existing forest ecosystems likewise depends on the future of forest disturbance regimes across the regions of the United States (Turner 2008). Our modeling approach forecasts forest conditions based on disturbance dynamics reflected in historical inventories, e.g., a proportion of southern pine forests reflect damage from southern pine beetle in the South consistent with historical insect dynamics, and a proportion of lodgepole pine forests in the West reflects historical mountain pine beetle dynamics. In the East and the Pacific Coast regions, we explicitly forecast timber harvesting but leave other disturbance activities as "background" disturbances—not explicitly modeled but influencing forest conditions through donor pools. In the Rocky Mountains Region, we explicitly model probabilities of fire and insect

damage (as measured on the FIA plots and as a function of climate and site variables) and then the probability of a stand replacement contingent on these events. Unprecedented disturbance vectors, for example those generated by new nonnative pests, have not been addressed. Incorporating their effects defines a potentially useful line of future inquiry, e.g., in ongoing work, we are addressing the spread of emerald ash borer in the North Region.

Carbon accounting allows for a comprehensive evaluation of forest carbon pools consistent with inventory measures of carbon and potentially policy relevant information from the forecasts. This accounts for the temporal dynamics of forests and how they may be influenced by human uses, disturbances, and climate-driven productivity changes. Our approach is to monitor net carbon change consistent with all of these dynamics. Our findings highlight different carbon trajectories in the various regions of the United States. In the South, carbon stocks reach a peak and then either level off or decline somewhat depending on the scenario. In general, losses due to removals are offset by strong growth and management responses. In western regions, where removals are small portions of standing inventories, carbon stocks are flat to declining as forests reach ages where mortality begins to outweigh removals. The greatest potential decrease in carbon forecast is in the North where, under RPA scenario A1B, removals could increase substantially but countervailing investment in forest management is not simulated. This type of unprecedented demand futures would likely lead to unprecedented management responses in the North, but this was not addressed by the models. Nationwide, the greatest influence on future carbon is forecasted change in forest area related to urbanization. Some portion of the projected loss of carbon from forest pools would therefore be transferred to carbon stored in other land uses, e.g., suburban or crop uses, and would not be emitted to the atmosphere. Ongoing analysis addresses these carbon transfers among land uses.

The Forest Assessment System is designed to support strategic analysis of forest conditions in the United States as a part of the RPA assessment and in support of various forest futuring efforts. The results presented in this paper describe the first implementation of this modeling system and we anticipate refining the methods and updating models as new data become available from FIA. Future work on the Forest Dynamics Model will focus on refining the algorithms used to transition forest plots through time, including forest type transitions and forest harvesting. The latter is an essential element of the linkage between the Forest Dynamics Model and Forest Products Model. As currently formulated, the model allows for economic modeling of harvest choices on plots only for the South, where data are the most plentiful. In other regions, we rely on aggregate supply equations to simulate markets in the Forest Products Model and downscale harvests in the

Forest Dynamics Model to plots by adjusting relative harvest probabilities for various plot types. Regional differences among forest type transition models reflect differences in data availability. Future models might further consider the timeframe of potential transitions and differentiate models to ask short-run and long-run questions.

Additional work is needed to more precisely address the potential for and implications of novel conditions and to explore methods for examining unprecedented forest conditions in the future. In addition to exploring potential climate novelty, models might examine the influence of highly invasive pest species, e.g., emerald ash borer, expanded forest management (especially in the North Region), and genetically modified production forests (especially in the South). All elements of the modeling should be improved as additional panels of data are provided by the ongoing FIA forest inventories across the United States.

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LITERATURE CITED

- Alig, R.J.; Zheng, D.; Spies, T.A.; Butler, B.J. 2000. Forest cover dynamics in the Pacific Northwest west side: regional trends and projections. Res. Pap. PNW-RP-522. Portland, OR: U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station. 22 p.
- Bachelet, R.R.; Neilson, P.; Lenihan, J.M.; Drapek, R.J. 2001. Climate change effects on vegetation distribution and carbon budget in the United States. *Ecosystems*. 4(1): 161-185.
- Breiman, L.; Friedman, J.H.; Olshen, R.A.; Stone, C.J. 1984. Classification and regression trees. Belmont, CA: Wadsworth International Group. 358 p.
- Buongiorno, J.; Zhu, S.; Runikar, R.; Prestemon, J. 2012. Outlook to 2060 for world forests and forest industries: a technical document supporting the Forest Service 2010 RPA Assessment. Gen. Tech. Rep. SRS-151. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 119 p.
- Buongiorno, J.; Zhu, S.; Zhang, D. [and others]. 2003. The Global Forest Products Model: structure, estimation, and applications. San Diego: Academic Press/Elsevier. 301 p.
- Butler, B.; Wear, D.N. [In press]. Forest ownership. In: Wear, D.N.; Greis, J.G., eds. The southern forest futures project: technical report. Gen. Tech. Rep. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station.

- Cortes, C.; Vapnik, C. 1995. Support-vector networks. *Machine Learning*. 20: 273-297.
- Coulson, D.P.; Joyce, L.A.; Price, D.T. [and others]. 2010a. Climate scenarios for the conterminous United States at the county spatial scale using SRES scenarios A1B and A2 and PRISM climatology. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Research Station. http://www.fs.fed.us/rm/data_archive/dataaccess/US_ClimateScenarios_county_A1B_A2_PRISM.shtml. [Date accessed: August 3, 2010].
- Coulson, D.P.; Joyce, L.A.; Price, D.T.; McKenney, D.W. 2010b. Climate scenarios for the conterminous United States at the county spatial scale using SRES scenario B2 and PRISM climatology. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Research Station. http://www.fs.fed.us/rm/data_archive/dataaccess/US_ClimateScenarios_county_B2_PRISM.shtml. [Date accessed: August 3, 2010].
- Coulson, D.P.; Joyce, L.A. 2010. Historical climate data (1940–2006) for the conterminous United States at the county spatial scale based on PRISM climatology. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Research Station. http://www.fs.fed.us/rm/data_archive/dataaccess/US_HistClimateScenarios_county_PRISM.shtml. [Date accessed: August 2, 2010].
- De'ath, G.; Fabricius, K.E. 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. *Ecology*. 81(11): 3178-3192.
- Ford, B.L. 1983. An overview of hot-deck procedures. In: Madow, W.G.; Olkin, I.; Rubin, D.B., eds. *Incomplete Data in Sample Surveys* vol. 2, Part IV. New York: Academic Press Inc: 185-207.
- Gosz, J.R.; Sharpe, P.J.H. 1989. Broad scale concepts for interactions of climate, topography, and biota at biome transitions. *Landscape Ecology*. 3(3/4): 229-243.
- Hansen, A.J.; Nielson, R.P.; Dale, V.H. [and others]. Global change in forests: responses of species, communities, and biomes. *BioScience*. 51(9): 765-779.
- Haynes, R.W.; Adams, D.M. 1985. Simulations of the effects of alternative assumptions on demand-supply determinants on the timber situation in the United States. Washington, DC: U.S. Department of Agriculture Forest Service, Forest Resources Economics Research. 113 p.
- Haynes, R.W.; Adams, D.M.; Alig, R.J. [and others]. 2007. The 2005 RPA timber assessment update. Gen. Tech. Rep. PNW-GTR-699. Portland, OR: U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station. 212 p.
- Haynes, R.W., coord. 1990. An analysis of the timber situation in the United States 1989–2040. Gen. Tech. Rep. PNW-GTR-199. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Forest and Range Experiment Station. 286 p.
- Haynes, R.W.; Adams, D.M.; Mills, J.R. 1995. The 1993 RPA timber assessment update. Gen. Tech. Rep. RM-GTR-259. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Forest and Range Experiment Station. 66 p.
- Ince, P.J.; Kramp, A.D.; Skog, K.E. [and others]. 2011. U.S. Forest Products Module for RPA forest assessment. Research Paper FPL-RP-662. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 61 p.
- Intergovernmental Panel on Climate Change (IPCC). 2007a. Climate change 2007, the fourth IPCC assessment report. <http://www.ipcc.ch/ipccreports/index.htm>. [Date accessed: December 2008].
- IPCC. 2007b. General guidelines on the use of scenario data for climate impact and adaptation assessment. http://www.ipcc-data.org/guidelines/TGICA_guidance_sdciaa_v2_final.pdf. [Date accessed: January 27, 2010].
- Iverson, L.R.; Prasad, A.M. 1998. Predicting abundance of 80 tree species following climate change in the Eastern United States. *Ecological Monographs*. 68(4): 465-485.
- Iverson, L.R.; Prasad, A.M.; Matthews, S.N.; Peters, M. 2008. Estimating potential habitat for 134 Eastern U.S. tree species under six climate scenarios. *Forest Ecology and Management*. 254: 390-406.
- Joyce, L.A.; Price, D.T.; McKenney, D.W. [and others]. 2011. High resolution interpolation of climate scenarios for the conterminous United States and Alaska derived from general circulation model simulations. Gen. Tech. Rep. RMRS-GTR-263. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Research Station. 87 p.
- Joyce, L.A.; Price, D.T.; Coulson, D.P. [and others]. [In press]. Projecting climate change in the United States: a technical document supporting the Forest Service RPA 2010 assessment. Gen. Tech. Rep. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Research Station.
- McKeand, S.; Mullin, T.; Byram, T.; White, T. 2003. Deployment of genetically improved loblolly and slash pines in the South. *Journal of Forestry*. 101(3): 32-37.
- Miles, P.D.; Brand, G.J.; Alerich, C.L. [and others]. 2001. The Forest Inventory and Analysis database: database description and users manual version 1.0. Gen. Tech. Rep. NC-218. St. Paul, MN: U.S. Department of Agriculture Forest Service, North Central Research Station.
- Mills, J.R.; Kincaid, J.C. 1992. The aggregate timberland assessment system—ATLAS: a comprehensive timber projection model. Gen. Tech. Rep. PNW-GTR-281. Portland, OR: U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station. 160 p.
- Mills, J.R.; Zhou, X. 2003. Projecting national forest inventories for the 2000 RPA timber assessment. Gen. Tech. Rep. PNW-GTR-568. Portland OR: U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station. 58 p.
- Moisen, G.G.; Frescino, T.S. 2002. Comparing five modeling techniques for predicting forest characteristics. *Ecological Modeling*. 157: 209-225.
- Nakicenovic, N.; Swart, R., eds. 2000. Special report on emissions Scenarios. A special report of working group iii of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom, and New York, NY, USA. Cambridge University Press. 599 p. <http://www.ipcc.ch/ipccreports/sres/emission/index.htm> [Date accessed: May 22, 2012].
- NIST/SEMATECH. 2012. e-Handbook of Statistical Methods. <http://www.itl.nist.gov/div898/handbook/>. [Date accessed: May 22, 2012].
- Norby, R.J.; DeLucia, E.H.; Gielen, B. [and others]. 2005. Forest response to elevated CO₂ is conserved across a broad range of productivity. *Proceedings of the National Academy of Sciences*. 102: 18,052–18,056.
- Penman, J.; Gytarsky, M.; Hiraishi, T. [and others], eds. 2003. Good practice guidance for land use, land use change, and forestry. Hayama, Kanagawa, Japan: Institute for Global Environmental Strategies for the Intergovernmental Panel on Climate Change. 502 p. <http://www.ipcc-nggip.iges.or.jp/public/gpplucf/gpplucf.htm>. [Date accessed: April 13, 2007].
- Polyakov, M.; Wear, D.N.; Huggett, R. 2010. Harvest choice and timber supply models for forest forecasting. *Forest Science*. 56(4): 344-355.
- Press, W.H.; Flannery, B.P.; Teukolsky, S.A.; Vetterling, W.T. 1987. Numerical recipes: the art of scientific computing. New York: Cambridge University Press. 818 p.
- Price, D.T.; McKenney, D.W.; Papadopol, P. [and others]. 2004. High resolution future scenario climate data for North America. In: *Proceedings of the 26th Conference on Agricultural and Forest Meteorology*. Boston, MA: American Meteorological Society: 1-13. Vol. 77.

- Reams, G.A.; McCollum, J.M.** 2000. The use of multiple imputation in the southern annual forest inventory system. In: Hansen, M.H.; Burk, T., eds. Integrated tools for natural resource inventories in the 21st century: an international conference on the inventory and monitoring of forested ecosystems. Gen. Tech. Rep. NC-212. Boise, ID: U.S. Department of Agriculture Forest Service, North Central Research Station: 228-233.
- Rehfeldt, G.E.; Crookston, N.L.; Warwell, M.V.; Evans, J.S.** 2006. Empirical analyses of plant-climate relationships for the Western United States. *International Journal of Plant Science*. 167(6): 1123-1150.
- Rehfeldt, G.E.; Ferguson, D.E.; Crookston, N.L.** 2008. Quantifying the abundance of co-occurring conifers along Inland Northwest (USA) climate gradients. *Ecology*. 89(8): 2127-2139.
- Shafer, S.L.; Bartlein, P.J.; Thompson, R.S.** 2001. Potential changes in the distributions of western North America tree and shrub taxa under future climate scenarios. *Ecosystems*. 4(1): 200-215.
- Smith, J.E.; Heath, L.S.; Nichols, M.C.** 2007. U.S. forest carbon calculation tool: forest-land carbon stocks and net annual stock change. Gen Tech. Rep. NRS-13. Newtown Square, PA: U.S. Department of Agriculture Forest Service, Northern Research Station. 28 p.
- Smith, W.B., tech. coord.; Miles, P.D., data coord.; Perry, C.H., map coord.; Pugh, S.A., data CD coord.** 2009. Forest Resources of the United States, 2007. Gen. Tech. Rep. WO-78. Washington, DC: U.S. Department of Agriculture Forest Service, Washington Office. 336 p.
- Turner, M.G.** 2008. Disturbance and landscape dynamics in a changing world. *Ecology*. 91(10): 2833-2849.
- U.S. Department of Agriculture (USDA) Forest Service.** 1920. Timber depletion, lumber prices, lumber exports, and concentration of timber ownership. Report on Senate Res. 311, 66th Congress, 2d session. [The Caper Report]. Washington, DC: U.S. Government Printing Office. 71 p.
- USDA Forest Service.** 1933. A national plan for American forestry. S. Doc. 12, 73rd Congress, 1st session. [The Copeland Report.]. 2 vols. Washington, DC: U.S. Government Printing Office. 1677 p.
- USDA Forest Service.** 1958. Timber resources for America's future. [The Timber Resources Review Report.] For. Resour. Rep. 14. Washington, DC: U.S. Government Printing Office. 713 p.
- USDA Forest Service.** 1965. Timber trends in the United States. For. Resour. Rep. 17. Washington, DC: U.S. Government Printing Office. 235 p.
- USDA Forest Service.** 1974. The outlook for timber in the United States. For. Resour. Rep. 20. Washington, DC: U.S. Government Printing Office. 367 p.
- USDA Forest Service.** 1982. An analysis of the timber situation in the United States: 1952-2030. For. Resour. Rep. 23. Washington, DC: U.S. Government Printing Office. 499 p.
- USDA Forest Service.** 2001. 2000 RPA assessment of forest and range lands. FS-687. Washington DC: U.S. Department of Agriculture, Forest Service. 78 p.
- USDA Forest Service.** 2005. Projections of timber harvest in western Oregon and Washington by county, owner, forest type, and age class. Gen. Tech. Rep. PNW-GTR-633. Portland, OR: U.S. Department of Agriculture Forest Service, Pacific Northwest Research Station. 30 p.
- USDA Forest Service.** [In press]. Future scenarios: a technical document supporting the Forest Service 2010 RPA Assessment. Gen. Tech. Rep. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.
- USDA Natural Resources Conservation Service.** 2000. Summary report 1997 National Resources Inventory (revised December 2000). Ames, IA: Iowa State University, Statistical Laboratory. 94 p. http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs143_012094.pdf. [Date accessed: October 13, 2011].
- Van Deusen, P.C.** 1997. Annual forest inventory statistical concepts with emphasis on multiple imputation. *Canadian Journal of Forest Research*. 27: 379-384.
- Van Deusen, P.C.** 2006. Projecting biomass in Georgia with inventory plot matching and harvest scheduling. *Canadian Journal of Forest Research*. 99: 1-12.
- Vokoun, M.; Wear, D.N.; Abt, R.C.** 2009. Testing for change in structural elements of forest inventories. *Forest Science*. 55(5): 455-466.
- Wear, D.N.** 2011. Forecasts of county-level land uses under three future scenarios: a technical document supporting the Forest Service 2010 RPA Assessment. Gen. Tech. Rep. SRS-141. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 41 p.
- Wear, D.N.; Greis, J.G., eds.** [In press]. The southern forest futures project: technical report. Gen. Tech. Rep. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station.
- Williams, J.W.; Jackson, S.T.** 2007. Novel climates, no-analog communities, and ecological surprises. *Frontiers in Ecology and the Environment*. 5(9): 475-482.
- Woods and Poole Economics.** 2007. Complete Economic Data Source (CEDDS) technical documentation. Washington, DC: Woods and Poole Economics, Inc. 101 p.
- Woudenbergh, S.W.; Conkling, B.L.; O'Connell, B.M. [and others].** 2010. The forest inventory and analysis database: database description and user's manual version 4.0 for phase 2. Gen. Tech. Rep. RMS-GTR-245. Fort Collins, CO: U.S. Department of Agriculture Forest Service, Rocky Mountain Research Station. 336 p.
- Zarnoch, S.J.; Cordell, H.K.; Betz, C.J.; Langner, L.** 2010. Projecting county-level populations under three future scenarios: a technical document supporting the Forest Service 2010 RPA assessment. e-Gen. Tech. Rep. SRS-128. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 8 p.

APPENDIX: STRUCTURE OF THE FOREST DYNAMICS MODEL

This report focuses on the forecasts of forest conditions provided by the Forest Dynamics Model (fig. A1). Discussion of methods concentrates on this component of the U.S. Forest Assessment System (fig. 1), while the U.S. Forest Products Model is described in Ince and others (2011) and the All Land Use Model is described in Wear (2011).

Within the Forest Dynamics Model, forecasts of the development of forest conditions in the United States are constructed for each observed forest plot in the inventories.¹ This is the constituent scale of the inventory of the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture, and forecasting at this level allows for re-aggregation of findings at different scales of resolution, though not at levels finer than appropriate for reporting historical inventory data. For example, forecasts described in this report have also been used as a foundation of the Southern Forest Futures Project (Wear and Greis, in press) and the Northern Forest Futures Project (<http://nrs.fs.fed.us/futures/>). To the extent possible, simulations start with direct evaluation of FIA plot data and results are expanded to broader scales using the area frame design of the forest survey. These methods generate full inventory datasets for each time step of the forecast.

To model and forecast changes in forest conditions, the U.S. Forest Assessment System forecasts the condition of each plot in the forest inventory in response to multiple vectors of change. Each plot record contains a set of measured variables combined with an expansion factor which describe the area (portion of the sampled population of forests) that each plot represents. Expansion factors are reconciled at the county level in the FIA system. The information set for each plot $I(p)$ is defined as:

$$I(p) = \{S, Z, C, E\} \quad (1)$$

where

S represents a vector of state variables

Z = a vector of condition variables

C = a vector of climate variables

E = a vector of expansion factors for the plot

S and Z together comprise the measured variables for each plot from phase 2 (field measurements) of the FIA inventory

¹ The use of the term “plot” in this report refers to what is technically called a “condition” within a plot in the FIA system. Where plots can have more than one forest condition, e.g., they occur on a boundary between forest types, then multiple conditions are recorded for each plot. Use of the word “plot” simplifies the language in this report without loss of precision.

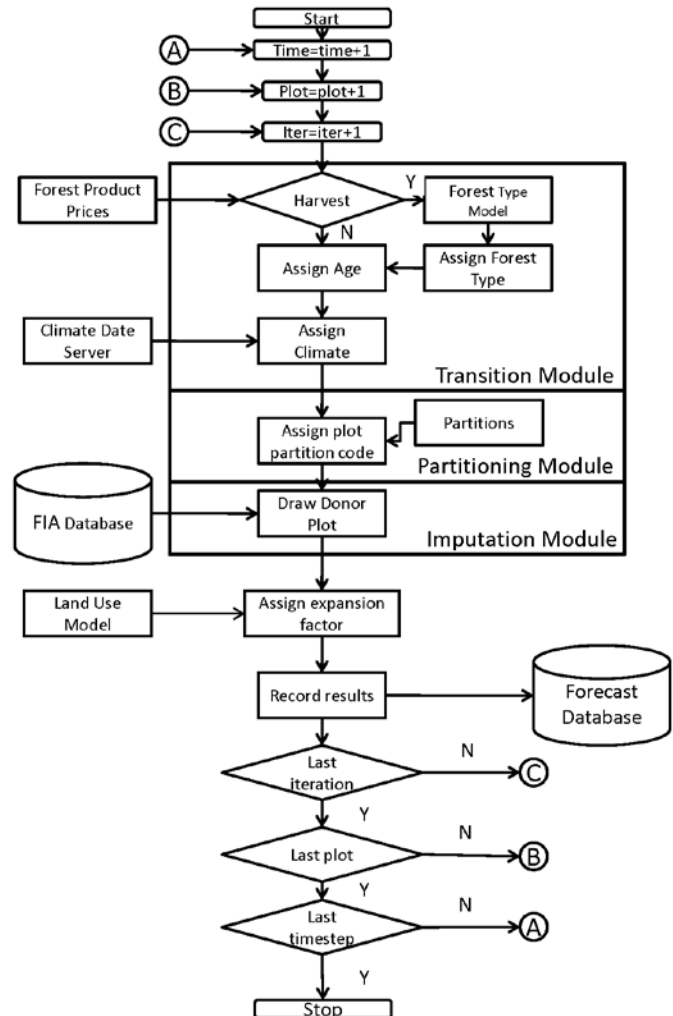


Figure A1—Flow chart of the Forest Dynamics Model’s approach to projected forest inventories.

while climate variables are derived from ancillary datasets and E is derived from phase 1 (aerial measurements) of the FIA inventory. Our definition of state and conditional variables facilitates descriptions of modeling approaches.

Forecasting plot conditions starts with projecting changes in the state variables (S) using transition models. For example, the future age of a forest plot is determined by adding the time step of the simulation to the current age unless a forest disturbance causes the age to be reset to another age (typically to zero). Once the forecasted state variables have been established, then a plot record is assigned based on an imputation or resampling of the historical database of plots with comparable values for the state variables. Changes in the expansion factors (E) for each plot are

determined by a land use model that forecasts urbanization and other land use choices driven by the population and economic variables contained in the RPA scenarios (Wear 2011).

Key decisions in developing the projection models involve choosing which variables are state variables, how to project changes in state variables, and the structure of the imputation algorithm. These choices are based in part on the frequency of FIA inventories which varies among the regions of the country. In all regions however, the basic structure of the modeling approach is defined by three modules. Changes in key state variables for each forest plot are forecasted in response to projected forest aging, climate conditions, and human use choices (the transition module). After forecasting the state variables, a historical plot record with comparable conditions is selected to represent the simulated plot in the future inventory (the imputation module). The modeling starts with an algorithm that clusters similar plots according to a set of independent variables (the partitioning module). These partitions of plots define the groupings of plots for the imputation module and also define which variables are the state variables that need to be forecasted within the transition module.

In most cases, models are developed on a State-by-State basis because of disparities in inventory dates. In some cases, multiple adjacent States are modeled together either because a concurrence of inventory dates allowed for pooling of dates—thereby enhancing the information content of the resulting models—or because a State was too small to support model estimation. For example, we pooled southeastern States (Virginia, North Carolina, South Carolina, and Georgia) and aggregated the Delaware data with adjacent survey units from Pennsylvania.

The Partitioning Module

The objective of the partitioning model is to define aggregates of plots that share common distributions of variables of interest, in this case the biomass contained on each plot (softwood and hardwood growing stock or live tree volumes). Plots are clustered according to several state variables and a clustering rule provides a compact description of the relationship between the state variables and the biomass distributions. Applying the clustering rule to an inventory places each plot into a partition with a similar joint distribution of biomass variables. Multivariate regression trees are used to generate the partitioning model, i.e., to sort plots into clusters for the imputation module. A detailed description of the partitioning approach can be found in Vokoun and others (2009).

Regression tree analysis is a nonparametric method for describing the relationship between independent state variables and the dependent variables (Breiman and others 1984).

Univariate regression tree techniques split a dataset, referred to as the root node, into a set of nodes (or bins) where the values of a single index or response variable are similar (De'ath and Fabricus 2000). Variation of the dependent variable within each node (called impurity) is measured by the sum of squared differences from the node mean. The technique begins by splitting the root node into two subsets, or daughter nodes, based on the value of a state variable. The best split is defined by the partition of a single state variable that minimizes the total of the two sums of squares across the daughter nodes or equivalently, maximizes the reduction in the sum of squares in the aggregate dataset (De'ath and Fabricus 2000). Subsequent splits are performed until a stopping criterion is met, usually a minimum threshold for reductions in the sums of squares. The terminal nodes have the least impurity or variation about the mean of the index variable. The partitions based on values of the state variables define the clustering rule for a tree.

Univariate or multivariate regression trees extend the univariate case by allowing more than one index or response variable. Node impurity in the multivariate case is the total of the sum of squared differences from the node mean across all dependent variables (De'ath and Fabricus 2000). Splitting is accomplished by choosing the partitions in the state variables that maximize the reduction in the multivariate sum of squares. We included various specifications of climate variables and FIA plot attribute variables as candidates for constructing the regression trees.

The R statistical software package with the MVPART (MultiVariate PARTitioning) package was used to generate state-level multivariate regression trees and the corresponding clustering rules to describe the relationships between the state variables and dependent variables for FIA plots. The regression tree algorithm sorts among several plot level variables and climate variables in determining the final tree. For each of the modeled States or State aggregates, we generate a multivariate regression tree for each of several forest type groups. Accordingly, the forest type is one state variable for our partitioning of plots into clusters. Other state variables are defined by the splits in each regression tree which vary by State and forest type, and include forest age, various climate variables, and site attributes such as ownership, aspect, and slope.

The specification of candidate variables for constructing regression trees greatly influences the outcome. For measured plot records, average values of variables were applied, e.g., average age, average diameter. For climate records, multiple formulations and variables were possible. We studied Iverson and Prasad's (1998) classification trees of individual tree species for guidance on useful climate variables, e.g., average temperatures in January and July, average annual precipitation, and potential evapotranspiration. In addition, we experimented with various approaches to averaging the climate data and settled on different approaches for the East and the West based

on the fit of these models. In the East, climate variables were averaged over the life of a forest—i.e., a 25-year-old plot would have climate conditions averaged over the previous 25 years—for the West, climate variables were averaged over a fixed time period—generally 20 years—for constructing the regression trees. In all cases, a large number of variables were provided for regression tree construction and the algorithm selected state variables for partitioning the FIA plots. Table A1 shows the number of regression trees in each region that contained specific climate variables.

The Transition Module

Regression trees separate inventory plots into partitions based on two types of state variables: (1) time invariant variables associated with plot conditions, for example slope or aspect, and (2) those that may change over time, for example forest age or climate. Forecasted changes in the latter variables predict changes in the plot cluster each plot location would be associated with in the future. Time variant variables are either exogenous climate variables—projected by general circulation models for the modeled scenarios (Joyce and others, in press)—or are driven by human choices and plot dynamics which we model with a set of transition probabilities or rules. We develop models to yield three interlinked transitions: (1) forest harvesting, (2) forest aging, and (3) forest type changes.

Harvesting

Conditional harvest probabilities simulate the harvesting of plots in the inventory in response to changes in forest conditions and economic factors. The specification of these models varies between the regions and most importantly depends on the frequency of inventory measurements. For example, in the South Region, where the inventory interval is shortest, models derive from an explicit economic choice model that accounts for the effects of timber price levels on the likelihood of harvesting forest plots. In the North Region, the interval between forest inventories is longer and while harvest models show significant relationships between harvesting and biophysical attributes of the plot, timber prices did not yield significant effects. In the Western United States, the inventories are too infrequent to deduce harvesting relationships between matched inventories, so the distribution of harvest activity was inferred from a single inventory coupled with ancillary harvesting data. Resulting empirical models were calibrated to reflect historical patterns of timber removals.

In all cases, harvest probabilities can be adjusted to simulate future market outcomes. In the South, harvest probabilities are explicit functions of timber prices. In the other regions of the country, where harvest probabilities are not explicitly linked to prices, regional harvest levels can be shifted up or down using a scalar adjustment factor applied to the harvest probabilities. Market simulations for the U.S. Forest Assessment System, using the Forest Products Model, are based on information regarding

Table A1—Occurrence of averaged climate variables in regression trees for each of the Resources Planning Act (RPA) regions (the Rocky Mountains Region is separated into its Great Plains [Plains] and Mountain State [RM] components)

Climate variable	RPA Region				
	South	North	Plains	RM	Pacific Coast
	<i>number of regression trees</i>				
Annual average temperature	4	8	3	2	5
Average temperature in January	5	6	1	2	2
Average temperature in July	5	3	1	1	3
Average temperature May-September	2	2	1	0	1
Total annual precipitation	3	8	1	5	5
Average potential evapotranspiration	5	4	0	3	2
Average aridity July-August	4	7	1	3	4

timber supply derived from the Forest Dynamics Model for the South and from aggregate supply models for the North and West. Because forest inventory dynamics alter supply futures, the Forest Products Model (with aggregate supply models) and the Forest Dynamics Model (with plot level harvest choice models) need to be reconciled.

In the South, harvesting models have the following general form and are described in detail in Polyakov and others (2010):

$$\Pr(\text{Harvest}) = f\{BH, BD\} \quad (2)$$

Harvest probabilities are modeled as a function of the differences between the marginal benefits of delaying harvest (*BD*) and the marginal benefits of harvesting (*BH*). These benefits can accrue not only to timber revenues but also to nonmonetary returns to holding the forest. Conditional logit models define the probability of observing harvests of two intensities (partial harvest and complete harvest) as functions of revenue and forest attribute variables which could proxy for nonmarket returns as well as site-specific costs. The logit harvest model has the following form:

$$\Pr(\text{harvest} | p, q) = \frac{\exp(\mu_i(h, p, q))}{\sum_{k \in H} \exp(\mu_i(k, p, q))} \quad (3)$$

where

h = one of three harvest options: (1) no harvest, (2) partial harvest, and (3) complete harvest

μ proxies for the difference in returns to harvesting and not harvesting as a function of revenue and forest attribute variables (p and q respectively) for each harvest option (h). Harvest simulations therefore depend on conditions of the the plot and timber prices which together define the revenue terms of equation 3.

Harvest choice models described by equation 3 were developed for each of the States in the South.² Separate harvest models were estimated for the five broad forest management types (planted pine, natural pine, mixed pine-hardwood, upland hardwood, and lowland hardwood) and for public and private ownership groups. Ten States or State aggregates, five forest management types, and two ownership groups define 100 separate harvest choice models.

Models similar to those estimated for the South were attempted in the North, but estimation results did not support their use. Correlations between harvest probability and revenue variables were generally inconsistent and lacked significance, perhaps reflecting the large variety of hardwood products harvested

from forest stands and less frequent FIA records in this region. An alternative, two-step empirical harvest probability model was estimated for each forest type in each State of the North. In the first step, harvest probability was modeled as a function of a set of biophysical attributes in the inventory, including sawtimber volumes observed at the beginning and predicted for the end of the period, stand age, slope, ownership class, average stand diameter, and an index that gauges the diversity of the tree species on the plot. In the second step, harvests were defined as full or partial based on the frequency of these harvest types observed for the paired inventories for each State-forest type permutation.

Models for the North can apply observed harvest patterns from the historical period (generally, the mid-1990s to the mid-2000s) to future forest inventories to project future harvests. Alternatively, aggregate timber harvests can be adjusted up or down using the following equation:

$$\Pr(\text{Harvest}) = \delta f\{Z\} \quad (4)$$

where

d = a scaling parameter used to increase or decrease harvest $f(Z)$ defines the harvest probability as a function of the set of attributes (Z) that are described above.

Adjusted harvest levels therefore preserve the ordering of harvest probability across plot attributes observed in inventory records while allowing simulations of increasing or decreasing harvest levels. We use this approach to describe the effects of market futures on forest conditions.

In the West, inventories and especially harvests are even less frequent than in the North and harvests are modeled in different fashion with separate modeling approaches applied in the Rocky Mountain and the Pacific Coast regions. For the Rocky Mountains Region, instead of modeling harvests separately, we model the probability of a stand replacement event (indicated by a plot with forest age of between 0 and 10 years). In this region, plot records indicate harvests of very low frequency—too low to estimate with empirical models. Stand replacement is therefore modeled using sequential logit models that (1) estimate the probability of fire occurrence, (2) estimate the probability of insect occurrence, and (3) estimate the probability of stand replacement as a function of forest type, forest age, and the insect and fire occurrences. Stand replacement therefore accounts for harvest effects but is more strongly influenced by other types of forest disturbances.

In the Pacific Northwest, especially on the west side of the Cascade Mountains, timber harvesting dominates forest disturbance but the infrequency of FIA inventories precluded estimating harvest probabilities using paired inventory

²In some cases, small sample sizes precluded estimating separate models for a State. For example, we applied the harvest choice model for Tennessee to FIA plots in Kentucky and used Arkansas models for harvest choices in Oklahoma.

observations. Instead we developed a set of net harvest probabilities that accounted for natural disturbance and reproduced historical proportions of partial and full harvests. Removal intensities were adjusted to simulate historical removal totals. We used inventory records from reserved public land to infer the mortality rates for forests associated with natural disturbances in all forests—assuming that plots aged 0–10 had experienced mortality in the previous 10 years.

$$m_j = \frac{F_{\leq 10, R, j}}{F_{\leq 10, R, j} + F_{> 10, R, j}} \quad (5)$$

where

$F_{\leq 10, R, j}$ = the area of forest from age 0 to 10 years in reserved areas

$F_{> 10, R, j}$ = the area of reserved forest with age > 10 years

m_j = the derived mortality rate for forest type j .

The area of clearcutting was estimated as the area of forests with ages of 0–10 years that was not explained by the background mortality rates. The literature on forest harvesting in the Pacific Northwest (Alig and others 2000, Zhou and others 2005) suggests that private landowners on the westside of the Cascades typically conduct final harvests at between 45 and 65 years for both Douglas fir and hemlock forest types. We used the estimated clearcut area along with the pool of eligible acres—defined for example, for Douglas fir, as forests in the 40–80 year age range plus the harvested acres—to estimate the previous period’s rates of final harvest by ownership and forest type for the eligible age class. Separate models were developed for the east and west sides of the Cascades to account for differences in forest conditions.

$$\Pr(\text{clearcut} | \text{owner } i, \text{forest type } j) = \frac{F_{\leq 10, NR, i, j}(1-m_j)}{F_{\text{eligible}, NR, i, j} + F_{\leq 10, NR, i, j}} \quad (6)$$

where

$F_{\text{eligible}, NR, i, j}$ = the area of nonreserved forest of ownership i and forest type j eligible for clearcutting (defined as 40–80 years old for Douglas fir) and other variables are defined above.

For public forests, this approach generated little evidence of stand-replacing harvests over the last decade, consistent with Forest Service management reports. As a result, nearly all harvesting on this ownership is expected to be from partial cutting.

Ancillary data on the proportion of harvested area accounted for by partial cutting and clearcutting (State of Oregon) was then used to assign an acreage estimate for the area of partially harvested plots for both west and east sides. As a final step, removal rates for partial cuts and clearcuts (as a portion of total growing stock) were used to estimate total harvest removals, and removal rates were adjusted to simulate

historical removal levels for the region [based on Smith and others (2009) and Haynes and others (2007)]. This algorithm provides sets of harvest probabilities for clearcutting and partial harvesting by major forest type groups, ownership types, and age classes. The resulting harvest probabilities can be scaled or adjusted up or down to reflect increasing or decreasing harvest levels in the region as predicted by market forecasts for various scenarios from the Forest Products Model (Ince and others 2011).

Aging

The second stage of the transition module addresses changes in the attributes of unharvested plots. In addition to several climate variables, the partitioning module identified forest age as an important state variable. We predict change in the average forest age (Age) either using a fixed time step or a regression equation where

$$Age_{t+1} = f\{Age_t, FT\} \quad (7)$$

Within the inventory framework, the relationship between age and the time step of the simulation may not always be additive. Because forests are often collections of trees of multiple ages, plot level age is based on the average age of individual trees measured for the plot, and the rate of age change may vary with the age of the plot. For example, in a case where older cohorts of trees are replaced by younger trees in a multi-aged plot, the rate of aging for the overall plot could decline with time, suggesting an approach toward an age asymptote or even an eventual decline in age at some point in forest development due to mortality.

Forest Type Change

Forest type transition models vary between regions and model choice reflects data availability and model performance. For the South, models use a combination of rules and empirical probabilities to forecast forest type changes. In the North, empirical transition frequencies based on matched inventories define conditional transition probabilities. For the West, where only one useable forest inventory was available and forest type transitions could not be explicitly modeled, a classification approach was applied where the probability of observing each forest type was modeled as a function of plot and climate variables. Each approach is described in turn below. Our definition of forest type for modeling is technically the forest type group or aggregates of these groups defined by FIA (table A2).

For the South, after experimenting with a variety of forest type transition models we adopted a combination of rules and

Table A2—Forest type groups as defined in the database of the Forest Inventory and Analysis (FIA) Program of the Forest Service, U.S. Department of Agriculture

100 White / red / jack pine group	300 Hemlock / Sitka spruce group	606 Atlantic white-cedar
101 Jack pine	301 Western hemlock	607 Baldcypress / water tupelo
102 Red pine	304 Western redcedar	608 Sweetbay / swamp tupelo / red maple
103 Eastern white pine	305 Sitka spruce	609 Baldcypress / pondcypress
104 Eastern white pine / eastern hemlock	320 Western larch group	700 Elm / ash / cottonwood group
105 Eastern hemlock	321 Western larch	701 Black ash / American elm / red maple
120 Spruce / fir group	340 Redwood group	702 River birch / sycamore
121 Balsam fir	341 Redwood	703 Cottonwood
122 White spruce	342 Giant sequoia	704 Willow/705 Sycamore / pecan / American elm
123 Red spruce	360 Other western softwoods group	706 Sugarberry / hackberry / elm / green ash
124 Red spruce / balsam fir	361 Knobcone pine	707 Silver maple / American elm
125 Black spruce	362 Southwestern white pine	708 Red maple / lowland
126 Tamarack	363 Bishop pine	709 Cottonwood / willow
127 Northern white-cedar	364 Monterey pine	722 Oregon ash
128 Fraser fir	365 Foxtail pine / bristlecone pine	800 Maple / beech / birch group
129 Red spruce / Fraser fir	366 Limber pine	801 Sugar maple / beech / yellow birch
140 Longleaf / slash pine group	367 Whitebark pine	802 Black cherry
141 Longleaf pine	368 Miscellaneous western softwoods	805 Hard maple / basswood
142 Slash pine	369 Western juniper	809 Red maple / upland
150 Tropical pine group	370 California mixed conifer group	900 Aspen / birch group
151 Tropical pines	371 California mixed conifer	901 Aspen
160 Loblolly / shortleaf pine group	380 Exotic softwoods group	902 Paper birch
161 Loblolly pine	381 Scotch pine	903 Gray birch
162 Shortleaf pine	383 Other exotic softwoods	904 Balsam poplar
163 Virginia pine	384 Norway spruce	905 Pin cherry
164 Sand pine	385 Introduced larch	910 Alder / maple group
165 Table mountain pine	390 Other softwoods group	911 Red alder
166 Pond pine	391 Other softwoods	912 Bigleaf maple
167 Pitch pine	400 Oak / pine group	920 Western oak group
168 Spruce pine	401 East wh pine/ northern red oak /white ash	921 Gray pine
170 Other eastern softwoods group	402 Eastern redcedar / hardwood	922 California black oak
171 Eastern redcedar	403 Longleaf pine / oak	923 Oregon white oak
172 Florida softwoods	404 Shortleaf pine / oak	924 Blue oak
180 Pinyon / juniper group	405 Virginia pine / southern red oak	931 Coast live oak
182 Rocky Mountain juniper	406 Loblolly pine / hardwood	933 Canyon live oak
184 Juniper woodland	407 Slash pine / hardwood	934 Interior live oak
185 Pinyon / juniper woodland	409 Other pine / hardwood	935 California white oak (valley oak)
200 Douglas-fir group	500 Oak / hickory group	940 Tanoak / laurel group
201 Douglas-fir	501 Post oak / blackjack oak	941 Tanoak
202 Port-Orford-cedar	502 Chestnut oak	942 California laurel
203 Bigcone Douglas-fir	503 White oak / red oak / hickory	943 Giant chinkapin
220 Ponderosa pine group	504 White oak	960 Other hardwoods group
221 Ponderosa pine	505 Northern red oak	961 Pacific madrone
222 Incense-cedar	506 Yellow-poplar /white oak /northern red oak	962 Other hardwoods
224 Sugar pine	507 Sassafras / persimmon	970 Woodland hardwoods group
225 Jeffrey pine	508 Sweetgum / yellow-poplar	971 Deciduous oak woodland
226 Coulter pine	509 Bur oak	972 Evergreen oak woodland
240 Western white pine group	510 Scarlet oak	973 Mesquite woodland
241 Western white pine	511 Yellow-poplar	974 Cercocarpus (mountain brush) woodland
260 Fir / spruce / mountain hemlock group	512 Black walnut	975 Intermountain maple woodland
261 White fir	513 Black locust	976 Miscellaneous woodland hardwoods
262 Red fir	514 Southern scrub oak	980 Tropical hardwoods group
263 Noble fir	515 Chestnut oak / black oak / scarlet oak	982 Mangrove
264 Pacific silver fir	516 Cherry / white ash / yellow-poplar	983 Palms
265 Engelmann spruce	517 Elm / ash / black locust	989 Other tropical hardwoods
266 Engelmann spruce / subalpine fir	519 Red maple / oak	990 Exotic hardwoods group
267 Grand fir	520 Mixed upland hardwoods	991 Paulownia
268 Subalpine fir	600 Oak / gum / cypress group	992 Melaleuca
269 Blue spruce	601 Swamp chestnut oak / cherrybark oak	993 Eucalyptus
270 Mountain hemlock	602 Sweetgum / Nuttall oak / willow oak	995 Other exotic hardwoods
271 Alaska-yellow-cedar	605 Overcup oak / water hickory	999 Nonstocked
280 Lodgepole pine group		
281 Lodgepole pine		

Note: The forest type names used by FIA do not come from a single published reference. The current list of forest type names has been developed over time using sources such as historical FIA lists, lists from the Society of American Foresters, and FIA analysts who developed names to meet current analysis and reporting needs. (Source: Woudenberg and others 2011).

empirical probabilities to forecast forest types. Inventory plots reveal few transitions between five broad forest management types in the South—planted pine, natural pine, mixed pine-hardwood, upland hardwood, and lowland hardwood—likely reflecting the physiographic basis for these broad forest management types. Instead we observe strong associations between forest age and the occurrence of fine scale forest types within the broad type group (e.g., poplar/sweetgum on young upland hardwood plots and red oaks predominately on older upland hardwood plots). Accordingly, for this set of simulations we hold the broad forest management type of the plot constant over time except when the plot is predicted to be harvested. Transitions among forest types within each forest management type are simulated through the imputation algorithm described below. When harvest occurs, the plot returns to its historical forest management type or is transitioned to a planted pine management type. The probability of being planted derives from the observed planting frequency (*PF*) for each forest management type within the modeled State and adjusted to reflect market conditions.

$$pr(\text{planting}|\text{harvest}, FT) = f\{\gamma, PF[FT]\} \quad (8)$$

where

γ = a scaling factor which is used to adjust the expansion in planted pine area consistent with the economic conditions of the scenario

FT = the observed forest type.

Forest type transitions in the South rely on these rules and empirical probabilities and are not directly influenced by changes in climate conditions. As explained later, the imputation module allows the species composition within each of these forest type groups to shift in response to climate variables.

Forest type transitions in the North are modeled based on empirical transition matrices derived from matched plots. A separate model was derived for each State or State-aggregate in the North based on the most recent pair of inventories. In each State, forest types representing more than 2 percent of the forest area in the most recent survey were selected for inclusion in the transition matrix (table A3).

$$pr(FT_{t+1} = I | FT_t = j) = f_{ij} \quad (9)$$

where

f_{ij} = the observed frequency of transitions between inventories. Equation 9 defines a transition matrix for all modeled forest types. Plots of all other forest types (those with < 2 percent of forest area) have fixed forest types throughout the simulation. Forest type transitions in the North therefore rely strictly on transition propensities observed across recent inventories and are not directly influenced by changes in climate conditions. As explained later, the imputation module allows the species composition within each of these forest type groups to shift in response to climate variables.

Table A3—Modeled forest type groups [Forest Inventory and Analysis (FIA) codes] and modeling units (States or State aggregates) for the North Resources Planning Act Region

Forest type group (FIA code) ^b	State or State/Survey unit-aggregate ^a											
	MN	MI	WI	MO	ME	IA	VT-NH	MA- CT-RI	East PA- East MD- NJ-DE	East OH-West PA-West MD-WV	IL-IN-West OH	NY
Aspen-birch (900)	X	X	X		X		X		X			X
Elm-ash-cottonwood (700)	X	X	X	X	X	X	X	X	X	X	X	X
Maple-beech-birch (800)	X	X	X		X	X	X	X	X	X	X	X
Mixed pine hardwood (400)	X	X	X	X	X	X	X	X	X	X	X	X
Oak-hickory (500)	X	X	X	X	X	X	X	X	X	X	X	X
Spruce fir (120)	X	X	X		X		X					X
White/red/jack pine (100)	X	X	X		X		X	X	X			X
Loblolly/shortleaf pine (160)				X					X			
Oak-gum-cypress (600)									X			
Eastern red cedar (171)				X								

^a States are named by their postal abbreviations.

^b See table A2 for explanations of FIA codes.

For the West, matched pairs of inventory plots were unavailable for modeling. Instead, a classification model for forest types in the West defines the occurrence probability of each forest type (rather than the transition between types) as a function of various site and climate variables. After experimenting with various approaches including naïve Bayes and clustering models, we chose a quadratic programming approach to derive conditional probabilities of observing a forest type conditioned on site and climate variables (Cortes and Vapnik 1995). For each forest type, the model generates a “supporting hyperplane” as a function of climate and site variables that separates the referenced forest type from all other observed forest types.

The quadratic programming approach defines a classification model. Given k forest plots and a set of m explanatory variables (which could include interaction terms), the quadratic program is specified to minimize the classification noise, i.e., to maximize the match between actual and predicted forest types. The measure of model fitness (an L_2 norm or Euclidean error norm) is based on the classification rates for the modeled forest type as a relative measure of accuracy.

Given the following variables as vectors:

X_i = Predicted occurrence of forest type i for each observation using the model ($k \times 1$ matrix)

$Actual_i$ = Actual forest type i for each observation, a vector of binary variables with 1 indicating the plot has the modeled forest type ($k \times 1$ matrix)

α_i = estimated coefficients from the quadratic model ($m \times 1$ matrix)

$B = m$ explanatory variables for the k observations ($k \times m$ matrix)

The objective function is to minimize L_2 :

$$L_2(X_i) = (X_i - Actual_i)^2 \quad (10.1)$$

Subject to:

$$B \times \alpha_i = X_i \quad (10.2)$$

Separate models are estimated for each forest type and result in probabilities of observing the specified forest type conditioned on the climate and site variables (B) observed for the plot. For each plot the probabilities of observing all forest types are normalized so that they sum to one. As climate variables are shifted by the scenarios, the QP approach generates new probabilities of observing each forest type for each forest plot. In each State or State aggregate, forest types representing more than 2 percent of forest area in the most recent survey were modeled (tables A4 and A5).

This classification approach to modeling future forest types for the Western United States is structurally similar to several studies that address future ranges of either broad biome types or individual tree species using nonparametric models. For example, Iverson and others (2008) in the Eastern United States and Rehfeldt and others (2006) in the West use similar approaches to constructing classification models—e.g., Random Forests models—to predict suitable habitat for individual tree species as functions of similar sets of climate and site variables. A longer history of data envelopment studies also describe (classify) boundaries between broad biome types—such as between prairie and forest (Gosz and Sharpe 1989). Applying climate projections to these models allows for inferences regarding the potential responses of species/biome ranges to future climates. A related body of work predicts forest inventory characteristics based on site attributes and ancillary data from satellite imagery (Moisen and Frescino 2002), not to produce temporal forecasts but to develop spatial interpolation of inventory data to maps of forest conditions.

In contrast to the transition models developed for eastern regions and explicitly linked to existing conditions, these classification models for western forests allow for more rapid transitions in type in response to projections of future climates. This suggests placing most emphasis in the longer term projections, e.g., focusing mostly on 30- to 50-year projections. Still, projections are provided for 10-year time steps to allow for insights into model behavior.

Tree species-climate envelope models correspond most directly to our forest type classification models. However, our approach—predicting forest type groups to support whole plot imputation modeling—does not allow for novel species assemblages that can be implied by projections from species-climate envelope models (Williams and Jackson 2007). By construction, our approach constrains future assemblages to be consistent with historical occurrences, an assumption that seems reasonable given the 50-year timeframe of forecasts, the inertia of persistent vegetation, and uncertainty about mechanisms of these changes.

The Imputation Module

The implementation of the forest harvesting, aging, and planting equations are set within a Monte Carlo modeling framework. Projections of exogenous variables for the various scenarios (e.g., climate variables and timber prices) and fixed variables for plots (e.g., slope) are used to assign forest type, harvest and planting probabilities, and ages based on equations 2–10. Implementation of the probabilities using random number generators defined predicted outcomes for the state variables.

Table A4—Modeled forest type groups [by Forest Inventory and Analysis (FIA) codes] and modeling units (States or State aggregates) for the Rocky Mountain Resources Planning Act Region

Forest type group (FIA Code) ^b	State or State-Aggregate ^a								
	CO-UT	MT	WY	ID	NV	AZ	NM	ND-SD	KS-NE
Aspen birch (900)	X	X	X	X	X			X	
Douglas fir (200)	X	X	X	X		X	X		
Deciduous oak woodland (970)	X								
Fir-spruce-mountain hemlock (260)	X		X		X	X	X	X	
Lodgepole pine (280)	X	X	X	X					
Piñon juniper (180)	X		X		X	X	X	X	
Ponderosa pine (220)	X	X	X	X		X	X	X	X
Other western softwoods (360)			X						
Fir-spruce-hemlock (260)		X		X					
Piñon juniper plus (180+)		X		X					
Western larch (320)		X		X					
Other western hardwoods (920)					X	X	X		
Elm-ash-cottonwood (700)								X	X
Oak-hickory (500)								X	X
Eastern redcedar (171)									X
Mixed pine hardwood (400)									X

^a States are named by their postal abbreviations.

^b See table A2 for explanations of FIA codes.

Table A5—Modeled forest type groups [by Forest Inventory and Analysis (FIA) codes] and modeling units (States or State aggregates) for the Pacific Coast Resources Planning Act Region

Forest type group (FIA Code) ^b	State or State-Aggregate ^a		
	CA	OR-WA West side	OR-WA East side
California mixed conifer (370)	X		
Douglas fir (200)	X	X	X
Fir-spruce-mountain hemlock (260)	X	X	X
Lodgepole pine (280)	X		X
Other western hardwoods (920)	X		
Piñon juniper plus (180+)	X		
Ponderosa pine (220)	X		X
Tanoak-laurel (940)	X		
Redwood (340)	X		
Western oak (920)	X		
Alder-maple (910)		X	
Hemlock-Sitka spruce		X	
Other western softwoods (360)			X

^a States are named by their postal abbreviations.

^b See table A2 for explanations of FIA codes.

Forecasts of all state variables using climate projections, price forecasts, and the transition module, place each plot into a plot cluster defined by the partitioning module. To construct the future inventory, a historic plot is drawn at random and with replacement from the plot cluster. Plot draws for all plot locations define a complete set of plot records for the future inventory. This set of resampled historic plot records provides estimates of all forest attributes measured by the forest inventory.

Using whole plot records to populate the inventory defines this imputation procedure as a “hot-decking” technique from the literature on the analysis of incomplete data or missing observations in survey processing. Here we extend the structure of hot-deck imputation from missing data to provide the entire forecasted dataset using historical plot records as proposed by Van Deusen (1997, 2006).

Our partitioning model using regression trees defines what Ford (1983) calls a classification process for the hot-decking model, whereby observations within each partition are as homogenous as possible. Our objective in applying this hot-decking approach is to produce forecasts that have reasonable joint and marginal distributions for measured forest inventory attributes. We should expect that the distributions within each partition are unbiased. Reams and McCullum (2000) demonstrate that this type of whole plot imputation procedure is equivalent to using regression equations to estimate average biomass volumes for historical simulations but that it preserves the joint distribution attributes between multiple independent variables. What’s more, the hot-decking approach preserves the variability of the data generation process inherent in the inventory (Reams and McCullum 2000) and contributes to estimates of the variance of the forecasts.

Simulation Structure

Recalling the definition of the information set for each plot in the inventory:

$$I(p) = \{S, Z, C, E\} \quad (1)$$

The Partitioning, Transition, and Imputation models provide a mechanism for predicting the plot attributes (S, Z) for the entire inventory conditioned on the climate (C). Linking the forecasted plot record to the scaling framework defined by the survey design, or the expansion factor (E), then completes the projection. To account for changes in the area frame of the survey we employed a land use model (Wear 2011) estimated with county-level data derived from the National Resource Inventories (U.S. Department of Agriculture Natural Resources Conservation Service 2000). This model provides estimates of the distribution of non-Federal land uses, including cropland, pasture, range, developed, forest, and other uses, in response to population, economic, and

biophysical variables while Federal land area is held constant. Non-Federal FIA forest area within a county is assumed to change in direct proportion to the forest area change forecasted by the land use model. The expansion factors for all non-Federal plots in the county are adjusted to reflect these forecasts of changes in county forest area over time. These land use forecasts are driven by the population and income forecasts of the RPA scenario and, in the South, by timber price forecasts associated with the model run.

We seek to generate aggregate estimates of inventory values for reporting units such as ecological sections, State survey units, and State totals, consistent with the sampling design of the inventory. To test the performance of the modeling framework we conducted validations at two different levels: aggregate forecasts and the distribution of attributes within each of the partitions defined by the partitioning model. During the design phase for several States in the East, we simulated the development of the inventory between two measured inventories and compared actual values with those forecasted by the model. For aggregate validation, we compared a forecasted 95-percent confidence interval for six variables using 26 iterations of the model: trees per acre, total biomass (measured as growing stock volume), and sawtimber biomass (volume in trees > 9 inches in diameter) for both hardwood trees and softwood trees. Validation tests proved useful for identifying specification and programming errors.

The structure of the Monte Carlo simulation algorithm is described in figure A1. Simulation experiments indicated a convergence of variance estimates after about 20 simulations and we chose to run the model for 26 iterations for each scenario (limits of computing time kept us from constructing more simulations). For the display of forecast results, we selected one of the 26 model runs as a “representative” realization of the future inventory based on the minimum proportional distance of six variables from the means for the run over the 50-year simulation period. These six variables were total growing stock volume (cubic feet), trees per acre, and sawtimber volume for hardwoods and softwoods for the State or State-aggregate being modeled.

Models were implemented for individual States or aggregates of two to four States or adjacent survey units across States and results were summed up to display results for the RPA regions. The time step for each model in the East was defined by the time interval of the paired inventories used to build the transition module and in the West was defined as a fixed 10-year step. Inventories commenced from the date of the latest inventory available, so the years for which forecasts were generated varied across States. To construct regional aggregates for the reporting years (2020, 2030, 2040, 2050, and 2060), we assigned the inventory with the age closest to the reporting year to the aggregate, consistent with methods used to generate historical aggregates with FIA data (Smith and others 2009).



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Wear, David N.; Huggett, Robert; Li, Ruhong; Perryman, Benjamin; and Liu, Shan. 2013.

Forecasts of forest conditions in regions of the United States under future scenarios: a technical document supporting the Forest Service 2012 RPA Assessment. Gen. Tech. Rep. SRS-170.

Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 101 p.

The 626 million acres of forests in the conterminous United States represent significant reserves of biodiversity and terrestrial carbon and provide substantial flows of highly valued ecosystem services, including timber products, watershed protection benefits, and recreation. This report describes forecasts of forest conditions for the conterminous United States in response to multiple scenarios evaluated by the 2010 Resources Planning Act Assessment. The results are based on the U.S. Forest Assessment System, a modeling system designed to forecast alternative futures for U.S. forests, and provide a forward-looking adjunct to the Forest Inventory and Analysis Program of the Forest Service, U.S. Department of Agriculture. Scenarios address a range of future conditions regarding population growth, economic change, global forest product markets, and climate change. Forest forecasts are described for each of four Resources Planning Act regions (South, North, Rocky Mountain, and Pacific Coast) across the Resources Planning Act scenarios. In the Eastern United States, the range of socioeconomic futures leads to greater variation in future forest conditions than does the range of climate projections. Because of the dominance of public forests in the Western United States, socioeconomic changes hold less sway over forest futures there. Built directly from and as a forecasting adjunct to the monitoring system of the Forest Inventory and Analysis Program, the modeling components will be enhanced by additional forest inventory data as they become available.

Keywords: Forecasts, forest inventory, integrated assessment.



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