Projecting the spatial distribution of tree planting under different policy incentive structures

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1 Introduction

The establishment of new forestland is becoming an increasingly popular strategy in global climate mitigation efforts by increasing the forest carbon sink. There are many climate benefits associated with creating and maintaining healthy forests using either method, particularly in their ability to store carbon and maintain healthy ecosystems in terms of light reflectivity (albedo), water and carbon cycles, and biodiversity[1]. Forest Expansion on certain land types, such as those used for agricultural production, can potentially improve overall environmental outcomes through the provision of carbon sequestration and other forest-related ecosystem services. Per unit-area, tree planting can provide substantially higher greenhouse gas (GHG) mitigation benefits than agricultural mitigation strategies such as reduced nitrogen fertilizer application and switching from conventional to no-till farming. Further, in the case of marginally productive agricultural lands and under uncertain market conditions, tree planting projects can offer higher and more risk-neutral income sources to farmers [2–4]. Given the climate, economic, and sociocultural benefits of tree cover expansion, there has been a global push to design policies and raise private capital to support tree planting programs. Initiatives such as the Trillion Tree Campaign [5] have stimulated interest and investment in tree planting globally, and particularly in the developing world, and are supported by data exchanges such as the Reforestation Hub [6]. Recent efforts in the U.S. include direct financial support for tree planting efforts, including sections of the Inflation Reduction Act[7] and the Repairing Existing Public Lands by Adding Necessary Trees (REPLANT) Act [8]. Despite the advancing policy dialog and increasing resource allocation toward global forest expansion efforts, there is still limited information on the most cost-effective and socially desirable places to plant and the associated tradeoffs of different incentive structures, particularly in the United States (where tree planting is typically driven by market developments and occurring on privately-owned lands). Given the growth in financial resources and policy efforts to implement tree planting programs as a GHG reduction strategy, it is vital to utilize land in a way that generates the greatest climate benefits ideally at the lowest costs, while recognizing the importance of competing policy objectives such as rural income growth, biodiversity protection, and equity goals. Ignoring potential trade-offs between carbon sequestration and other policy objectives could result in inefficient financial resource allocation and unintended negative consequences of tree planting efforts over the long-term.

Tree planting programs can be designed with different primary policy goals in mind; one initiative might focus solely on assisted natural regeneration of forests, while another might incentivize planting through the creation of plantation forests for timber or bioenergy production. Incentives could also prioritize allocation of funds to underserved communities, recognizing other important societal as well as environmental benefits. It is crucial for policymakers to assess the potential impacts of incentives on the forest sector and human populations more broadly. Quantifying estimated trade-offs of tree planting programs can be complex and require on various factors such as land characteristics (soil and water quality, feasibility for growing trees, etc.) and economic characteristics (establishment costs, market conditions, land prices, etc.), all of which need to be considered when identifying ideal locations for tree-planting. This highlights one difficulty in creating and executing tree planting programs is the presence of spatial heterogeneity in land productivity, feasible tree species, costs, and ecological qualities like soil type or elevation. Temporal considerations also add policy complexity– goals focused on near-term carbon sequestration (within a few decades) could prioritize different forest types and areas than efforts focused on longer-term carbon storage goals. Similarly, goals to maximize planted area or the gross number of trees planted will result in vastly different spatial distributions of planting, carbon effects, and market impacts. Spatial frameworks that estimate potential distribution of forest growth using location-specific costs, ecological characteristics, and sociodemographic factors[9–12] can help policy-makers compare relative costs across regions and prioritize outreach efforts. The capability to adjust model parameters provides vast opportunity for sensitivity analyses to determine the magnitude and directionality of the simulated outcomes. For this reason, they are also well-suited for analyzing other aspects of policy design and implementation issues, such as addressing tradeoffs between economic, environmental, and social factors over time. Such partial equilibrium economic models are useful tools for evaluating opportunities under varying price incentive structures while accounting for resource competition but have rarely addressed policy design issues and typically do not capture spatial heterogeneity on a small scale.

The objective of this paper is to assess simulated changes in the spatial distribution of tree planting under different policy structures, and their associated levels of carbon sequestration, using a spatial allocation optimization framework in the contiguous United States. We compare estimated cost efficiency, land use change, and ideal spatial allocation of investments under policies that seek to maximize carbon storage over two different time frames (15 and 30 years) and three budget expenditures (5, 10, and 15 Billion USD). To mimic the differences between potential policy incentives and existing offset protocols, we also compare model outcomes when only changes in aboveground live tree carbon storage are incentivized versus a wider range of carbon pools.

2 Background

2.1 Forest Loss and Expansion

For decades, global forests were rapidly deteriorated and removed due to urban sprawl, increased agricultural production, and the expansion of demand for forest products, resulting in net forest area losses as well as other environmental, economic, and social losses [13]. Globally, forest loss has contributed to approximately 11 percent of global greenhouse gas (GHG) emissions [14]. Increased focus on using forests as a climate change mitigation strategy, could help slow the loss of forests and create new incentives for reforestation and forest expansion [1, 15–19]. In many areas of the world, the historical trends of deforestation have reversed in recent decades due, in part, to carbon-oriented incentives, driven by a combination of complementary policy goals (e.g., Great Green Wall in China [20]) and market demands for forests and wood products. Global development initiatives have contributed to this reversal of deforestation and the creation of new forests. Goal 15 of the United Nations Sustainable Development Goals, for example, aims to "sustainably manage forests, combat desertification, and halt and reverse land degradation"[21]. Further, patterns of land use change in agricultural land provide insights into the various motivations for landowners to undergo transformation into forestland. Frequently, intensively managed and harvested agricultural land can become unprofitable or unproductive due to soil degradation and reduced productivity [22]. In some cases, the best option may be to temporarily leave land to fallow and allow forests to naturally regenerate [23]. Some landowners see direct economic benefits of transforming marginal agricultural land into managed forests. For example, the southeastern region of the US has seen expansion of planted pine plantations due to the comparative advantage of the species and management approach in timber production. Growth in conversion from marginally productive agriculture to forest plantations has also been driven in part by technological advances, including genetic improvements for planted pine species [24] and improved silvicultural practices [25, 26], coupled with regional shifts in forest sector infrastructure and new sources of market demand like wood pellets for bioenergy [27, 28]. These factors have created increased opportunity for high production and profitability of managing land for forests in the Southern US, while increased plantation area has also helped increase carbon sequestration rates in the region [29, 30]. The southeastern region was estimated to have the fastest accumulation of tree carbon in the US in a regional 1995 study based on yield information and net ecosystem productivity [31].

As governmental and organizations more frequently promote increasing carbon storage through forest expansion, there is a need to determine when, where, and how to provide financial resources. Therefore, the literature assessing cost efficiency and carbon impact of various approaches or initiatives has grown substantially. Much of this research is retrospective, looking at the economic, carbon, and human impacts of existing initiatives to determine what worked and what didn't. Based on the conclusions of these various studies, there is also a growing body of forward-looking research focused on modeling and projecting the impact of tree-planting policies on these factors in the future [16, 32–35]. This combined body of research aims to provide governments and landowners with a road-map for increasing forestland area and the associated carbon sink via forest expansion efforts.

2.2 Policy Considerations

Although protection of forests has played a part in the discussion of climate change mitigation for decades, there has been a large recent global push for initiatives focused on the importance of actual growth in forestland area (as opposed to protecting or managing *existing* forests). Article 5 of the 2015 Paris Agreement addresses the need for conserving sinks of greenhouse gasses, but particularly emphasizes the importance of forests and land use change in that carbon sink [36]. Since then, interest in land-based mitigation options has grown in public and private sectors in many regions of the world. New initiatives have been promoted and analyzed on global [5, 36], national [37, 38] and local [39–41] scales, providing a vast array of case studies that allow us to analyze their successes and failures. Existing research reflects the notion that success of tree-planting efforts are highly dependent on the ecological, economic, social, and policy environment where implementation occurs. This variability motivates the need to determine the factors that create successful initiatives for application in current or future programs. Thus, many studies aim to better capture these dynamic interactions to assess outcomes of a wide range of policy objectives, incentive structures, and resource allocation scenarios. Common outcomes of interest include an initiatives impact on the environment, the economy, and social or political structures. This type of analysis can ensure that new forest expansion efforts, such as the REPLANT Act of 2022, can have the largest impact on climate change mitigation while keeping expenses low.

A common theme across the existing literature is the importance of thoughtful execution of reforestation based on lessons learned and knowledge of individual contexts. The approaches used to increase tree planting vary and the objectives of these initiatives have been shown to greatly impact their outcomes [42]. Common objectives in afforestation policy are (1) maximizing the number or acres of trees planted, (2) creating the largest carbon sink through changes in management, and (3) minimizing costs of afforestation [7, 38, 43]. An approach for the first objective might be planting as many trees per acre as possible, though this method may fail to consider the common trade-off between trees per acre and long-term forest health. Further, not all tree species or planting locations are equal in their carbon impacts or economic feasibility. The choice of tree species is increasingly important as climate change continues to change the environmental conditions and viability of different tree species in different geographic locations. Accounting for expected climate change-driven ecosystem changes means, for example, focusing on species that are more resistant to fire, drought, temperature changes [44], and invasive species [45, 46]. The second policy objective aiming solely to maximize total carbon storage raises concerns about the cost-effectiveness of implementation. Urban afforestation can provide multiple social and environmental benefits [47], but available land is limited, and urban reforestation is often more costly than on other land use type [48]. Another policy approach to afforestation efforts is to focus instead on minimizing the associated costs of tree-planting or explicit carbon sequestration goals given a fixed budget constraint. Minimizing the costs of tree-planting could become more prominent as policymakers seek to determine the best allocation of public funds for afforestation. However, this could similarly lead to lower levels of carbon storage and often ignores the human systems involved in global forests.

Assessments on tree-planting policy look at a wide range of environmental, economic, and social outcomes on multiple spatial scales. Much of the literature on forest expansion started on the ecological impacts to determine whether planting trees could even have large-scale impacts and explore potential risks and trade-offs involved. A 2022 paper finds that the largest ecological constraint to this transformation is the soil quality, heavily impacted by sediments and limited nutrient availability [49]. On the other hand, Jiao et. al (2012) suggests potential negative soil impacts in the Loess Plateau region, emphasizing the importance of thoughtful planning and considering of ecological conditions[50]. Alternatively, recent literature indicates high carbon-storage potential in regions of the US: Tian et al. (2018) project a continuation of the U.S. forest carbon sink driven in part by new forest planting [51]; Wade et al. (2022) illustrate how growing market demands for forest products can increase forest area and associated carbon sinks [52], and [53] show that carbon storage from tree-planting could increase total capacity by roughly 20 percent per year. After having a general picture of differences in global forest expansion potential, there was new research interest in the magnitude of this potential. A 2020 paper seeks to elucidate variations in tree-planting potential, considering political, social, and environmental constraints[54]. The results emphasize the high carbon impacts that are available from reforestation, while emphasizing roadblocks to implementation and effectiveness in regions like sub-Saharan Africa, who experience political instability and poor tree-planting conditions. After highlighting the restrictions of political conditions can place on tree-planting feasibility, a study argues that these constraints can be reduced with support by governments and large stakeholders[14]. The potential for forest expansion is further reduced by limited community involvement that results from top-down approaches [38].

Although studies have suggested promising carbon impacts of global forest expansion efforts, there is still much debate regarding how exactly to implement them. If these initiatives are to be successful on a large scale, many economic considerations must be made to use resources in an efficient way. Many studies focus on the economic benefits of the timber industry as a way to encourage tree-planting and harness existing market dynamics. A way to work with the growing markets is to use resources to increase the returns of entering the private sector [38]. Forest expansion has been shown to be largely impacted by agricultural demand, economic value of the timber market, and policy efforts [39], factors which are also found to be important determinants of forest loss as well. This corroborates the notion of the importance of the consideration of economic conditions in the success or failure of tree-planting. [55] finds that tree-planting profitability and execution was highly dependent on the price put on carbon storage as an incentive. Even early research on tree-planting highlights the array of potential outcomes that are associated with various economic conditions, with a 2000 paper noting that forest suitability will be highly limited if economic opportunities are not available to tree-growers once stands reach maturity [56].

Finally, there is emerging research in how forest expansion resources should be allocated for the best outcomes. A 2020 study performs a retrospective analysis of the first phase to a tree-planting initiative in Bejing, finding lower-than-expected environmental benefits [40]. The study additionally uses optimization methods to project outcomes of different spatial allocations of initiatives, finding large variations in carbon, economic, and other environmental outcomes depending on the scenarios. Similarly, [57] uses ecological and socio-economic information to establish prime locations to target resources to increase the carbon sink and encourage economic growth simultaneously. These locations are recommended to be those with high social and economic activity and, in urban areas specifically, will have better carbon impacts with little existing tree-cover. By comparing the financial outcomes of three land-use scenarios in abandoned agricultural land in Sweden, [58] suggests explanations as to why conversion to pastureland was the most profitable over time. They find that economic factors such as demand for cattle, interest rates, and costs of conversion contribute the most to choice in land use change. The importance (and difficulty) of these spatial projections is growing as the future of climate conditions become more unclear due to climate change [39]. For this reason, sensitivity analysis using multiple scenarios is being heavily encouraged in the research space. Studies such as [59] use spatial analysis to assess a combination of factors including food security, land costs, and agricultural market conditions, all of which were suggested to be vital to consider to create context-based planning.

2.3 Literature Gap

The research interest in forest expansion implementation is growing substantially, with studies ranging from how a small-scale initiative might impact soil carbon [60] to global assessments of environmental[33, 40, 50] and socioeconomic [11, 37, 59, 61] effects of increasing forest area. However, there is still much analysis to be done, particularly given the speed at which new tree-planting initiatives are being created and executed. The literature has shown that although there is much opportunity for climate mitigation, there are numerous trade-offs involved that must be assessed on multiple spatial and temporal scales. Given the ecological, economic, and social dynamics involved, further research must consider all of these factors in combination. More specifically, this consideration should be done on a spatially resolute scale.

This paper combines data on afforestation potential, costs of tree-planting, existing land use, and growth potential of prominent tree species in the US, this study is designed optimizes for highest carbon potential given different budget constraints and policy objectives. This differs from existing research in its accounting for the trade-offs of afforestation between economic and environmental objectives. By using census tracts as spatial units, this paper also allows for in-depth and more spatially disaggregated analysis of afforestation opportunities in the United States. Given the quickly-changing state of forest management practices and the timber industry, it is also important to recognize the impact that changes in forest composition have on current and future carbon storage levels. Our approach applies a flexible modeling framework that can be applied to various contexts, policy scenarios, and spatial scales.

3 Data and Methods

We develop a spatial allocation optimization model that integrates land cover data with forest expansion costs, empirical growth and yield estimates for common forest types, and forest potential estimates by different land use types. The flexibility of the model allows for different objectives or constraints to be activated to mimic different policy objectives or targets – e.g., we can consider maximizing carbon or forest area given a fixed budget, or the objective function can be augmented to project a cost-minimizing spatial distribution of expansion across regions and forest types to hit an explicit policy target (e.g., tons of additional carbon sequestration). The advantage of this approach in the U.S. context is that we can evaluate the ideal spatial distribution of tree-planting investments given a narrowly defined policy goal, and then compare the outcome of this solution to more nuanced policies that consider, for example, equity in funds allocation or promoting rural development through tree-planting efforts (e.g., linking tree-planting efforts with investments in mill or bioenergy infrastructure). The following sections describe the mechanics of the model as applied in this analysis, as well as the underlying spatial datasets used to calibrate the framework.

3.1 Model Description

In this framework, we endogenize the choice of forest area expansion, as defined by spatial node (i), forest type (j), and current land use (k). Total expanded area for a particular forest type within a spatial node and original land use is defined by the variable $ForArea_{i,j,k}$. Each acres of forest has an associated yield (in biomass and carbon terms) and costs. Tree growth and yield are defined by empirically-estimated growth curves that follow a standard Von Bertalanffy functional form and are estimated directly from U.S. Forest Inventory and Analysis (FIA) data (see the Data Description section for additional details). Land use classifications from 2016 data in the National Land Cover Database (NLCD) are used as the current land use type. Economic costs of forest expansion include both establishment costs ($EstCosts_{i,j,k}$) and opportunity costs ($LandCost_{i,j,k}$), defined as the foregone economic rents from alternative land uses (e.g., economic rents from crop production). Economic costs of tree-planting are drawn from previous studies conducted at the U.S. county- and sub-county scales [10]. The model is structured to solve for forest acres for each census tract, land use type, and forest type ($ForAcres_{i,j,k}$).

For the various scenarios, the main policy objective in this paper is to maximize carbon storage given different budget constraints. Formula 1 below takes the sum of each variable for each census tract i, land use type, j, and forest type, k. $Storage_{i,j,k}$ is the sum of carbon storage, which is based on the optimized forest expansion and growth and yield estimates for each forest type. $ForArea_{i,j,k}$ is the acres of forest expansion and is used as the decision variable in optimization.

$$\textbf{Max Carbon} = \sum_{i,j,k} Storage_{i,j,k} * ForArea_{i,j,k} \tag{1}$$

3.2 Constraints

There are several optimization constraints needed to depict more accurately some ecological, economic, and policy factors. First, planting cannot occur where it is not feasible, as determined by TNC reforestation potential estimates. Similarly, we cannot allocate more trees on one acre than is ecologically feasible.

The cost of tree-planting, which is the limiting constraint on the optimization problem, is broken down into two parts– the establishment costs, $EstCosts_{i,j,k}$, and the foregone income (opportunity cost) from the current land use, $LandCost_{i,j,k}$. Total costs of forest expansion is the sum product of expansion area and total costs by tract, forest type and current land use. Total costs are restricted by an exogenous (policy-driven) budget constraint represented by equation 2.

$$\sum_{i,j,k} (EstCosts_{i,j,k} + LandCost_{i,j,k}) * ForArea_{i,j,k} \leq Budget \tag{2}$$

The final two constraints limit forest expansion at each census tract to align with the Reforestation Hub limits on potential by original land use (Equation 3), as well as limiting total forest expansion to be less than or equal to total land available on each tract (Equation 4).

$$\sum_{i,j} ForArea_{i,j,k} \leq Potential_k \tag{3}$$

$$\sum_{i,j,k} ForArea_{i,j,k} \leq TotalPotential \tag{4}$$

Although this study focuses solely on the United States on a census-tract level, the simple yet comprehensive model structure allows for applications at different scales, environmental and economic conditions, and policy intensity. There are also several potential insights that could be drawn from this work that are outside the scope of this paper, such as the distributional variation in outcomes of forest expansion across different socio-economic groups. Similarly, one could adjust the constraints to provide sensitively analysis for different budgets, interest rates, and targeted land use types.

3.3 Data Description

We merge different datasets into a common database using data on the 83,343 U.S. Census tracts in the CONUS as a common template using RStudio [62] to capture the complexity and trade-offs associated with different forest expansion policies. First, 2016 land use cover data is extracted from the USGS National Land Cover Database (NLCD), which provides a count of land use in 20 different categories at a 30x30m resolution [63]. RStudio is used to develop limits for each land use type of interest based on NLCD data. The following packages are used to perform spatial data analysis within R: 'sp' [64], 'sf' [65], 'raster' [66], 'rdgal' [67], and 'exactextractr' [68]. This provides the number and location of 30x30m pixels for each land use type in 2016, which is converted to acres and used as the base-level land usage. To aggregate the NLCD data to a census tract level, we use the 'exactextract' function to extract NLCD data within each census tract boundary. This output provides the coverage area, in square meters, which is then grouped by census tract and land use type and converted to acres by dividing by the conversion factor of 4047. We focus on four land use categories: cropland, pastureland, rangeland, and shrubland. Table 1 provides the land use categories and their labels and definitions from NLCD and Reforestation Hub data.

Data from the Reforestation Hub [6] is used, which provides an estimate for the acres of different land uses that are suitable for tree planting at a US county level for non-working lands. The estimates for reforestation potential are based on variations in carbon capture ability, costs, co-benefits of tree planting, and ecological feasibility [9]. The potential for

<table>
<tr><th>Land Use</th><th>NLCD</th><th>Reforestation Hub</th></tr>
<tr><td>Crop</td><td>Cultivated Crops: areas used for the production of annual crops and perennial woody crops such as orchards and vineyards</td><td>Marginal Cropland: croplands with soil types that constrain production</td></tr>
<tr><td>Pasture</td><td colspan="2">Pasture/ Hay: areas of grasses, legumes, or grass-legume mixtures planted for livestock or production of seed or hay crops</td></tr>
<tr><td>Shrub</td><td>Shrub/ scrub: areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation</td><td>Shrub: areas dominated by shrubs and/or young trees in an early successional stage or trees stunted by environmental conditions</td></tr>
<tr><td>Range</td><td>Grassland/ Herbaceous: areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation</td><td>Grassy areas: areas with more than 25% grass coverage that cannot be used for crop production but can be used for grazing</td></tr>
</table>

Table 1: Four land use types eligible for tree-planting under this model and their equivalent classifications in NLCD and Reforestation Hub data

reforestation by county is disaggregated to a census tract-level scale using formula 3 below where l represents the county that each tract resides in, $TotalAcres_{i,j}$ is the number of acres for each land use in a census tract, and $TotalAcres_{j,i}$ is the acres of each land use for the whole county.

$$Potential_{i,j} = \frac{TotalAcres_{i,j}}{TotalAcres_{j,l}} * Potential_{j,l} \tag{3}$$

Data on establishment costs by county and land type from [10] reflect both technoeconomic costs of tree planting, as well as opportunity costs of land use change on working agricultural lands. The county-level data are broken down to a census tract level using RStudio. Establishment costs are assumed the same across land types, and the land costs are available for three of the six land land use types of interest: cropland, pastureland, and rangeland. For existing forestland, we assume no opportunity costs of land and no establishment costs. For shrubland and urban areas, we assume the existence of establishment costs, but no opportunity cost of land. Although opportunity costs of urban land exist and can be substantial, there is no recent data to our understanding that provides appropriate estimates for open urban space. We account for this by placing a strict restriction on the acres of urban land that can be allocated for tree-planting. Using the 'tidyr' package [69], these datasets are merged to create data giving current land use, forest expansion potential, and establishment costs for each census tract in the CONUS. We depict spatial heterogeneity in carbon and biomass yield potential of planted stands for 13 forest types including: natural and planted Oak-Pine, Maple, Aspen, natural and planted Doug-fir, natural and planted Pine, natural and planted softwood, Juniper, Hardwood, and Oak.

Biomass and carbon baselines are made with the derivation of empirical growth curves for each Forest Inventory and Analysis (FIA) plot as outlined in [70]. An average for each census tract is then calculated weighted by inverse distance in miles of all FIA plots within a 0.5 decimal degree radius of the tract midpoint. The spatial allocation framework is built using GAMS Studio optimization software [71]. For each scenario we maximize carbon sequestered subject to physical and policy constraints, we assess the spatial allocation, mitigation potential and total costs associated with each allocation for a direct comparison of incentive structures. We maximize this subject to three budget constraints of 5, 10, and 15 billion USD cumulative expenditure over 15- and 30-year simulation periods. We consider natural regeneration only by prioritizing hardwoods and locations with limited forest product mill capacity. We assume purpose-driven tree planting on monoculture plantations (namely, planted pine and douglas fir) in areas that are suitable for growth of plantation-species and in close proximity to forest product mills, and use [10] cost estimates scaled to include harvest revenue. Finally, we analyze the impact of which carbon pools are included in carbon estimates with two different incentive structure scenarios. In the first, we account for all pools of forest carbon soils, litter, and belowground pools. Alternatively, we represent a production-focused incentive directed towards private-landowners where only the merchantable pools of biomass are accounted for, excluding soil, litter, deadwood, and underground carbon pools. This limited pools scenario is more consistent with current voluntary carbon offset markets.

3.4 Scenarios

We run 12 simulations consisting of 2 simulation periods, 3 budgets, and 2 carbon calculations. Table 2 provides the parameters of each scenario. We assess the distribution of forest types by using 15 and 30 year time-frames, based on the varying speeds of growth for different tree species. For example, softwood trees will have high levels of growth early in their life and that slows as they age. On the other hand, hardwood species have slower growth early in life but grow to be larger over time. The models has three budget constraints of 5, 10, and 15 billion dollars. These comparisons can assess the extent to which carbon storage increases in response to increased resources. Lastly, we have two carbon calculation approaches to assess the sensitivity of carbon storage to the inclusion of below ground, non-harvested carbon pools. The "All" carbon scenario consists of the following carbon pools: down deadwood, litter, standing deadwood, above-ground under-story, below ground under-story, boles, stumps, and saplings. The alternative carbon calculation removes the carbon pools that aren't related to harvesting including down deadwood, litter, standing deadwood, above-ground under-story, below ground under-story. We expect that the inclusion of all carbon pools will increase the total carbon pool and reduce the overall cost of carbon.

4 Results

Using the combination of data from FIA [72], NLCD[63], Reforestation Hub[6], and data on the expansion costs[10], we simulate potential for future carbon storage from tree-planting under multiple combinations of budget constraints, time horizons, forest types, and land use types. This allows us to see the impact of these factors on the potential distribution of tree-planting. For each simulation scenario, we estimated levels of cumulative carbon, total acres, and total costs by optimizing for carbon storage under different scenarios on a census

Scenario	Time	Budget	C Pools
1	15 years	$5 billion	All
2	30 years		
3	15 years		AG
4	30 years		
5	15 years	$10 billion	All
6	30 years		
7	15 years		AG
8	30 years		
9	15 years	$15 billion	All
10	30 years		
11	15 years		AG
12	30 years		

Table 2: Model scenarios with two simulation periods (15 and 30 years), three budget constraints ($5, $10, and $15 billion), and two carbon pool definitions. The "All" carbon pool includes: down deadwood, litter, standing deadwood, above-ground under-story, below ground under-story, boles, stumps, and saplings. The above-ground ("AG") carbon pool includes only boles, stumps, and saplings.

tract level. On a national level, we estimate both the cost of planted acres and the cost per ton of CO2. We present and discuss maps of carbon, costs, and area allocation under chosen scenarios. Finally, we break these values down by initial land use and projected forest type.

4.1 Forest Expansion

Table 3 below provides summaries of projected area, total CO2 storage, and the cost per ton of CO_2 for each scenario. The extreme values for each outcome exist within the $5 and $15 billion budget scenarios. The highest projected expansion and associated carbon storage occurs in scenario 10, which has a 15 billion dollar budget, a 30 year simulation period, and includes all carbon pools. This scenario has an estimated forest expansion of 28.14 million acres, which will yield 662.84 million tons of CO_2. The price of carbon associated with this scenario is $25.27 Alternatively, scenario 3 ($5 billion budget, 15 year simulation period, and only aboveground carbon pools) has the lowest projected area of forest growth and total carbon storage of 17.94 million acres and 393.9 million tons, respectively. Scenario 2 has the lowest projected cost of CO_2 storage ($11.19 per ton), while scenario 11 has the highest costs ($25.27 per ton).

The projected area of forest growth ranges from 17.94 to 28.14 million acres. For all scenarios, growth area increases with the simulation period and is not sensitive to the carbon pools included in carbon estimates. Similarly, increasing the budget results in increased forest growth. Figure 1 maps the spatial allocation of forest expansion, in acres, for simulation periods of 15 and 30 years on census-tract level. These maps further support the notion that longer simulation periods result in higher levels of forest growth. It is important to

Scenario	Budget	Acres	CO2	$/ ton
1	$5 billion	17.943	394.00	$ 12.69
2	$5 billion	19.174	446.88	$ 11.19
3	$5 billion	17.943	393.89	$ 12.69
4	$5 billion	19.174	446.79	$ 11.19
5	$10 billion	22.194	507.31	$ 19.71
6	$10 billion	24.131	568.83	$ 17.58
7	$10 billion	22.194	507.18	$ 19.72
8	$10 billion	24.131	568.71	$ 17.58
9	$15 billion	25.766	593.78	$ 25.26
10	$15 billion	28.138	662.84	$ 22.63
11	$15 billion	25.766	593.62	$ 25.27
12	$15 billion	28.138	662.70	$ 22.63

Table 3: Millions of acres of forest expansion, total accumulated Mt of CO_2, Mt of storage per year, and the cost per ton of CO_2 storage for each scenario.

note that although these maps suggest large levels of expansion across all regions on the US, they do not account for the size of each census tract. For example, trees in a census tract in Nevada that contains 4 million acres may be projected to expand by 1,000 acres. However, this is a relatively low level of forest growth compared to a census tract with 100,000 acres that experiences the same acreage of growth. Another important point is the range of forest growth that exists across US census tracts. A tract having forest growth of less than an acre may seem counter-intuitive, but this trends reflects the potential for micro-financing of forest expansion for small-scale landowners. Lastly, comparing the 15 year simulation to the 30 year simulation, we see expansion of growth further into the Western regions.

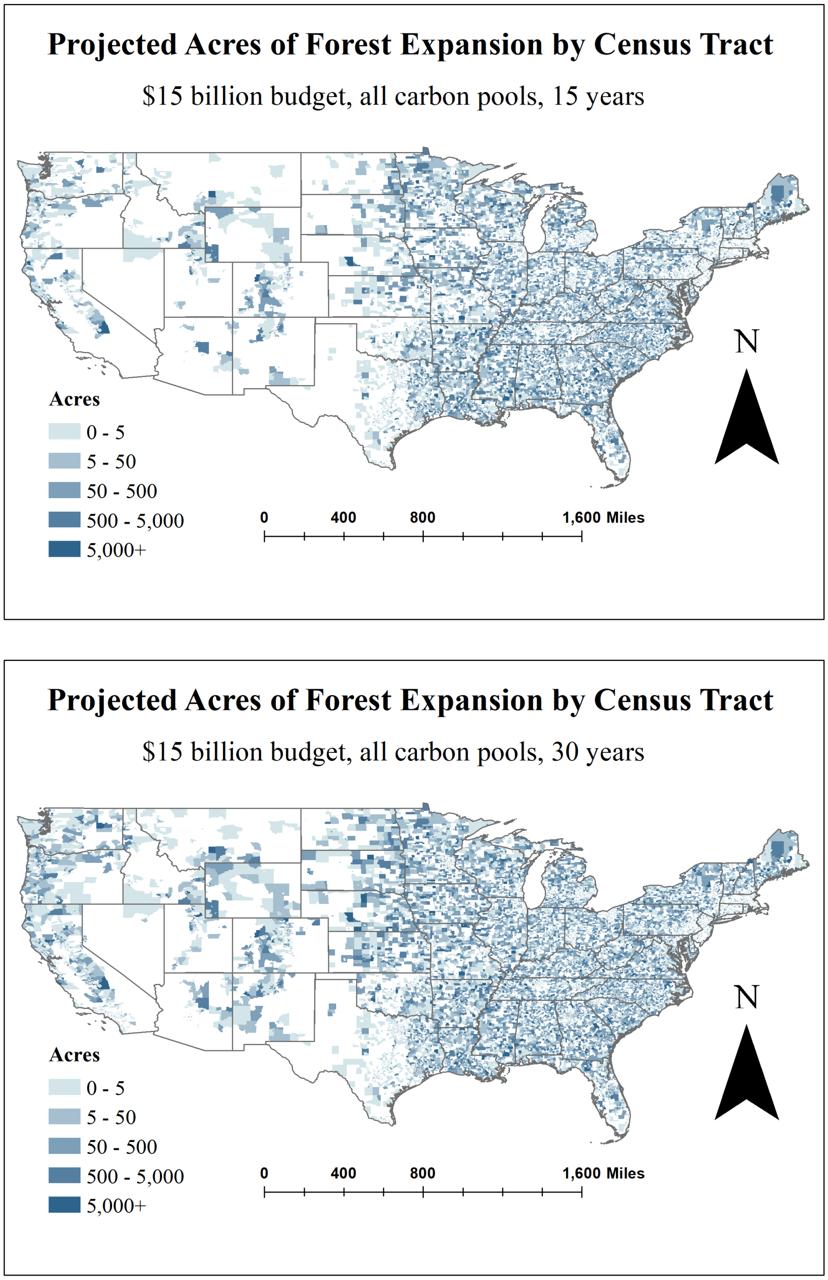
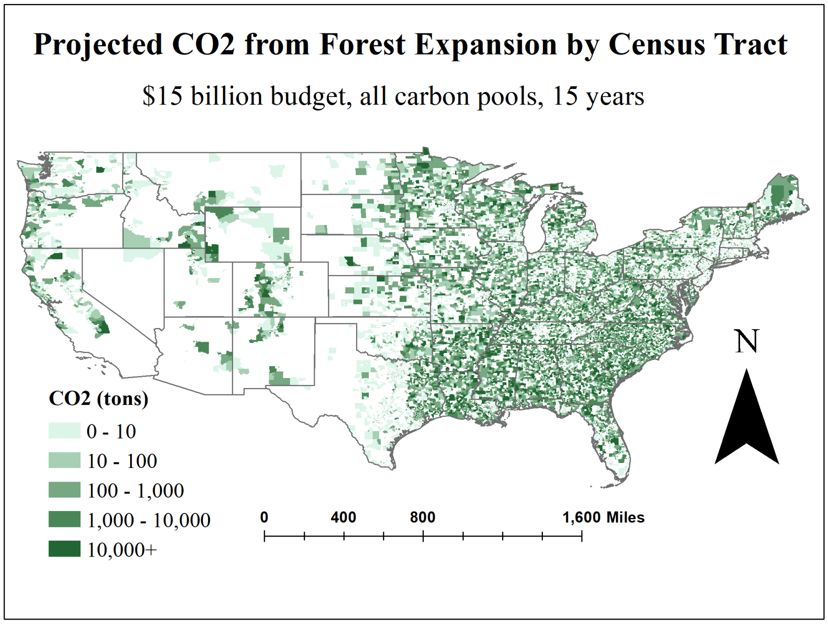


Figure 1: Distribution of Forest Expansion Area (acres) for a $15 billion budget, all carbon pools, for a 15 year simulation (top) and 30 year simulation (bottom).

The level of CO_2 storage from forest expansion range from 393.9 million tons in scenario 3 to over 660 million tons in scenario 10. CO_2 projections increase with the budget and when including all carbon pools. Increasing the simulation period results in increased levels of CO_2. Figure 2 maps the spatial distribution of CO_2 storage for scenarios 9 and 10. In a longer simulation, we see a denser CO_2 distribution in the eastern US and expansion of CO_2

into the midwest and western regions. In both scenarios, the highest amount of storage in a census tract occurs in Gregg County, Texas and accounts for 12.3 million and 17.8 million tons in scenarios 9 and 10, respectively. However, this is one of only 123 (scenario 9) and 143 (scenario 10) census tracts with projections higher than 1 million tons of additional carbon storage over the simulation horizon.



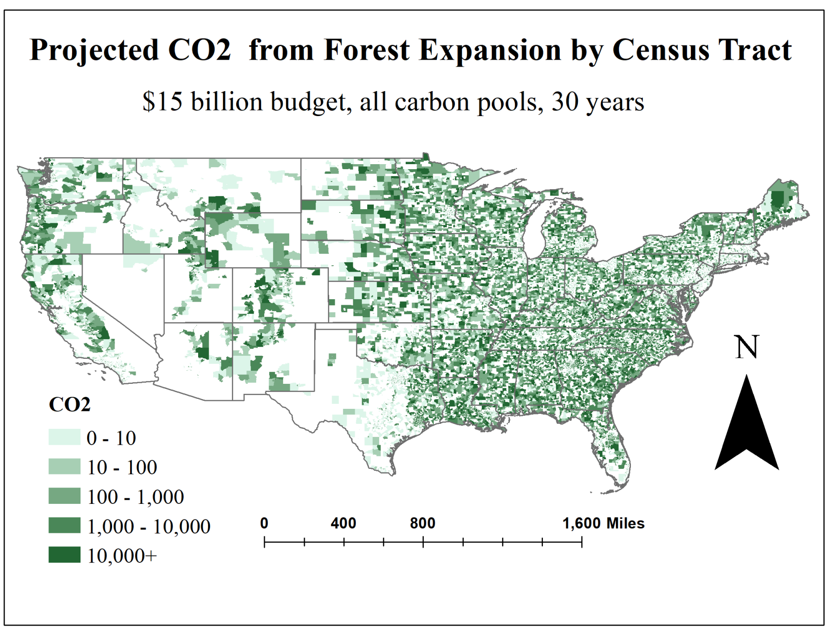
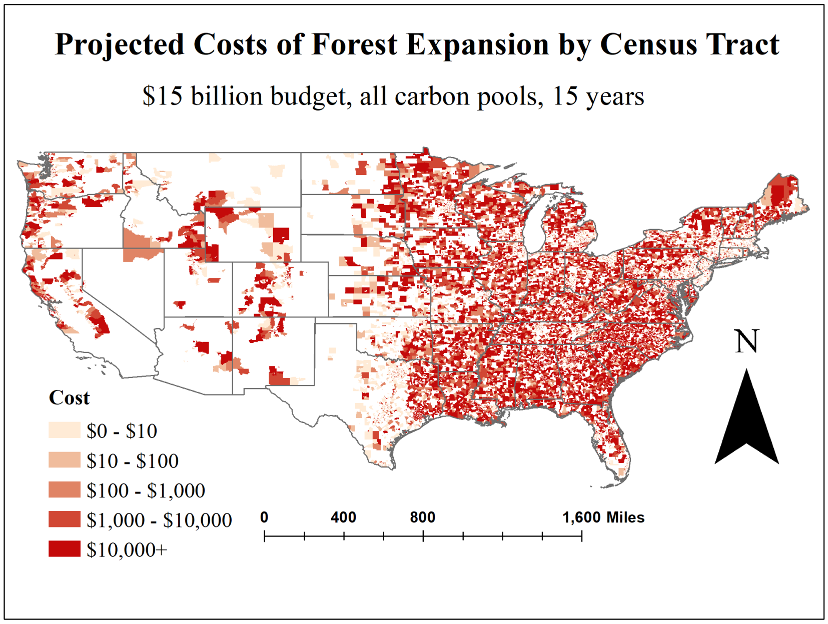


Figure 2: Distribution of CO_2 growth for a \$15 billion budget, all carbon pools, for a 15 year simulation (top) and 30 year simulation (bottom).

The cost of CO_2 was estimated as the cost per ton of storage and ranges from \$9.79 to \$22.35. All other factors constant, an increased simulation period results in lower per-unit cost of storage and a higher budget leads to higher costs per unit. This indicates marginal returns of increased spending, although the cost more than doubles from \$11.13 to \$22.39 between the lowest and highest budget scenarios. Like the projections for expansion area and resulting CO_2, accounting for only aboveground carbon pools has minimal impact on the cost of storage. Figure 3 maps spatial variations in the cost of forest expansion by census tract for scenarios 9 and 10.



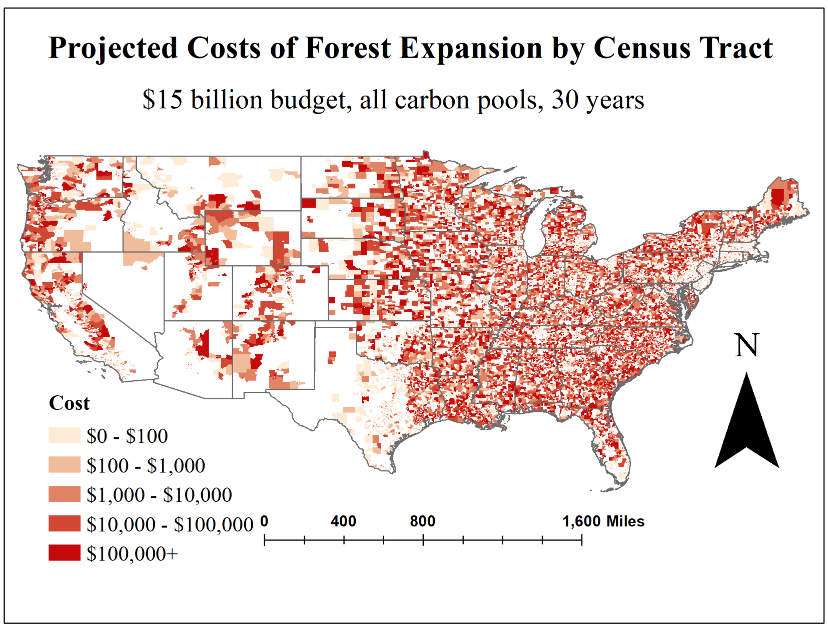


Figure 3: Spatial variation in the costs of forest expansion for a $15 billion budget and all carbon pools for 15 year (top) and 30 year (bottom) simulations.

4.2 Forest Expansion by Initial Land Use

To further dissect and understand these results, we compare model outcomes for different initial land uses and forest types. Table 4 gives the number of acres by current land use, specifically looking at crop, pasture, range, and shrubland. It is important to note that Reforestation Hub data only includes cropland classified as "marginal", meaning that all cropland is not eligible. This allows for deeper insight into the remaining three land use types and avoids the trade-offs that exist between tree-planting and food security. This restriction to marginal croplands is shown in the fact that the lowest amount of planting is occurring on cropland in all scenarios. Rangeland is the next lowest land type, but it's lowest projection of of 6.2 million acres (Scenario 3) greatly exceeds the highest projection of 1.1 million acres on cropland (Scenarios 10 and 12). For the $5 billion budget scenarios (1-4), the largest amount of planting occurs on shrubland, but this changes for the $10 and $15 billion scenarios where more occurs on pastureland. A potential reason for this is the assumption of zero land costs on shrubland and the high carbon storage potential of pastureland. If there is a smaller budget, planting will occur where the costs are lowest. However, as available resources increase the carbon potential of pastureland starts to outweigh the additional costs. This is also supported by pastureland having the greatest variation in projected expansion, with a 5.4 million acre difference between the highest projection (Scenario 10) and lowest projection (Scenario 2).

Scenario	Crops	Pasture	Range	Shrub
1	0.58	6.32	4.02	7.02
2	0.47	6.20	4.65	7.85
3	0.58	6.32	4.02	7.02
4	0.47	6.21	4.65	7.85
5	0.83	8.85	5.14	7.37
6	0.91	9.16	5.90	8.16
7	0.83	8.85	5.14	7.37
8	0.91	9.16	5.90	8.16
9	1.07	11.06	6.12	7.52
10	1.14	11.57	6.86	8.56
11	1.07	11.06	6.12	7.52
12	1.14	11.57	6.86	8.56

Table 4: Acres of tree expansion (millions) by initial land type for each scenario.

4.3 Forest Expansion by Forest Type

We continue the analysis by breaking down the optimized allocation by forest type for each scenario. Table 5 gives the millions of acres of expansion for natural and planted Pine, natural and planted Softwood, Juniper, Hardwood, and Oak forest types. Table 6 gives projected acres (in thousands) of the remaining forest types including Oak-Pine, Planted Oak-Pine, Maple, Aspen, natural and planted Doug-Fir, and Misc Pine forests. Planted pine species are estimated to experience the largest growth in land area across all scenarios, ranging from 5.2 million acres over 30 years with a 5 billion dollar budget to 12.6 million over 30 years and 15 billion dollar budget. The significant level of planting for this type of forest follows economic and ecological reasoning due to the lower costs of management and their fast-growing nature. However, the trend in planted pine acres differs from the other species. Whereas most forest types are projected to increase with a longer simulation period, planted pines experience a decrease when running a 30 year simulation.

Although potentially counter-intuitive, this speaks to the nature of the fast-growing forest type. Pine species tend to grow substantially in the first two decades after planting before slowing down to see negative marginal growth. Consequently, these species are often harvested earlier for market use, and consequently the FIA data on planted loblolly pine yield for ages greater than 30 years are limited (hence, the asymptote for the loblolly pine growth function may under-value total growth potential for older stands) to use the land for more pine growth. The same trend is seen in natural softwood forests. On the other hand, hardwood species take longer to mature, but store larger amounts of carbon over time. Hardwoods will continue to grow and store more carbon after pine species hit their peak volume. Relatively close to hardwoods in growth projections, oak species are estimated to account for between 1.13 and 2.26 million acres of expansion. Juniper and planted Softwood forests are similar in estimates ranging from 0.43 to 1.3 million acres and 0.94 to 1.3 million acres, respectively.

The remaining six forest types trail significantly behind in projected growth, with only 30-year scenarios showing any level of growth in natural Douglas-fir forests. Similarly to planted pine and softwood forests, natural oak-pine stands are projected to have less expansion in the longer simulation scenarios. Another interesting trend is in the difference in Maple forest growth between 15 and 30 year simulations. All 15-year simulations project between 2.28 and 4.35 thousand acres of expansion but the 30-year scenarios range between 71.3 and 89.2 thousand acres.

Scenario	**Pine**	**Planted Pine**	**Softwood**	**Planted Softwood**	**Juniper**	**Hardwood**	**Oak**
1	2.30	7.64	3.56	0.94	0.34	1.04	1.13
2	4.77	5.20	3.11	1.09	0.55	2.14	1.56
3	2.30	7.64	3.56	0.94	0.34	1.04	1.13
4	4.77	5.20	3.11	1.09	0.55	2.14	1.56
5	2.37	10.54	3.96	1.17	0.49	1.29	1.33
6	6.13	6.82	3.55	1.18	0.91	2.69	2.03
7	2.37	10.55	3.96	1.17	0.49	1.29	1.33
8	6.13	6.82	3.55	1.18	0.91	2.69	2.03
9	2.63	12.62	4.45	1.30	0.59	1.52	1.46
10	6.84	8.44	3.87	1.27	1.04	3.36	2.26
11	2.63	12.63	4.45	1.30	0.59	1.52	1.46
12	6.84	8.44	3.87	1.26	1.04	3.36	2.26

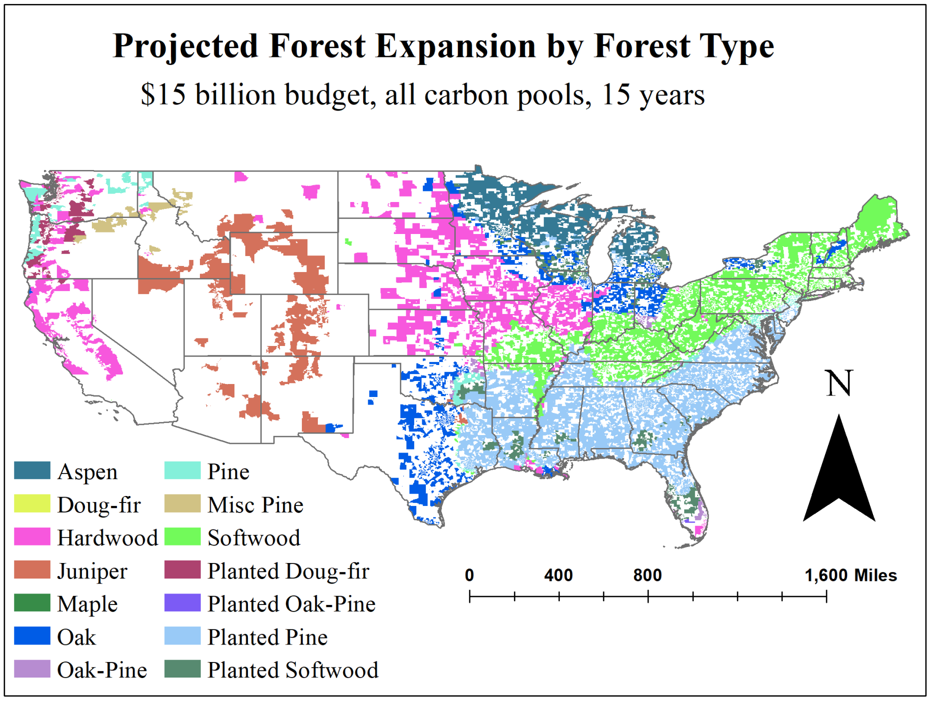
Table 5: Millions of acres of expansion for natural and planted Pine, natural and planted softwood, Juniper, Hardwood, and Oak forest types by scenario.

Scenario	Oak-Pine	Planted Oak-Pine	Maple	Aspen	Doug-Fir	Planted Doug-Fir	Misc Pine
1	379.03	11.63	2.28	435.81	-	161.51	0.00
2	331.91	10.82	71.30	67.33	0.07	266.85	0.02
3	379.03	11.63	2.28	434.91	-	161.51	0.00
4	331.91	10.82	71.30	67.33	0.07	266.85	0.02
5	381.98	11.63	2.29	460.75	-	180.36	0.05
6	335.22	10.82	75.14	73.78	0.07	324.94	3.61
7	381.98	11.63	2.29	459.85	-	180.36	0.05
8	335.22	10.82	75.14	73.78	0.07	324.94	3.61
9	391.28	11.63	4.35	586.67	-	190.02	2.59
10	412.95	10.82	89.21	126.92	0.07	390.26	31.91
11	391.28	11.63	4.35	585.56	-	190.02	2.59
12	412.95	10.82	89.21	126.92	0.07	390.26	31.91

Table 6: Thousands of acres of expansion of natural and planted Oak-Pine, Maple, Aspen, natural and planted Doug-fir, and Misc Pine forest types for each scenario. The Misc Pine category represents Pine species that account for small areas of land across different eco-provinces.

Although levels of planting in each forest type are mostly consistent across scenarios, much less consistency is expected on a spatial scale due to differences in costs, ecological conditions, and species suitability. For example, we would expect significantly more planted pine expansion in the southern region of the US, where they are more economically and environmentally suitable, as compared to the northwest region. Figure 4 further illustrates this point by mapping the spatial distribution of forest expansion by forest types for scenarios 9 (top) and 10 (bottom). There are large variations in the distribution by forest type between 15 and 30 year simulations, with some regions showing complete changes in prominent forest types. This is highlighted by the distribution of planted and natural pine in the southeastern region. Similarly, the type of forests planted in the Great Lake states switches from mostly Aspen to planted Pine between scenarios 5 and 10.

If incentives are based on shorter time-frames, this will encourage planting of fast-growing species such as planted pine plantations that are heavily managed for timber production. However, incentives for longer-term carbon storage will reduce the need for this fast growth. This results in the planting of less heavily-managed forest types that have slower growth rates, such as natural pine forests. Similarly, large concentrations of softwood tree species are projected across the northeast for a 15-year simulation period. With a 30-year simulation, much of this area is instead planted with oaks and hardwoods, which have lower yields at early ages but more growth and, thus, carbon storage, over a longer time-frame. Further, an increased simulation period resulted in expansion of hardwood forests in the midwest and California.



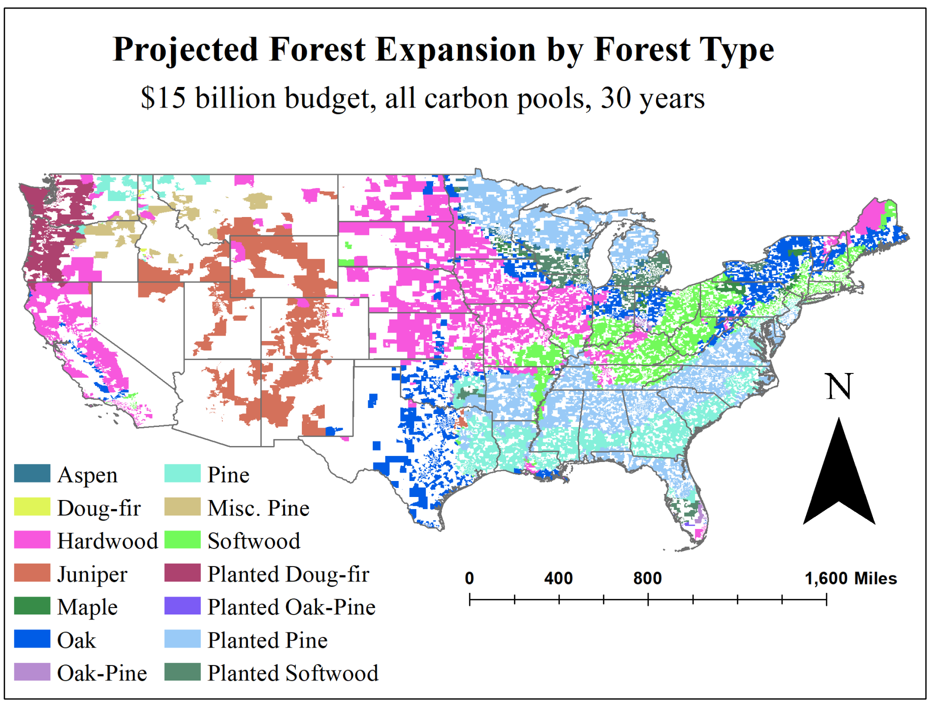


Figure 4: Distribution of forest expansion by forest type for a $15 billion budget and all carbon pools for 15 (top) and 30-year (bottom) simulation periods.

5 Discussion and Conclusions

This study utilizes data from the NLCD, Reforestation Hub, and Nielson et. al (2014) on a census tract level to project forest growth and associated CO2 and costs by optimizing for carbon storage given various budget constraints, carbon pool definitions, and simulation periods. The scenario with highest total forest growth and CO_2 storage, was projected to be over 28 million acres with an associated 662.8 million tons in a scenario with a $15 billion budget and a 30-year simulation period. Alternatively, the lowest levels of expansion and CO_2 occur in a simulation with a $5 billion budget and 15-year simulations. We assess the spatial distribution of these outcomes on a census-tract level with a $15 billion budget for both 15 and 30-year simulation periods. We find that the longer simulation period results in denser levels of forest area and CO_2 storage in the eastern region of the country and an increased level of growth in the midwest and northeast.

These projections are further broken down by initial land use and forest type. The most expansion occurs on pastureland in all scenarios, followed by shrubland, rangeland, and cropland. The maximum expanded area on each of these land use types are projected to be 11.57, 8.56, 6.86, and 1.14 million acres, respectively. The most prominent forest types across all scenarios are planted pine and the least are natural Doug-fir. Across scenarios, we project that increasing the simulation period changes the species makeup to favor slower-growing forest types that require less active management. We show the spatial distribution of forest type growth, finding some interesting trends in forest type make-up as simulation periods increase. For example, almost all of the southeast was projected to increase pine plantations over 15 years, but a large portion of that area is covered in natural pine forests over 30 years. Similarly, there was a large shift from natural softwood species to oak forest types in the northeastern US.

There are several conclusions regarding the dynamics of forest expansion policy that can be drawn from this study. First, higher budget constraints result in higher levels of forest expansion, but at a decreasing marginal rate. For this reason, the marginal cost of CO_2 storage from forest expansion increases with the budget as well. This is reflected by the cost of abatement from forest expansion ranging from $11.19 per ton of CO_2 to $25.27 as forest expansion budgets increase.

Next, we find that the time-frame of forest expansion policy has a significant impact on levels of growth and forest type distribution. Specifically, when the goal is to store the most carbon as quickly as possible, the carbon-maximizing species distribution favors larger areas of heavily-managed and faster growing forest types, such as pine plantations. Alternatively, a longer time horizon results in higher expansion species, such as hardwoods, that take longer to mature but are less heavily managed and store more carbon over time. We additionally find that the initial land use type of converted lands is spatially variant across budgets and policy timescales, with pastureland conversion to forests accounting for the largest area of forest expansion in all scenarios. The levels of conversion from crop and pastureland decrease for longer simulation periods, while planting on range (or grasslands in the Eastern U.S.) and shrubland conversion increase with time.

Lastly, we find evidence of highly variable spatial allocation of forest expansion with respect to economic, ecological, and policy assumptions and dynamics. These results can inform policy related to forest expansion and emphasize the importance of spatially planning allocation of tree-planting efforts. This optimization framework can be used to support research and outreach in other contexts, scales, and policy environments. Future research will incorporate other policy objectives such as distributing forest expansion payments to underrepresented or environmental justice communities, limiting water scarcity concerns from tree planting, and supporting climate change adaptation/resilience goals.

There are some limitations to this study that should be recognized addressed in future research. The first of which is related to the handling of cropland, forestland, and urban land. Although transitions from the included land use types are highly informative, there are transitions from crop, clear-cut forests, and open urban space for housing and industrial development that do and will occur and should be assessed in future studies. However, there are benefits to the simplified land use classifications including allowing us to ignore major trade offs between forest expansion and factors like food security and urban land rents. Additionally, there is no accounting for the large potential carbon sink that is likely to grow with increased use of timber for building, energy, and wood products. Instead, we assume that these new forests will remain untouched for the entire simulation. This is not, however, reflective of the growing timber market landscape that is prevalent in regions like the southeastern US. By accounting for the value, production, and use of wood products, future studies will likely higher levels of projected carbon storage created by forest expansion. Partial equilibrium models an effectively capture this dynamic, but miss nuanced spatial information that could limit forest expansion investments at a local scale. However, including timber production potential potential could result in a larger distribution of faster-growing forest types that are managed for harvesting and re-planting.

Lastly, the effects of climate change and the impact of the forest carbon sink will only grow more important over time. It will be important moving forward to expand the time frame of these simulations and to account for potentially offsetting effects of CO_2 fertilization from higher atmospheric concentrations and lower productivity/higher tree mortality from temperature and precipitation changes. However, given the near-term focus of existing forest expansion policies, this is still quite reflective of the current policy landscapes.

Despite these limitations, this study significantly contributes to the literature on forest expansion efforts by spatially optimizing carbon storage given 12 different scenarios on a census-tract level. To the best of our knowledge, attempts have not been made to spatially project forest expansion by forest type and initial land use at such a small resolution. Further, the model framework provides a road-map for future studies aiming to assess spatial and temporal outcomes of forest expansion. Studies should expand on these methods and findings by building on this optimization framework to address additional policy considerations such as social equity, economic growth, and forest management practices. By delving into these important policy topics, this field of research has potential to significantly increase the contribution of forests in the global carbon sink and increase the effectiveness of vital efforts to reduce the effects of global climate change.

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State	Pine	Planted Pine	Softwood	Planted Softwood	Juniper	Hardwood	Oak
AL	-	1,094,348.89	-	-	-	-	-
AR	3,119.26	822,649.54	148,422.96	-	-	7,296.36	-
AZ	-	-	-	-	91,956.36	-	-
CA	-	-	0.01	-	-	570,313.79	0.36
CO	-	-	-	-	230,367.57	307.41	-
CT	-	-	67,608.77	-	-	-	-
DE	3,461.93	80,357.98	-	-	-	-	-
FL	77.27	1,097,225.09	178.81	598,943.39	-	138,731.54	48,419.00
GA	1,674.10	1,778,692.58	-	83,372.43	-	-	-
IA	-	-	-	189.28	-	112,559.71	19,266.24
ID	11,320.23	-	-	-	136,793.24	5,748.29	-
IL	-	7,554.90	91,319.35	42,350.58	-	168,589.59	164,651.96
IN	-	-	168,872.03	70,786.26	-	40,317.06	128,347.24
KS	-	-	996.24	-	-	47,285.39	9,809.35
KY	-	109,529.20	486,151.00	-	-	7.48	-
LA	2,779.19	894,781.49	15,267.96	119,488.35	-	5,895.01	10,099.21
MA	-	-	92,520.38	-	-	431.66	430.48
MD	351,515.31	253,339.36	157,261.18	-	-	431.12	-
ME	-	-	345,339.78	-	-	-	-
MI	-	23,212.89	14,191.98	36,784.51	-	-	233,261.55
MN	-	243.60	-	18,534.16	-	20,614.80	20,952.11
MO	-	42.97	255,183.51	-	-	164,480.21	-
MS	17.93	736,300.67	33,334.85	40,177.24	-	313.73	-
MT	-	-	-	-	15,176.95	0.00	-
NC	10,220.90	1,494,075.91	2,169.01	3.92	-	-	-
ND	-	-	-	-	-	20,483.95	39.25
NE	-	-	-	-	-	65,491.39	4,360.23
NH	-	-	215,925.65	-	-	-	3,547.58
NJ	160,142.26	72,576.34	8,216.10	-	-	-	-
NM	-	-	-	-	33,418.87	-	0.00
NV	-	-	-	-	0.49	4,836.95	-
NY	1,733,795.51	-	526,449.52	35,628.81	-	1,182.71	277,270.43
OH	-	-	365,897.51	14,493.19	-	8,876.06	92,127.44
OK	53,961.74	83,800.66	1,161.02	11,365.30	1.22	13.94	103,328.23
OR	27,101.69	-	-	-	-	24,248.83	-
PA	23,337.96	121,242.69	565,361.69	-	-	4,279.42	-
RI	-	-	174,571.19	-	-	-	-
SC	-	956,495.95	-	21,586.17	-	-	-
SD	-	-	0.20	-	-	7,288.49	304.98
TN	7,681.92	543,192.20	144,111.60	-	-	-	2.63
TX	191,392.58	905,911.78	2,603.25	6,197.02	3,216.98	2.61	283,347.40
UT	-	-	-	-	29,128.33	-	-
VA	42,907.69	1,431,898.42	54,266.45	-	-	-	-
VT	-	-	26,088.16	-	-	-	559.95
WA	7,418.96	-	3.76	-	-	90,206.04	-
WI	-	4,239.27	769.29	203,490.34	-	-	60,238.92
WV	-	-	487,081.14	-	-	7,063.55	-
WY	-	-	-	-	51,077.67	-	-

Table 7: Acres of forest expansion in scenario 9 by state for natural and planted Pine, natural and planted Softwood, Juniper, Hardwood, and Oak species.

State	Oak-Pine	Planted Oak-Pine	Maple	Aspen	Planted Doug-fir	Misc Pine
AL	-	-	-	-	-	-
AR	38,764.0	-	-	-	-	-
AZ	-	-	-	-	-	-
CA	-	-	-	-	3.4	-
CO	-	-	-	-	-	-
CT	-	-	-	-	-	-
DE	-	-	-	-	-	-
FL	225,765.4	10,437.2	-	-	-	-
GA	-	-	-	-	-	-
IA	-	-	-	-	-	-
ID	-	-	-	-	-	304.1
IL	8.9	-	0.2	-	-	-
IN	1,540.0	-	-	-	-	-
KS	-	-	-	-	-	-
KY	25.8	-	-	-	-	-
LA	11,872.2	573.9	-	-	-	-
MA	-	-	-	-	-	-
MD	-	-	-	-	-	-
ME	-	-	-	-	-	-
MI	-	-	-	208,076.1	-	-
MN	-	-	4,335.7	234,509.4	-	-
MO	21.9	-	-	-	-	-
MS	-	-	-	-	-	-
MT	-	-	-	-	-	179.0
NC	400.0	-	-	-	-	-
ND	-	-	-	-	-	-
NE	-	-	-	-	-	-
NH	-	-	-	-	-	-
NJ	-	-	-	-	-	-
NM	-	-	-	-	-	-
NV	-	-	-	-	-	-
NY	17,971.2	-	-	-	-	-
OH	44,105.3	-	5.7	-	-	-
OK	1,365.3	-	-	-	-	-
OR	-	-	-	-	113,406.5	2,090.1
PA	0.0	615.4	9.4	-	-	-
RI	-	-	-	-	-	-
SC	-	-	-	-	-	-
SD	-	-	-	-	-	-
TN	873.5	-	-	-	-	-
TX	45,015.8	-	-	-	-	-
UT	-	-	-	-	-	-
VA	3,551.4	-	-	-	-	-
VT	-	-	-	-	-	-
WA	-	-	-	-	76,614.2	15.6
WI	-	-	-	144,082.1	-	-
WV	-	-	-	-	-	-
WY	-	-	-	-	-	-

Table 8: Acres of forest expansion in scenario 9 for natural and planted Oak-Pine, Maple, Aspen, planted Doug-fir, Misc. Pine, and Oak species.

State	Pine	Planted Pine	Softwood	Planted Softwood	Juniper	Hardwood	Oak
AL	103,283.0	980,431.4	-	-	-	-	-
AR	3,131.8	822,605.9	121,855.0	8.7	-	17,195.2	64,066.0
AZ	-	-	-	-	109,269.4	-	-
CA	-	-	7,229.4	-	16.1	1,564,599.5	103,097.0
CO	-	-	-	-	380,706.6	2,351.7	-
CT	-	-	67,859.4	-	-	-	-
DE	3,461.9	78,417.2	-	-	-	-	-
FL	346,766.4	772,516.2	-	253,549.6	-	138,622.8	48,730.3
GA	844,510.1	855,939.5	-	-	-	-	-
IA	-	-	-	2,543.4	-	161,896.2	29,733.5
ID	12,532.9	-	537.7	-	147,745.9	7,086.6	-
IL	-	7,554.9	79,433.2	72,541.8	-	213,277.4	122,050.4
IN	-	-	98,053.0	97,771.0	-	77,637.9	139,923.8
KS	-	-	313.6	-	-	118,851.1	22,805.7
KY	-	109,529.2	411,298.9	-	-	122,737.3	-
LA	822,377.0	99,533.4	24,609.3	-	-	9,870.1	31,212.8
MA	-	-	94,503.7	-	-	431.7	1,425.7
MD	356,444.5	252,260.9	148,204.8	-	-	1,496.5	17,047.2
ME	-	-	233,746.5	-	-	1,575.8	113,033.6
MI	-	292,233.4	1,869.0	279,616.6	-	-	53,399.9
MN	-	225,014.6	-	28,573.8	-	85,556.1	9,900.8
MO	-	43.0	148,922.2	-	-	344,222.0	9,574.0
MS	333,314.8	424,758.9	35,773.8	-	-	321.4	-
MT	4,836.3	-	-	-	20,149.7	34.6	-
NC	258,116.9	873,511.1	2,238.3	-	-	-	-
ND	-	-	-	-	0.0	29,799.1	210.1
NE	-	-	-	-	-	171,440.6	3,602.8
NH	-	-	213,761.7	-	-	8,358.7	12,170.8
NJ	160,142.3	72,576.3	8,216.1	-	-	-	-
NM	-	-	-	-	134,662.9	-	21.1
NV	-	-	-	-	7.8	18,532.3	1,522.2
NY	1,733,795.5	-	410,446.5	196,341.0	-	795.8	697,822.8
OH	-	-	362,369.7	20,622.8	-	37,403.9	124,325.4
OK	56,780.9	83,800.7	-	9,488.9	-	4,940.4	120,963.2
OR	0.0	0.0	2,877.5	-	-	10,879.5	-
PA	23,338.0	121,242.7	334,258.8	1,282.2	-	103,916.1	177,703.8
RI	-	-	222,241.6	-	-	-	-
SC	466,176.7	465,508.7	-	-	-	-	-
SD	-	-	1,976.5	-	-	45,500.3	823.9
TN	7,094.3	498,546.1	194,143.9	-	-	39,310.1	2.7
TX	1,035,310.6	44,329.9	1,340.5	19,407.2	11,375.4	604.4	286,367.6
UT	-	-	-	-	81,879.5	-	-
VA	255,488.4	1,018,827.5	100,237.2	-	-	1,142.0	8,692.0
VT	-	-	-	-	-	14,228.1	16,386.5
WA	10,133.7	-	82,627.7	-	-	2,578.6	-
WI	-	228,714.1	-	283,730.2	-	-	10,108.5
WV	-	-	463,015.5	-	-	7,428.5	30,080.2
WY	-	-	-	-	151,504.7	23.0	-

Table 9: Acres of forest expansion in scenario 10 by state for natural and planted Pine, natural and planted Softwood, Juniper, Hardwood, and Oak species.

State	Oak-Pine	Planted Oak-Pine	Maple	Aspen	Doug-fir	Planted Doug-fir	Misc Pine
AL	-	-	-	-	-	-	-
AR	-	-	-	-	-	-	-
AZ	-	-	-	-	-	-	-
CA	-	-	-	-	-	1,976.9	-
CO	-	-	-	-	-	-	-
CT	-	-	-	-	-	-	-
DE	-	-	-	-	-	-	-
FL	225,741.7	10,437.2	-	-	-	-	-
GA	-	-	-	-	-	-	-
IA	-	-	-	-	-	-	-
ID	-	-	-	-	72.5	-	350.2
IL	8.9	-	14.8	-	-	-	-
IN	4,228.8	-	-	-	-	-	-
KS	-	-	-	-	-	-	-
KY	-	-	-	-	-	-	-
LA	12,151.9	378.0	-	-	-	-	-
MA	-	-	-	-	-	-	-
MD	-	-	-	-	-	-	-
ME	-	-	1,226.5	-	-	-	-
MI	-	-	-	8,918.9	-	-	-
MN	-	-	12,832.5	94,237.8	-	-	-
MO	21.9	-	-	-	-	-	-
MS	-	-	-	-	-	-	-
MT	-	-	-	-	-	-	28,060.0
NC	400.0	-	-	-	-	-	-
ND	-	-	-	-	-	-	-
NE	-	-	-	-	-	-	-
NH	-	-	-	-	-	-	-
NJ	-	-	-	-	-	-	-
NM	-	-	-	-	-	-	-
NV	-	-	-	-	-	-	-
NY	17,971.2	-	26,146.1	-	-	-	-
OH	25,104.2	-	28,734.8	-	-	-	-
OK	14,448.2	-	-	-	-	-	-
OR	-	-	-	-	-	256,428.2	3,161.5
PA	0.0	-	20,252.0	-	-	-	-
RI	-	-	-	-	-	-	-
SC	-	-	-	-	-	-	-
SD	-	-	-	-	-	-	-
TN	1,206.4	-	-	-	-	-	-
TX	45,015.8	-	-	-	-	-	-
UT	-	-	-	-	-	-	-
VA	66,649.9	-	-	-	-	-	-
VT	-	-	-	-	-	-	-
WA	-	-	-	-	-	131,854.2	333.6
WI	-	-	-	23,763.3	-	-	-
WV	-	-	-	-	-	-	-
WY	-	-	-	-	-	-	-

Table 10: Acres of forest expansion in scenario 10 for natural and planted Oak-Pine, Maple, Aspen, natural and planted Doug-fir, and Misc. Pine species.

State	S1	S2	S3	S4	S5	S6
AL	683,423	539,486	683,423	539,486	1,027,066	857,057
AR	996,413	982,947	996,413	982,947	1,015,783	1,013,727
AZ	62,908	91,898	62,908	91,898	67,007	108,005
CA	418,090	858,649	418,090	858,385	468,172	1,239,234
CO	160,010	202,390	160,010	202,390	187,491	300,158
CT	67,609	67,609	67,609	67,609	67,609	67,609
DE	80,802	80,802	80,802	80,802	81,879	80,802
FL	1,378,016	1,331,989	1,378,016	1,331,989	1,618,214	1,540,521
GA	955,021	802,411	955,021	802,411	1,586,995	1,231,671
IA	52,304	130,146	52,304	130,146	70,757	160,792
ID	38,824	150,753	38,824	150,753	153,570	163,508
IL	383,771	411,103	383,771	411,103	423,941	449,264
IN	189,685	366,033	189,685	366,033	343,372	404,933
KS	43,238	57,642	43,238	57,642	52,522	92,262
KY	446,035	446,621	446,035	446,621	527,557	570,932
LA	690,781	665,307	690,781	665,307	950,210	958,488
MA	93,383	93,383	93,383	93,383	93,383	96,361
MD	620,228	621,208	620,228	621,208	681,771	647,791
ME	316,413	343,528	316,413	343,528	342,318	347,843
MI	464,436	500,744	464,436	500,744	485,114	555,784
MN	174,032	213,222	174,032	213,222	199,295	284,947
MO	178,194	290,204	178,194	290,204	366,379	443,341
MS	731,985	685,668	731,985	685,668	753,627	753,123
MT	312	10,462	312	10,462	4,581	22,561
NC	614,554	550,153	614,557	550,153	1,048,769	923,825
ND	2,857	20,561	2,857	20,561	19,612	23,996
NE	9,221	94,008	9,221	94,008	36,366	150,000
NH	201,128	205,481	201,128	205,481	203,447	228,663
NJ	240,935	240,935	240,935	240,935	240,935	240,935
NM	22,402	31,555	22,402	31,555	24,797	132,900
NV	-	8,207	-	8,207	2,571	17,840
NY	2,331,033	2,530,506	2,331,033	2,530,506	2,393,157	2,897,661
OH	409,756	523,335	409,756	523,335	478,035	563,694
OK	162,816	173,087	162,816	173,147	230,304	256,235
OR	141,110	168,585	141,110	168,585	154,772	226,664
PA	609,716	678,714	609,716	678,714	659,156	744,541
RI	174,383	174,571	174,383	174,571	174,571	222,242
SC	424,229	350,000	424,229	350,000	795,344	666,265
SD	5,821	7,889	5,821	7,889	6,597	18,693
TN	432,360	439,402	432,360	439,448	586,827	648,055
TX	881,717	872,530	881,684	872,530	1,198,576	1,183,916
UT	18,363	22,542	18,363	22,542	22,024	44,786
VA	920,378	899,618	920,378	899,618	1,147,550	1,114,212
VT	21,078	29,131	21,078	29,131	22,867	30,615
WA	145,255	189,114	145,255	189,114	164,964	204,525
WI	328,173	373,565	328,173	373,565	369,572	441,298
WV	468,896	484,175	468,896	484,175	484,198	494,742
WY	38,946	49,587	38,946	49,587	47,918	151,496

Table 11: Total acres of forest expansion by state for scenarios 1-6

State	S7	S8	S9	S10	S11	S12
AL	1,027,066	857,057	1,094,349	1,083,714	1,094,349	1,083,714
AR	1,015,783	1,013,727	1,020,252	1,028,863	1,020,252	1,028,863
AZ	67,007	108,005	91,956	109,269	91,956	109,269
CA	468,158	1,239,232	570,318	1,676,919	570,114	1,676,918
CO	187,486	300,158	230,675	383,058	230,675	383,058
CT	67,609	67,609	67,609	67,859	67,609	67,859
DE	81,879	80,802	83,820	81,879	83,820	81,879
FL	1,618,214	1,540,521	2,119,778	1,796,364	2,119,778	1,796,364
GA	1,586,995	1,231,676	1,863,739	1,700,450	1,863,739	1,700,450
IA	70,757	160,792	132,015	194,173	132,015	194,173
ID	153,570	163,508	154,166	168,326	154,166	168,326
IL	423,941	449,264	474,476	494,881	474,476	494,881
IN	343,372	404,933	409,863	417,615	409,863	417,615
KS	52,522	92,255	58,091	141,970	58,090	141,970
KY	527,557	570,932	595,713	643,565	595,713	643,565
LA	950,210	958,488	1,060,757	1,000,133	1,060,757	1,000,164
MA	93,383	96,361	93,383	96,361	93,383	96,361
MD	681,771	647,791	762,547	775,454	762,585	775,454
ME	342,318	347,843	345,340	349,582	345,340	349,582
MI	485,114	555,784	515,527	636,038	515,527	636,038
MN	199,295	284,947	299,190	456,116	299,190	456,116
MO	366,379	443,341	419,729	502,783	419,729	502,783
MS	753,627	753,123	810,144	794,169	810,144	794,169
MT	4,581	22,561	15,356	53,081	15,356	53,081
NC	1,048,769	923,825	1,506,870	1,134,266	1,506,870	1,134,266
ND	19,612	23,996	20,523	30,009	20,523	30,009
NE	36,366	150,000	69,852	175,043	69,852	175,043
NH	203,447	228,663	219,473	234,291	219,473	234,291
NJ	240,935	240,935	240,935	240,935	240,935	240,935
NM	24,797	132,900	33,419	134,684	33,419	134,684
NV	2,571	17,840	4,837	20,062	4,837	20,062
NY	2,393,157	2,897,660	2,592,298	3,083,319	2,592,297	3,083,319
OH	478,035	563,694	525,505	598,561	525,505	598,561
OK	230,304	256,235	254,997	290,422	254,997	290,422
OR	154,772	226,664	166,847	273,347	166,847	273,347
PA	659,156	744,541	714,847	781,993	714,847	781,993
RI	174,571	222,242	174,571	222,242	174,571	222,242
SC	795,344	666,265	978,082	931,685	978,082	931,685
SD	6,597	18,693	7,594	48,301	7,594	48,301
TN	586,827	648,055	695,862	740,303	695,855	740,303
TX	1,198,576	1,183,916	1,437,687	1,443,751	1,437,687	1,443,725
UT	22,024	44,786	29,128	81,879	29,128	81,879
VA	1,147,554	1,114,212	1,532,624	1,451,037	1,532,656	1,451,037
VT	22,867	30,615	26,648	30,615	26,648	30,615
WA	164,964	204,525	174,259	227,528	174,259	227,528
WI	369,572	441,296	412,820	546,316	412,820	546,263
WV	484,198	494,742	494,145	500,524	494,145	500,524
WY	47,918	151,496	51,078	151,528	51,078	151,528

Table 12: Total acres of projected forest expansion by state for scenarios 7-12.