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## Projecting the Spatial Distribution of Possible Planted Forest Expansion in the United States

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### Abstract

As the demand for forest products and carbon storage in standing timbers increases, intensive planting of forest resources is expected to increase. With the increased use of plantation practices, it is important to understand the influence that forest plot characteristics have on the likelihood of where these practices are occurring. Depending on the goals of a policy or program, increasing forest planting could be a desirable outcome or something to avoid. This study estimates a spatially explicit logistical regression function to assess the likelihood that forest plots will be planted based on physical, climate, and economic factors. The empirical results are used to project the potential spatial distribution of forest planting, at the intensive and extensive land-use margins, across illustrative future scenarios. Results from this analysis offer insight into the factors that have driven forest planting in the United States historically and the potential distribution of new forest planting in the coming decades under policy or market scenarios that incentivize improved forest productivity or certain ecosystem services provided by intensively managed systems (e.g., carbon sequestration).

### Keywords

plantation forest; land-use change; spatial econometrics; forest management

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Over the past decade, the US forest sector has seen unique changes defined by decreasing demand for traditional paper products, volatile housing markets and sawtimber demand,

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growing markets for packaging materials and biomass for energy generation, and environmental change. However, despite these structural changes and future uncertainty in market and environmental conditions, investment in the forest resource base has continued to grow, with foresters adopting management techniques that increase the productivity of forests at some additional cost<sup>1</sup>. Management intensification in forestry includes planting of new forests post-harvest, and managed forest systems in the US are often distinguished between planted and naturally regenerated forests, where planted forests are typically monoculture systems (e.g., planted pine in the Southeast or Douglas-fir in the Pacific Northwest) that offer greater productivity relative to naturally regenerated stands.

Naturally regenerated forests are increasingly being converted to planted and managed systems globally to meet the demand for wood, fiber, and ecosystem services, as planted forests have greater aboveground growth efficiency and production efficiency than unmanaged forests (Noormets et al. 2015). In addition, Row (1996) shows that changes in forest management can increase carbon sequestration by 0.6–0.8 tonnes of carbon per acre per year. Binkley et al. (2005) estimated that 35 percent of the industrial roundwood consumed worldwide in 2000 was supplied by forest plantations, and that by 2020 around 44 percent of industrial roundwood will be supplied by planted forests. Not only has the timber supplied by plantation forest increased, but the area of planted forest has increased despite total forest area declining. Between 2010 and 2015, global forest area declined by 3 percent, whereas planted forest increased by over 65 percent between 1990 and 2015 (Keenan et al. 2015). Using projected GDP per capita and roundwood production Nepal et al. (2019a) project that planted forest area in the United States could increase between 16.5 percent and 29.8 percent by 2070.

There are several reasons that management intensity and plantation forestry may continue to increase in the United States. First, the demand for traditional forest products is projected to increase over time because of increasing population and economic growth (Prestemon et al. 2015). Additionally, as the demand for renewable energy has increased over the past decade in many regions of the world, use of woody biomass for energy production has also increased. For instance, demand growth in the European Union for wood chips and pellets has partially been met by increased exports of woody biomass from the United States. Exports of wood pellets and chips increased by 40 percent between 2013 and 2014, whereas total forest exports grew 80 percent between 2010 and 2014 in the United States (USFS 2015). Biomass energy from forest products and residual by-products could also continue to increase in the future under a variety of policy drivers, which creates investment opportunities in forestry (e.g., Raunekar et al. 2010, Abt and Abt 2013, Cherubini et al. 2013, Latta et al. 2013, Baker et al. 2017, Kim et al. 2018).

Although the demand for forest products has increased overall, the reliance on global forests to mitigate the effects of greenhouse gas emissions has also increased. Forests are the largest sink of terrestrial carbon, and continued growth of standing timber and afforestation has the

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<sup>1</sup>The RPA Assessment 2010 estimated 63.2 million acres of planted forest in 2007 (Smith et al. 2009), whereas the RPA Assessment 2020 estimated 68.0 million acres of planted forest in 2017 (Oswalt et al. 2019). Similar management trends have been observed in other regions (Payn et al. 2015, Sedjo and Sohngen 2015).

potential to reduce greenhouse gases in the future via carbon sequestration and storage (Baker et al. 2017). Recent literature shows, however, that future accumulation of carbon in forests could slow in the coming decades because of aging forest stands, economic conditions, and continued urban development (Coulston et al. 2015, Latta et al. 2018). However, if favorable investment conditions persist as in Tian et al. (2018) or if policies are implemented that adequately incentivize increased carbon sequestration from the land-use sector, these conditions would create additional incentive not only to promote afforestation but to intensively manage forests to maximize carbon sequestration benefits in the near term. Such investment could slow down or reverse the projected decline in carbon stocks. Policy incentives designed to increase these separate carbon pools can expand forest planting at both the intensive margin (or an increase in planted systems within the existing forest land base) and the extensive margin (or new forest area added).

Currently in the United States, state agencies such as the California Air Resources Board are using market-based programs to reduce greenhouse-gas emissions through different mechanisms, including offsets from the land-use sectors. Under offset markets, forest landowners have increased incentives to invest in management practices, which improve the productivity of forests, such as planting and intensive management, with the goal of achieving higher net carbon sinks (Noormets et al. 2015). Greater investment in US forest plantations can help meet increased demand for various forests products, offset the need to harvest natural forests, and improve aggregate carbon outcomes. Thus, regional forest product market expansion and/or the potential emergence of other programs (e.g., voluntary offset markets) that seek to enhance terrestrial carbon stocks could expand plantation forestry in the United States and beyond.

Finally, forest area is in constant competition with land-use change and natural disturbances. Pressure from continued population growth and urban expansion can lead to deforestation, whereas natural pressures, including drought, wildfire, invasive species, and outbreaks of insects and disease (Tidwell 2016) put landowners at risk of losing their investment. Intensive forest planting allows land owners to hedge against these risks by shortening rotation lengths and increasing biomass production.

Although forest planting and management intensity of US forest resources have increased over time, and will likely continue to expand, limited work to date has focused on site-specific factors that may drive the decision to replace a naturally regenerated stand with a plantation forest post-harvest (intensive margin expansion). One example in previous literature is Sohngen and Brown (2006); they used a logistic regression approach to project the additional land rental rate that is necessary to prevent intensive expansion of planted forest in the South-Central United States. They found that without policy intervention, intensive expansion of plantation forests will continue because of market forces (e.g., increased demand for forest products, and increased productivity of plantation forests). Alig and Butler (2004) use a structural model to project future forest conversion, and project an additional 13.8 million acres of planted pine in the Southern United States through 2050. Nepal et al. (2019a) use an econometric model to project global expansion of planted forests at a regional scale, with the United States projected to have between 75.9 and 84.5 million acres of planted forests in 2070. This limited literature is partly due to data limitations, even

in the United States; see South (2005) and MacDicken (2015) for additional discussions. We seek to fill this critical data gap by performing a detailed spatial analysis on the factors currently driving planting decisions in US forestry. Specifically, we use the United States Forest Service's Forest Inventory and Analysis (FIA) data to estimate the probability that current unmanaged and naturally regenerated forests will convert to planted forests post-harvest. A logistic regression function is used to estimate the effects that physical, climate, spatial, and economic attributes have on the likelihood that a specific unmanaged forest plot will be converted to a planted/managed stand in the future after initial harvest.

By assessing the effects that these characteristics have on the likelihood of forest landowners converting their lands to forest plantations, this analysis can provide policymakers and industry stakeholders with improved information concerning ways to encourage (or discourage) certain forest-management activities, including planting practices. Although planted forests can increase the production of forest biomass, they can also lower biodiversity compared to naturally forests (Paillet et al. 2010). This phenomenon is due to differences in forest structure, composition, and dynamics between unmanaged, natural forests and managed, plantation style forests. The results of this research can be used to help define areas where conservation easements or limitations on areas of planted forests could protect species that rely heavily on natural forests.

Furthermore, there is a growing literature that seeks to project forest management, land use, and forest carbon outcomes across alternative future market and policy conditions. These analyses use a variety of frameworks, including structural economic models (e.g., Forsell et al. 2016, Latta et al. 2018, and Tian et al. 2018), and detailed geospatial simulation approaches tied to market models (e.g., Wear and Coulston 2015). These varying approaches have led to alternative future trends of the United States forest sector. For example, the most recent Renewable Resources Planning Act Assessment (USFS 2012) shows a switch from forest carbon sink to source of emissions for most scenarios by 2040, with large carbon losses under high bioenergy expansion scenarios. However, this result was based on modeling frameworks that did not allow national harvest levels and regional management intensification to respond directly to current and anticipated market prices outside the Southern United States. Hence, the projected planted forest expansion from the 2010 RPA is only indirectly related to expected market and policy conditions, as opposed to dynamic optimization models in which management decisions today are based on perfect foresight of future conditions. Accounting for management change is critical in land-use projections across baseline and policy scenarios, as discussed in Tian et al. (2018), which applies a structural dynamic model of the global forest sector to illustrate linkages between endogenous land-management decisions and forest carbon stocks. Dynamic models, however, may lack the spatial detail for robust projections of management change, as forests are often treated as homogeneous systems across large regional aggregates. Our hope is that this analysis can be used to better parameterize forest planting possibilities in larger economic modeling frameworks by depicting the marginal economic costs of planting (which reflects spatial heterogeneity), technoeconomic limits, and the likely spatial distribution of future planting in the United States.

We apply the econometric results to project the spatial distribution of possible forest planting across future alternative scenarios. This analysis offers several contributions to the literature. First, we offer insight into potential intensive margin expansion in US forestry by simulating planting patterns under hypothetical future scenarios, and we compare these projections to the current planted area. This approach allows us to evaluate regions or spatial hotspots that may see a net increase in forest planting under an “optimal” business-as-usual scenario. Furthermore, we can project the potential distribution of forest planting under assumed large-scale investment scenarios, illustrating where we are most likely to see expansion in planted forest at the expense of naturally regenerated systems in the coming decades. Second, we extend the intensive margin framework to offer insight into the possible distribution of future extensive margin expansion (afforestation) across alternative land-use types, which is an important consideration given the anticipated role of afforestation apparent in recently published projections of GHG mitigation potential from the US and global land-use sectors (e.g., Fargione et al. 2018).

While we do not evaluate afforestation potential in the context of a structural model and defined policy or market conditions, our illustrative simulations nevertheless offer insight into potential forest expansion across alternative land-use types that exhibit traits similar to current planted forest area. These results demonstrate the importance of accounting for spatial heterogeneity in projecting land management and can be used to help create more robust projections of forest-management trends.

## Data and Methods

As the demand for forest products as well as carbon sequestration from standing forest increases in the future, it is important to know where natural forests may be harvested and converted to plantation forest. To better understand where these planted forests might be located, a binary response function is used to estimate the likelihood that land owners will convert forest from unmanaged to managed forest.

Logistic regression models are binary response functions that estimate the probability of an event occurring given a set of independent variables. Binary response models have been used to estimate stakeholders’ preferences for multiple forest values (Kumar and Kant 2007), to estimate how land use may change because of improved infrastructure (Nelson et al. 1999), to evaluate the link between land-use projections and forest fragmentation (Plantinga et al. 2007), and to approximate the harvest choice of different forest land owners (Prestemon and Wear 2000). Several articles used similar methods to address the management decisions of nonindustrial private forest land owners (Lee 1997, Conway et al. 2000, 2003, Prestemon and Wear 2000, Pattanayak et al. 2003). Finally, logistic regression techniques have been extensively used in the economics literature to examine factors that influence discrete land-use change decisions (e.g., Plantinga et al. 1999, Lubowski et al. 2006, and Millington et al. 2007). Such analyses can be coupled with information on relative economic rents to project extensive margin expansion into one land use over another in the presence of policy incentives (e.g., carbon sequestration payments for afforestation projects).

While these studies have offered an insight into factors that have driven land-use change historically, especially in a forestry context, there is currently a lack of literature examining the factors influencing intensive margin investment of forest resources. This study seeks to fill this gap by employing similar empirical methods that have been applied to land-use change contexts in the literature. Specifically, this study develops a logistical regression model to estimate the likelihood that current unmanaged forest plots will convert to planted forests after harvesting based on a wide range of explanatory variables, including physical factors of the landscape, climate data, soil data, state-level taxes, market data, and ownership type. We recognize that a change from naturally regenerated forests to planted does not result in a discrete change in land use per definition of forest land-cover standard, although a distinct change from naturally regenerated stands to monoculture systems is a definitive shift in land use, making the use of logistical regressions context appropriate. Estimated regression coefficients are then used to project the potential spatial distribution of future planted forest expansion in the US, under several hypothetical forest-management scenarios.

The econometric framework developed in this analysis is designed to estimate the probability that a given forest plot in the US is currently planted based on key physical and economic factors. To estimate this logistical regression, four different datasets were used. The first is the 2015 FIA National Program, which is collected by the United States Forest Service each year<sup>2</sup>. The second dataset is the Parameter-elevation Regressions on Independent Slopes Model (PRISM) data from the Northwest Alliance for Computational Science and Engineering (PRISM 2012). This dataset is spatially explicit historical weather and climate data throughout the United States. The third dataset is the SSURGO dataset from The National Cooperative Soil Survey which includes information on soils throughout most of the continental United States. Finally, state-level forestland tax schemes were collected from the National Timber Tax website.

Plot-level forest characteristics are gathered from the 2015 FIA National Program, which provides a unique census of forest resources in the United States. The dataset includes information on location, species, size, and health of trees. In addition, it includes tree growth, mortality, and removal from harvest. Especially important for this analysis, the FIA data also include designations for forest sites that are currently managed. This designation is the dependent variable used in the probability estimation. Overall there are 150,350 condition classes, or homogenous components of plots included in the FIA dataset, with 15,711 of those condition classes planted.

This analysis remains agnostic about when forests were converted from naturally regenerated to planted systems, which ignores temporal considerations, such as market changes, that could drive forest-resource investment. Such considerations would require spatially disaggregated information on timber prices, over time, that could be linked to forest plots. Given the lack of comprehensive price data across the contiguous US and in order to maintain the rich spatial detail in the framework, price information is excluded from the analysis. Instead, the model includes longer-term economic factors related to infrastructure,

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<sup>2</sup>.After the passing of the 1998 Farm Bill, FIA is required to collect data on 20 percent of the plots annually within each state. Thus, although the entire inventory is not updated yearly, each plot will be measured every 5 years.

productivity, and harvest/access costs that drive forest planting. Additionally, research has shown that current prices for forest products have limited effect on landowner decisionmaking because of the long-time frame between forest planting and harvesting. This difficulty in attributing land-use decisions to prices was first recognized by Dennis (1989, 1990) and Newman and Wear (1993). The latitude/longitude values for the centroid of each plot are included in the FIA data. The plot centroids were overlaid with various geospatial data sources using a geographic information system (GIS) to provide additional characteristics for the forest lands in the model, such as climate, drainage class of the soil, and slope.

The role of technology and mechanization is continually expanding in silvicultural choices (Silversides 1984). Although originally focused on harvesting (Macdonald et al. 2010), it is also important in site preparation and more recently tree-planting decision (Laine and Saksala 2018). Unlike the potential biological effects of slope, the operational effects of slope related to the higher cost associated with working on steep terrain are largely a function of the limitations of particular machines. It has been shown that harvesting cost on steep land can be almost 37 percent higher than comparable flat land (Amishev et al. 2009). As such, slope classes were used rather than actual slope to reflect the discrete costs associated with the use of applicable equipment required for working on different slope types. Data for plot level slope were used from the FIA and then categorized into groups of 0–15°, 15–30°, 30–45°, and >45°.

The FIA data also include information on the ownership of each plot. It is assumed that different land owners will have different goals for their forest land, so indicator variables are included to account for these differences. Privately managed timberland is most likely to be planted, as this land is often managed rotationally to optimize timber outputs, whereas publicly managed resources are often managed to maintain a suite of recreational and ecosystem services. The following ownership classes are included in the modeling framework (the Other federal category is dropped in the regression model to avoid the dummy variable trap):

- Private.
- State.
- Bureau of Land Management (BLM).
- US Forest Service.
- Other federal.

Long-term weather observations were collected from PRISM. The PRISM data include 30-year averages for high, low, and mean temperatures, and 30-year averages for yearly precipitation, both of which are incorporated into the regression. The PRISM data are composed of high-resolution raster layers that integrate easily into a GIS. The centroids from the FIA data were intersected with these spatially explicit data, and the average mean temperature and average yearly precipitation were recorded for each plot (PRISM 2012).

Soil data used in the regression include hydrologic soil groups from the SSURGO dataset. A soil's ability to drain water is paramount in determining the potential productivity of different sites (Coops and Waring 2001, Waring et al. (2014). Four hydrologic soil groups exist (Groups A–D). These are based off the soil's runoff potential, where Group A's generally have the smallest runoff potential, and areas in Group D have the highest. Group A is sand or sandy loam types of soils and has low runoff potential and high infiltration rates. Group B is silt loam and has moderate infiltration rates. Group C includes sandy clay loam and has low infiltration rates. The final group, Group D, is clay loam, silty clay loam, silty clay, or silt and has a very high runoff potential and very low infiltration rates (in the regression model results, Group D is dropped to avoid the dummy variable trap).

The hydrologic soil group for each plot was determined by overlaying the plot centroids with the Map Unit shapefile to determine the MUKEY (map unit key) for the plot. Once this was determined, the major component for each plot was calculated, and the corresponding value for the hydrologic soil group was attributed to the plot. A Point Distance analysis was run within Environmental Systems Research Institute's ArcMap to determine the distance of all plot centroids within 10 miles of each individual FIA plot centroid. The resulting numbers were divided into managed and unmanaged plots to determine what percentage of all surrounding plots were currently managed.

State-level tax schemes were collected in order to see if taxes on forest-related income, forest land, and forest products can encourage or inhibit private investment in management of forestlands. Greene et al. (2013) found that the presence of federal and State taxes reduces the pre-tax value of forest land in the Southern US, from more than one-quarter to nearly half. Since all forest plots in this study face the same federal taxes, individually state policies are included to see if landowners have a preference to specific tax schemes when deciding to pursue active management. Butler et al. (2012) found that tax policies, while not able to solely determine how landowners manage forest, can influence management decisions. Although investigating the efficacy of tax incentives on encouraging forest landowners to pursue sustainable management practices, Greene et al. (2013) found that financial incentive programs are generally successful in meeting such goals. To test the effect of tax programs on the decision to plant forests, five commonly used tax plans are included in the model. To test this, five different tax plans that are relied upon heavily are included. The tax schemes are:

- Ad valorem property tax.
- Flat property tax.
- Property tax exemption.
- Yield tax.
- Severance tax.

Ad valorem, or "value-added," property taxes are based on the value of the land and the value of the standing timber. The flat property tax charges the same amount of money per acre no matter the value of the timber. In some states (Alaska, Delaware, Iowa, and Rhode Island) forestland is exempt from property tax. In addition to property tax, most states



charge one of two different types of harvest tax once timber has been cut. A yield tax is collected on the value of harvested timber, whereas a severance tax is a flat tax on a specific volume harvested. State-level tax schemes are collected from The National Timber Tax Website (<https://www.timbertax.org/statetaxes/>).

Finally, the distance from each forest plot to the nearest port and mill was calculated. This is the Euclidean distance between source location and destination location, and has been used in part to calculate total harvest costs in previous studies (see Latta et al. 2018). Table 1 presents summary statistics of the included variables described above.

## Model Results

We initially tested multiple regression specifications (including linear specifications for all independent variables, using FIA site classes instead of soil drainage class, and including regional dummy variables to account for differences across the landscape that would not be captured by things such as weather, distance to mills and ports, and local management intensity) but found only minor differences in predictive capability, direction and magnitude of estimated coefficients, and statistical significance across each specification. The regression results presented in Table 2 best capture the combination of physical, economic, and spatial characteristics of forest plots considered in this analysis. Both weather variables, average yearly temperature and average yearly precipitation, were included in the regression as both linear and quadratic terms. This treatment is due to the assumption that the marginal effect of either of these variables is nonlinear; that there is a temperature and precipitation amount that maximizes the likelihood that a forest plot is planted. Both the linear and nonlinear estimated coefficients for the weather variables are statistically significant in the results. Coefficients for average slope show that as plots become steeper, the likelihood of planting decreases. This result reflects the increased cost in planting and harvesting associated with steeper lands (Amishev et al. 2009). The results concerning the land ownership classes capture the priorities that different land owners have for forestland. Private and state-owned forest are the most likely to convert to planted forests, whereas federal lands are the least likely.

The prevalence of local planted forests (Percentage of planted plots within 10 miles) is a very robust independent variable in determining whether a plot is planted. This measure captures both cost and demand characteristics within a region, and in our results, we show that the effects of higher local intensity of planted plots lead to a higher likelihood of planting occurring. Distance to mill and distance to port measures are small, negative, and statistically significant. This result is expected because of the wide range of values seen in the set (range of 1.7–981.6 miles for distance to mill). The coefficients for hydrologic soil groups show that soils with higher infiltration rates will likely lead to higher rates of planted forest. This soil type typically allows more precipitation to percolate to the root systems of standing timber.

Finally, the estimated coefficients for the state-level taxes provide information on the cost associated with forest practices. Flat tax rates and ad valorem taxes are the most likely areas to see planted forest, although severance taxes and states where forestry is exempt from

property taxes are not statistically significant. One reason for this is a lack of observations. Only four states exempt forestry practices from taxation, whereas severance taxes are included in 10 states, and nine of these states also impose ad valorem taxes, which could lead to biases in the regression coefficients because of multicollinearity between independent variables.

To assure model significance, correlation coefficients between each independent variable were calculated. Five pairwise combinations of independent variables were recognized for being highly correlated (we used a coefficient value of  $>0.5$  as our cutoff) flat tax and ad valorem ( $-0.96$ ), USFS ownership and private ownership ( $-0.75$ ) mean temperature and percentage of managed plots within 10 miles ( $0.64$ ), private ownership and mean temperature ( $0.54$ ), and mean precipitation and percentage of managed plots within 10 miles ( $0.51$ ). Each of these variables exhibits spatial patterns that could lead to these relatively high levels of correlation; areas with high percentages of managed plots are located mostly in the southeast and northwest where weather patterns are going to be relatively consistent across each region. Similarly, most forest plots in the southeast are privately owned where mean temperature may not vary greatly across plots. To test for overall significance of the full model, a chi-squared test for significance was run on the full model and a restricted model that dropped the following independent variables:

- Mean temperature.
- Mean precipitation.
- USFS.
- Private.
- Percentage of managed plots within 10 miles.
- Flat tax.
- Ad valorem tax.

The resulting chi-squared statistic of 4,400 allowed us to reject the null hypothesis that the restricted model had greater overall significance than the unrestricted model.

### **Predictive Ability of the Logistical Regression**

To verify the predictive capabilities of the regression, accuracy measures, and two statistical measures, the  $F_1$  score and relative operating characteristic (ROC) are calculated. Additionally, the marginal effects of the independent variables are calculated to better understand the individual effects that these independent variables have on the likelihood that natural forests will convert to planted forests post-harvest.

The  $F_1$  score is the weighted average of precision and sensitivity of a binary classification and is measured between 0 and 1 (with 1 being the best and 0 the worst). Overall it is a measure of accuracy of the positive results from a binary classification. The  $F_1$  score takes into account the number of correctly identified planted plots; however, the  $F_1$  score does not take into account the number of true negatives, which in this example is the number of actual naturally regenerated plots that are estimated to be planted. The selected regression results

have an  $F_1$  score of 0.618. Because the number of true negatives is not accounted for, an additional statistical measure is used to determine which regression specification can best balance estimating the probability of planting on unmanaged plots successfully.

The ROC is also calculated. Although the use of ROC as a quantitative measure to validate land-use change models is relatively new, ROC has been used for decades to validate weather forecasting models, library information retrieval models, medical imaging diagnosis, material strength testing, and polygraph lie detection. The approach has also been used to compare probabilistic models of land-cover change (Pontius Jr and Schneider 2001). The area under the curve (AUC) is the primal measure of accuracy from the ROC. When the ROC curve is closer to the y-axis, the model does a better job at identifying true positives (in this example, correctly identifying existing plantation plots). When the ROC curve is closer to the line  $x = 1$ , the model predicts more false-positive values (currently unplanted plots as planted). As the ROC curve moves toward the upper-left corner of the ROC space, the AUC increases. The regression specification that is presented has an ROC curve with an area of 86.5 percent, with a slight bias toward the  $x$ -axis, which can lead to a higher number of false positives across the simulation results.

### Predicted Probabilities of Planting

Graphs on the relation between model parameters and predicted probabilities are presented in Figure 1 including visuals of mean temperature, average precipitation, distance to mill, distance to port, and percentage of managed plots within 10 miles. Figure 1 shows that plots that are within approximately 5 miles of a mill are, on average, almost 10 percent more likely to be planted forests than forests that are located approximately 100 miles from a mill. Thus, as plots are closer to mills, the likelihood that the plot will be planted increases. Distance to port is similar in its relation to predicted planting probability, but decreases linearly, and the predicted probability of planting increases as proximity to ports decreases.

The relation between the percentage of planted plots within 10 miles and predicted probability has an elongated s-shape, with an inflection point around 40 percent. Before this point, we see increasing probabilities of planted plots at an increasing rate. After this point, we see increasing probabilities of planting at a decreasing rate. Mean temperature and mean precipitation have both increasing and decreasing marginal returns, showing that there is an optimal temperature and amount of precipitation at which forest plots are expected to be planted. Marginal returns to a change in temperature and precipitation vary depending on the current level of each variable. From the predicted probability graphs, there are clearly increasing marginal returns to increased precipitation (temperature), up until an inflection point, where diminishing returns, and eventually negative returns, begin.

### Simulation Results

Using the estimated likelihoods, we first compare how current management practices align to an “optimal” distribution based on the estimated logistic regression coefficients. That is, holding total planted area constant, we evaluate the extent to which plots are currently planted and will continue to be planted in the coming years, and which currently planted plots are most likely to be naturally regenerated post-harvest. Recognizing that forest

resources are fungible, this approach allows us to identify areas that may see a net increase in forest planting over time based on current infrastructure and environmental conditions. Then, alternative planted forest (intensive margin) expansion scenarios are presented to assess the possible future distribution of managed forests based on harvest decision rules, and plot likelihoods of management.

Figure 2 shows the current distribution of planted forest within the United States (top) and the projected distribution of planted forest according to our econometric analysis (bottom). The projected distribution of forest planting is calculated by selecting the plots with the highest probability of planting activities until the desired amount of planted area is achieved. The resulting map shows more clustering of plantation practices than what is currently seen on the ground. For instance, most planted plots in the Lake States region are shifted to the Southeast and South-Central regions, and planted plots in these regions become more densely co-located. The Northeast region also sees a decline in planted plots. For both the Lake States and Northeast regions, the projected decline in planted plots is driven by the percentage of adjacent planted plots factor, plus the existence of fewer forest-product facilities, which is consistent with observed trends in declining forest product supply in these regions (Oswalt et al. 2014). Table 3 further shows the difference in actual area of planted forests at the state level (for the top 10 states by area of planted forest) compared to the projected area of planted forest. From here, we can see that our analysis predicts a similar amount of planted forest within each of the top 10 states. Oregon is a unique case where, according to our analysis, planted forest could be considered oversaturated, where our analysis predicts less planted forest area than the current amount. This could be due to spatial biases in the econometric approach because of the highest amount of currently planted forest being in the Southeast. However, these results can also point to what (if any) planting activities landowners may choose post-harvest given the physical, economic, and climatic properties of their plots.

Predicted probabilities are then applied to project the spatial distribution of future expansion of planted forests at the intensive margin, assuming scenarios with a net increase in total forest planting. Beginning with the estimated distribution of planted forests (BAU Predicted results), we assign three expansion scenarios and select plots based on stand age and probability of being intensively planted to show the spatial distribution of newly planted areas of 16 million (low expansion), 32 million (medium expansion), and 64 million acres (high expansion). Plots are restricted to those that are likely to be harvested in the next decade. We assume that softwood plots less than 20 years old, and hardwood plots less than 35 years old would not be harvested over the next decade. In order to achieve these expansion amounts, the predicted probabilities for plots to be included in low-, medium-, and high-expansion scenarios had to be greater than 56.4 percent, 37.7 percent, and 12.9 percent, respectively. Previous studies offer guidance on how to construct scenarios of potential intensive margin expansion in US forestry. Currently there are over 64 million acres of planted forests in the US, approximately 25 percent of the total timberland base included in the FIA database. Zhang and Polyakov (2010) estimates that between 1997 and 2027, the amount of privately managed pine plantations will rise by 40 percent, from about 27 million acres to almost 40 million acres in the southeastern United States. This growth in planted forest occurs whereas overall private forest area in the region is estimated to decline

by 7 percent in the same period. Table 3 shows the current area of planted forests across the United States, using the BAU Predicted as the initial distribution of planted forests.

In the low- and medium-expansion scenarios (as shown in Figure 3<sup>3</sup>), we project that most plantation activities in the future will occur in areas that currently have a high density of forest planting. In particular, the top 10 states could see about 8 million new acres of natural regenerated states convert to planted forests, whereas the rest of the country sees 10 million acres of naturally regenerated forests switching to planted forests.

At the state level in the low-expansion scenario, all of the top 10 states see higher amounts of new intensive planting occurring on current naturally regenerated plots as opposed to currently planted plots, with 8.9 million acres coming from naturally regenerated plots and less than 2.9 million acres coming from currently planted plots. Part of this result is due to the relatively young age of most planted forests in the southeastern United States. The rest of the country contributes very little new planted forests in the low-expansion scenario, with a total of 2.9 million new planted acres occurring between the BAU predicted scenario and the low-expansion scenario. In the medium scenario, we continue to project a higher contribution of new planted forests coming from natural stands than in the BAU predicted scenario (14.1 million acres compared to 1.9 million acres nationally). In the medium-expansion scenario, we begin to see some states with relatively high amounts of natural forests contributing significantly, states such as Oregon, South Carolina, North Carolina, Texas and Washington. If economic or societal changes occur that continue to incentivize increased forest productivity, these states could be at the forefront of meeting that challenge. In the highest-expansion scenario, in which new planted stands are equal to the current area of planted forests (64 million acres), Oregon is the single largest contributor of the top 10 states to meeting demand (an additional 3.9 million acres), with Washington also playing a large role (2.8 million acres). Additionally, states that currently have very little management activities could see very large transformations of the local forest sector with a total of 22.5 million acres of planted forests. Particularly, California, Maine, and Arizona could see the largest impacts if major shifts to the forest sector occurred with 5.7 million, 3.1 million, and 2.5 million acres, respectively, of natural forest being intensively managed in the next decade—half of all new acres projected in the other states (22.4 million acres).

### **Projected Extensive Margin Expansion of Planted Forest**

If recent trends hold, intensive margin expansion and planting of forests post-harvest will continue, although there are reasons to believe that extensive margin expansion—planting of new forests on alternative land-use types, will also expand under certain policy or market conditions (e.g., with strong policy incentives to increase terrestrial carbon sequestration). Additionally, because of the high level of planting practices already occurring in the southeastern United States, it may be unreasonable to assume that an additional 32 million acres of naturally regenerated stands will convert to planted forest (as assumed in our medium-expansion scenario), so it is important to consider extensive margin-expansion opportunities. Furthermore, recent literature suggests that the US may need to convert large

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<sup>3</sup>Table 3 presents results using a subset of the FIA database. Plots have been restricted to those that may be harvested in the next 10 years, and do not face restrictions on harvesting. In total, 45,745 plots are included in the expansion scenario.

areas to forest area (>80 million acres) to achieve long-term climate stabilization (UNFCCC 2016, Fargione et al. 2018), and that this expansion is not likely to compete with productive agricultural lands. With this policy consideration in mind, it is important to consider where and on what types of land afforestation could occur as a consistency check on other literature estimates.

To further investigate the expansion of planted forest in the United States, we applied the estimated regression coefficients from the regression model to alternative land-cover types. Although the methodology presented in this manuscript is designed to look at discrete management changes, we justify using these regression coefficients to project distributions, as planted forest expansion on other land uses will likely be driven by similar factors. Specifically, estimated regression coefficients from the FIA plots are interpolated across the landscape and onto other land-cover categories. This process allows us to identify locations and land-use types where extensive expansion of planted forests is most likely to occur under strong policy or market incentives.

We first extrapolate predicted probabilities of planting onto other land cover types using independent variables in the regression analysis; one benefit of the selected variables is that, other than ownership attributes, all other independent variables are not specific to only forest land. It is important to note that the regression presented above does not specifically predict the likelihood of land moving into forestry and focuses instead on the physical and economic factors that could drive the planting decision, including proximity to forestry infrastructure and marginal harvest costs (proxied through the slope variable). The relative likelihood of a parcel converting to a planted forest stand is extrapolated to other land-use types for 30 m pixels, using land-cover data from the National Land Cover Database (NLCD). The key assumption we make in the extensive analysis is that areas with similar physical, economic, and climactic characteristics to currently planted plots will have a higher likelihood of conversion relative to nonforested areas with different characteristics.

There is a rich literature that explores afforestation potential, costs, and possible factors influencing the land-use change decision, although these approaches are typically focused on comparing economic rent differentials between alternative uses and focus less on the location-specific factors that may influence the planting investment decision such as proximity to infrastructure (see Cai et al. 2018, for a recent examination of scenario-driven afforestation using structural modeling techniques). In this analysis, using estimates of reforestation potential in the US (Fargione et al. 2018), we consider two scenarios of extensive expansion of plantation forest in the United States. Each scenario chooses the pixels that have the highest estimated probability of planting across specific land classes (Figure 4 shows the results of this nationwide estimation of likelihood of planted forest at the extensive margin), as defined by the NLCD, until approximately 155 million acres of new planted forests is reached. In the first scenario, pasture and hay, shrub and scrub, grassland and herbaceous, emergent herbaceous wetlands, and barren land can move into forestry, which allows relatively low-opportunity-cost lands to convert to planted forest. For this pathway, we are excluding productive cropland areas that could support plantation forestry, as this exchange would require a strong economic or policy incentive to shift land from crop cultivation into planted forests (in order to hit this target, pixels had to have an

estimated probability greater than 8.0 percent). In the second extensive margin pathway, however, we allow cropland to be eligible for forest planting as well (when cropland is included, the estimated probability had to be greater than 14.0 percent for a pixel to be included).

Extensive expansion results are shown for both scenarios in Table 4. When cropland is restricted from being considered as a source for new managed forest area, pasture and hay are the largest contributors, consistent with Fargione et al. 2018). To achieve this amount of afforestation, societal taste and preferences would have to shift from meat-heavy diets to more plant-based diets. When extensive managed forest expansion includes cropland, nearly 40 percent of potential extensive expansion of forest could come from agricultural lands. Cropland reduces the pressure of conversion from pasture and shrub, but large-scale afforestation of cropland could potentially lead to food-security concerns. Furthermore, recent modeled projections of afforestation potential under high carbon sequestration price incentives show limited movement of productive US cropland into forests given the high opportunity costs of forgoing agricultural production (Baker et al. 2017, Cai et al. 2018). However, our results demonstrate the spatial extent of cropland that could compete with other land-use types under a strong policy incentive targeting afforestation in the United States given physical and economic commonalities between this cropland and existing planted forests. Spatially, the extensive expansion results mirror those of the intensive expansion. Even at large extensive expansion targets, most of the converted land is projected to be in the southeast and northwest regions.

Although national intensive and extensive margin expansion scenarios offer insight into the potential spatial distribution of future planting under hypothetical scenarios, we do not conduct an explicit policy or market analysis to assess conversion to planting or net afforestation. With the heterogeneity in forest product markets across the country and the large costs associated with transporting forest products, projecting regional intensive margin expansion through scenario analysis can provide important insight into possible regional changes that national simulations may not capture. This framework provides a first step in using probabilistic regression analysis to estimate the likelihood that forests in the United States will be intensively planted and can easily be adapted for region-specific analysis.

## Conclusions

With demand for forest products and various ecosystem services from forests (including carbon sequestration) increasing, it is likely that the prevalence of planted forests will continue to expand. This paper makes an initial effort to understand the influence of physical, economic, and ownership categories have on the likelihood of forests converting to plantations after harvest, but some limitations exist on the current data. By including slope as a categorical variable instead of a continuous variable, some influences of slope are not being accounted for. Averaging slope across entire forest plots and classifying them in large groups may overlook large areas within plots that have a low slope (or conversely a high slope), and thus a lower operability cost (higher conversion cost). By understanding the relative influence of certain factors on the likelihood that forests will be planted after

harvest, local governments and stakeholders will be better prepared to deal with both the positive and negative impacts that result from conversion to planted forest systems.

Planted forests can increase timber production, which not only provides the potential for greater output of forests products, but also increases the amount of carbon standing in the forests. This can be beneficial as regional carbon markets evolve, and states pursuing climate action strategies continue to monitor carbon stored in terrestrial systems and incentivize increased forest carbon storage. As the composition of forests changes across the nation, accurate projections of where forest-management intensity might change will provide policymakers with better estimates of carbon stocks and emissions from forest harvesting. Furthermore, estimates from this study can be used to inform structural economic models of forest-resource systems.

Also, because planted forests can reduce the variation in age class and limit the undergrowth when compared to natural forest, biodiversity in planted forests is less than that in naturally occurring forests (Paillet et al. 2010). As plantation area continues to expand, policies could be designed to target specific areas with higher likelihoods of conversion to limit the extent of forest planting in areas of high biodiversity. In the national expansion scenario, we see the potential for the continued expansion of planted forest in the Southeastern United States because of the large existence of planted forests in the region, along with favorable weather conditions. If national planted forest area were to double in the future, we predict about 81 percent of forest in the southeast to be intensively planted under regional expansion scenarios. Continued expansion of planted forests in areas with a high concentration of forest planting is consistent with results found in a previous analysis (Sohngen and Brown 2006).

Furthermore, whereas this manuscript identifies where land-use change may occur or to assess competition for land with cultivated crop production, we can integrate results from this analysis with spatial allocation economic optimization models of the forest resource base to improve projections of future land-use change patterns in the United States. This could reduce the regional bias of forest sector outlook studies such as the 2010 Resource Planning Act Assessment (USFS 2012), which included plantation expansion to meet future demand, yet limit it to the US South. By including the propensity that specific forest plots will convert to plantation forests after harvesting, models will have a greater ability to project future land use, land-use change, carbon storage, and production of forests products across the entire US land base. Furthermore, if temperatures increase or precipitation patterns change in the future, the optimal location of managed forests may move into regions that are currently too cold or lack requisite precipitation inputs.

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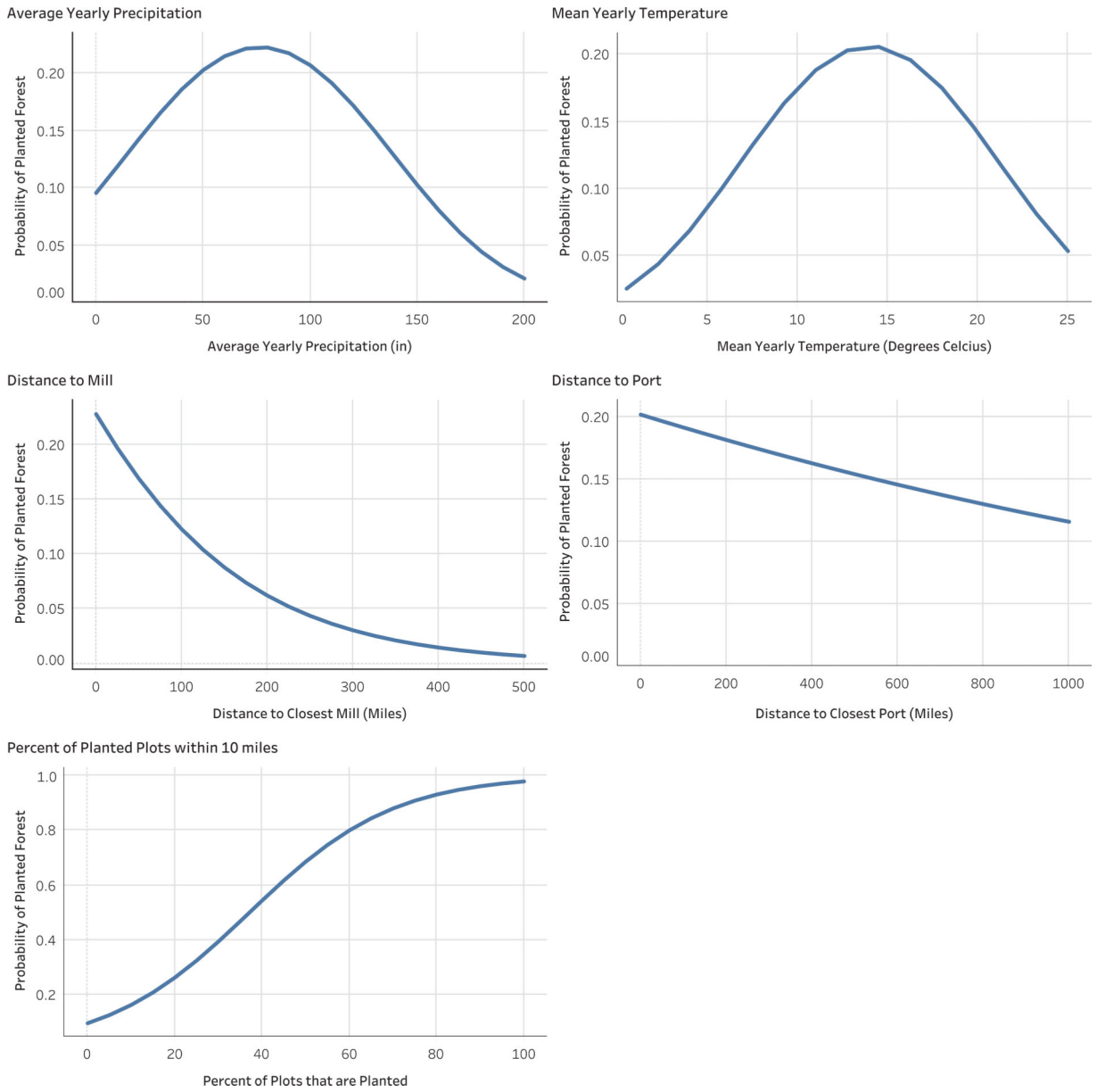
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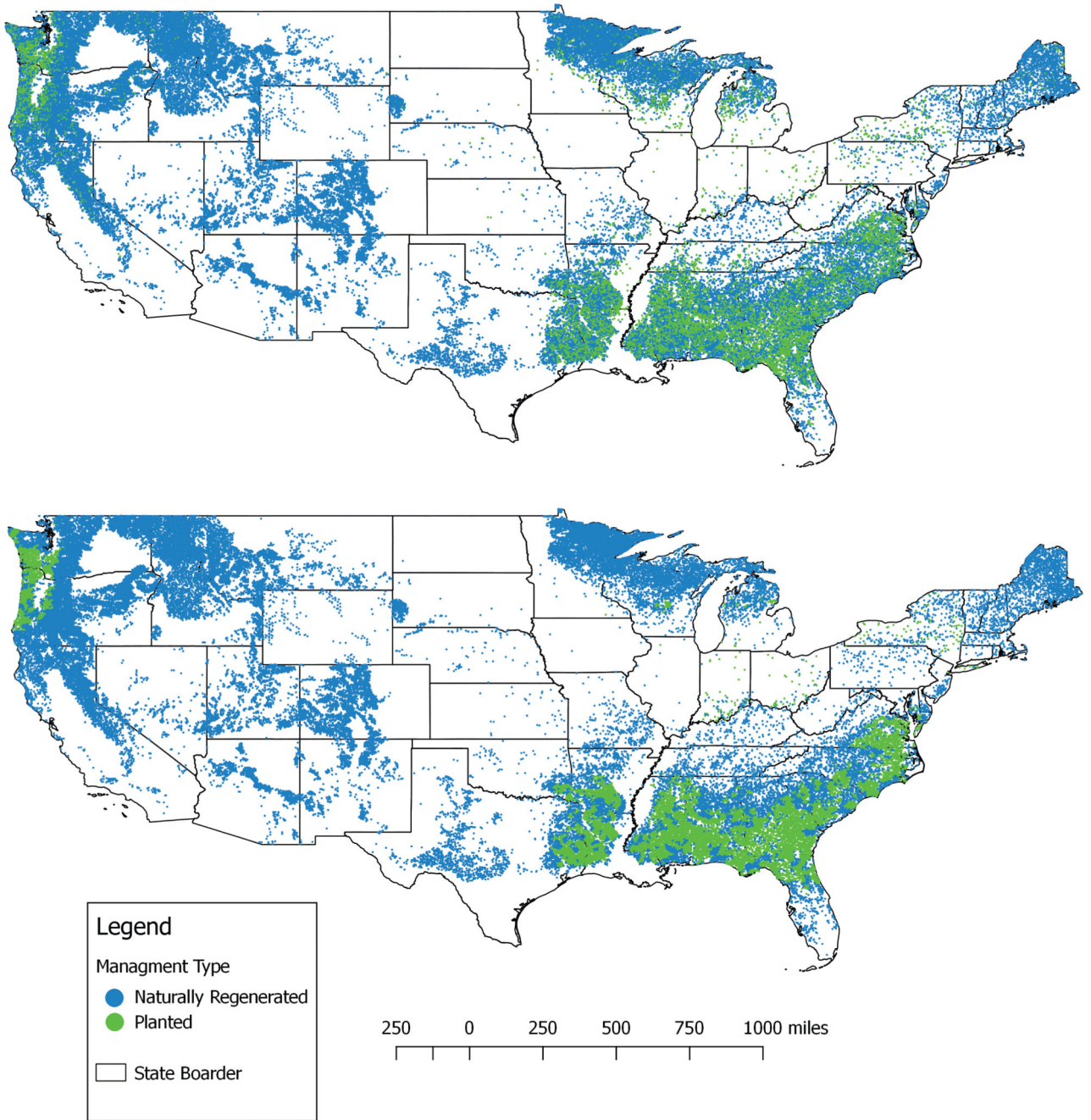
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### Management and Policy Implications

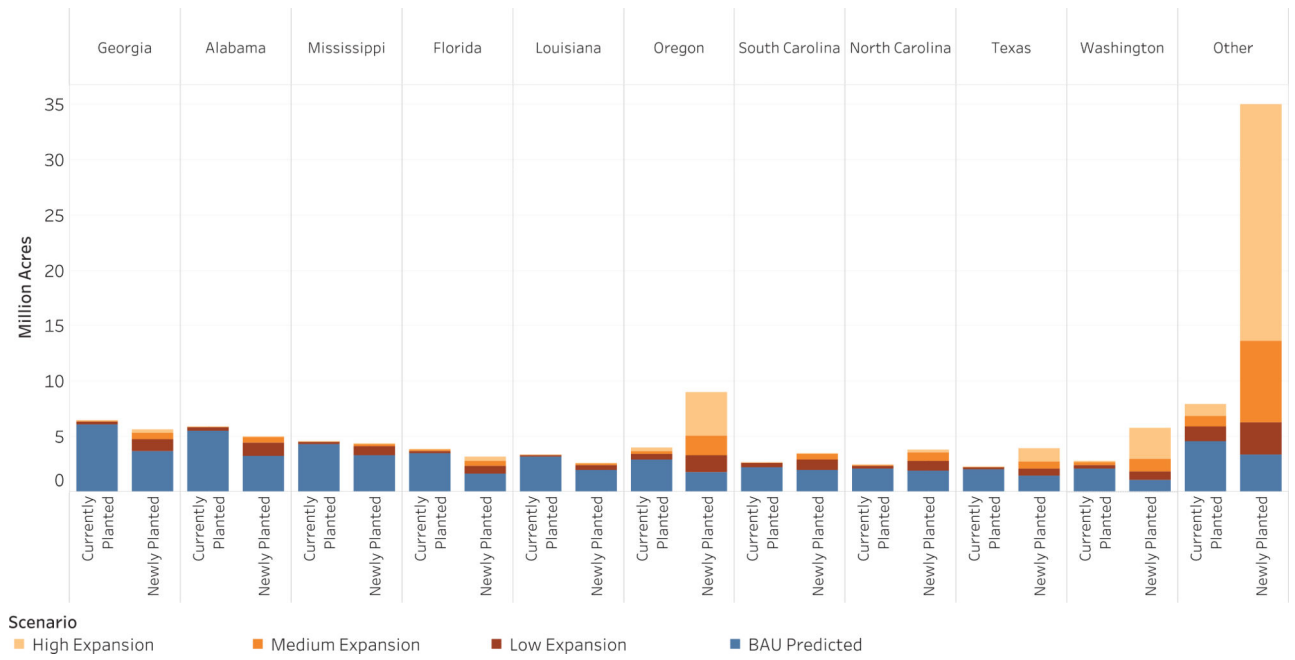
Efforts to replace aging forest inventory with more productive stands, increased demand pressure for forest products, and policy or private-sector initiatives promoting carbon sequestration from terrestrial sources could result in a net increase in forest planting and a spatial shift in where forests are planted. This research uses a spatial econometric model to estimate the likelihood that forest plots will be intensively planted post-harvest based on physical, economic, and climatic characteristics, and then projects forest planting on existing forests and other land-use types across hypothetical illustrative scenarios. This paper provides policymakers with a “first look” at where policies aimed at increasing terrestrial carbon sequestration could have the greatest impact by identifying spatial hotspots where future forest planting is most likely to occur (both on naturally regenerated stands post-harvest and on alternative land-use types). These results can provide stakeholders with information on the potential spatial extent of forest planting to aid in conservation planning, regional carbon sequestration programs, or economic incentives designed to boost the local forest products industry.



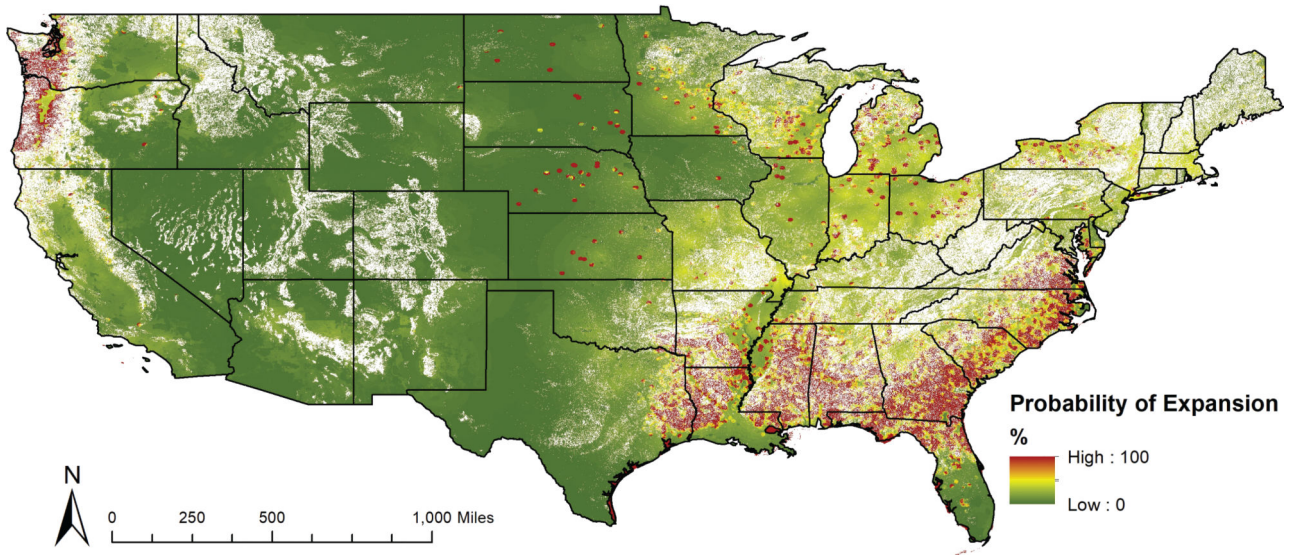
**Figure 1.** Estimated relations between climate and proximity variables on probability of forest plots being planted.



**Figure 2.** Current regeneration status of US forested FIA plots (top) and predicted spatial allocation of planting (bottom).



**Figure 3.** Intensive expansion scenario results for top 10 states by planted forest area, and the rest of the United States.



**Figure 4.** Potential extensive plantation expansion indicated by estimated likelihood of planting forest for nonforest NLCD land uses.



**Table 1.**

Summary statistics for data used in the logistic plantation probability model.

Variable	Observations	Mean	SD	Min	Max
Planted	13,176	0.216	0.412	0	1
Mean temp. (°C)	60,941	10.322	5.875	-2.090	24.270
Average precip. (in.)	60,941	35.437	15.584	1.664	190.864
Slope 0–15 deg.	36,306	0.596	0.491	0	1
Slope 15–30 deg.	8,406	0.138	0.345	0	1
Slope_30–45 deg.	5,047	0.083	0.276	0	1
Slope_45	11,182	0.183	0.387	0	1
BLM	1,992	0.033	0.178	0	1
Private	31,353	0.514	0.500	0	1
State	5,477	0.090	0.286	0	1
USFS	21,048	0.345	0.475	0	1
Other federal	1,071	0.176	0.131	0	1
Pct. planted 10 miles	60,941	0.120	0.157	0	1
Distance to mill	60,941	39.782	40.105	0.149	432.479
Distance to port	60,941	221.292	184.684	1.730	981.592
Hydrologic A	6,632	0.109	0.311	0	1
Hydrologic B	13,601	0.223	0.416	0	1
Hydrologic C	10,338	0.170	0.375	0	1
Hydrologic D	8,346	0.136	0.344	0	1
Hydrologic E	22,024	0.137	0.344	0	1
Ad valorem property tax	51,592	0.847	0.360	0	1
Flat property tax	9,894	0.162	0.369	0	1
Property tax exemption	58	0.001	0.031	0	1
Yield tax	16,794	0.276	0.447	0	1
Severance tax	34,809	0.571	0.495	0	1

**Table 2.**

Coefficient estimates for logistic plantation probability model.

Independent variable	b/SE	Exponent
Climate and physical variables		
Mean temperature squared (°C)	-0.013***	0.987
	0.001	
Mean temperature (°C)	0.351***	1.420
	0.018	
Precipitation squared (in)	-0.00017***	1.000
	0.000	
Precipitation (in.)	0.026***	1.026
	0.003	
Hydrologic Class A	0.360***	1.433
	0.039	
Hydrologic Class B	0.141***	1.151
	0.031	
Hydrologic Class C	0.134***	1.143
	0.034	
Ownership variables		
BLM	-0.133	0.878
	0.182	
Private	1.278***	3.589
	0.124	
State	0.919***	2.507
	-0.132	
USFS	0.838***	2.312
	0.128	
Economic variables		
Slope 0–15°	0.478***	1.613
	0.046	
Slope 15–30°	0.364***	1.439
	0.053	

Independent variable	b/SE	Exponent
Slope 30–45°	0.061	1.062
Percentage of plots managed within 10 miles	0.068	
	6.044***	421.576
	0.107	
Distance to mill (1,000 miles)	-0.007***	0.993
	0.001	
Distance to port (1,000 miles)	-0.001***	0.999
	0.0001	
Ad valorem tax	1.034***	2.812
	0.102	
Flat tax	1.505***	4.504
	0.101	
Exemption tax	-0.82	0.440
	0.440	
Severance tax	0.066*	1.068
	0.032	
Yield tax	0.153***	1.165
	0.039	
Constant	-7.474***	
	-0.198	

\*  $P < .05$

\*\*  $P < .01$

\*\*\*  $P < .001$ .

**Table 3.**

Comparison of current planted forest area and estimated area of planted forests from logistic regression results, and cumulative planted forest acres by expansion scenario for each of the top 10 states by area of planted forests and the rest of the country (all in million acres).

State	Status	BAU	BAU predicted	Low expansion (16 million acres)	Medium expansion (32 million acres)	High expansion (64 million acres)
Georgia	Currently planted	6.9	6.1	6.4	6.4	6.4
	Newly planted	-	3.7	4.7	5.4	5.6
	Remains natural	6.3	3.4	2.1	1.4	1.1
Alabama	Currently planted	6.6	5.5	5.8	5.9	5.9
	Newly planted	-	3.2	4.4	4.9	5.0
	Remains natural	5.9	3.7	2.2	1.7	1.6
Mississippi	Currently planted	5.2	4.3	4.6	4.6	4.6
	Newly planted	-	3.3	4.1	4.3	4.4
	Remains natural	4.9	2.4	1.3	1.1	1.1
Oregon	Currently planted	4.8	2.9	3.4	3.7	4.0
	Newly planted	-	1.8	3.3	5.1	9.0
	Remains natural	17.8	17.9	15.8	13.8	9.6
Florida	Currently planted	4.2	3.5	3.7	3.8	3.8
	Newly planted	-	1.7	2.4	2.8	3.2
	Remains natural	4.0	3.0	2.1	1.5	1.1
Louisiana	Currently planted	3.7	3.2	3.4	3.4	3.4
	Newly planted	-	2.0	2.4	2.6	2.6
	Remains natural	2.9	1.5	0.9	0.7	0.6
Washington	Currently planted	3.4	2.1	2.4	2.6	2.8
	Newly planted	-	1.1	1.8	3.0	5.8
	Remains natural	12.9	13.1	12.1	10.6	7.7
South Carolina	Currently planted	3.1	2.2	2.6	2.7	2.7
	Newly planted	-	1.9	2.9	3.4	3.5
	Remains natural	4.3	3.2	1.8	1.3	1.2
North Carolina	Currently planted	2.9	2.1	2.3	2.4	2.4
	Newly planted	-	1.9	2.8	3.5	3.8
	Remains natural	4.9	3.7	2.6	1.8	1.5

State	Status	BAU	BAU predicted	Low expansion (16 million acres)	Medium expansion (32 million acres)	High expansion (64 million acres)
Texas	Currently planted	2.8	2.0	2.2	2.3	2.3
	Newly planted	–	1.5	2.1	2.7	3.9
Other	Remains natural	12.5	11.8	11.0	10.3	9.1
	Currently planted	11.1	4.6	5.9	6.8	7.9
	Newly planted	–	3.4	6.3	13.6	35.0
Total	Remains natural	124.5	127.6	123.4	115.1	92.6
	Currently planted	54.6	38.6	42.7	44.6	46.2
	Newly planted	–	25.4	37.3	51.4	81.8
	Remains natural	200.6	191.3	175.3	159.3	127.3

**Table 4.**

Extensive forest expansion results: area by land class of potential planted forest conversion (million acres).

<b>Land use</b>	<b>Extensive without cropland</b>	<b>Extensive with cropland</b>
Pasture/hay	73.8	48.7
Shrub/scrub	42.7	26.5
Grassland/herbaceous	33.2	15.1
Emergent herbaceous wetland	7.6	5.0
Barren land	2.4	1.6
Cultivated crops		60.4
<b>Total</b>	<b>159.7</b>	<b>157.4</b>