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Impact of cost assumptions on forest carbon targets and supply dynamics

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ABSTRACT

Including both explicit and opportunity costs in valuing ecosystem services offers a comprehensive economic assessment, but practical applications often focus on explicit costs alone. This study examines the evolution of spatial targets and supply dynamics for forest carbon in the Central and Southern Appalachian Region, transitioning from a solely explicit-cost approach to one incorporating weighted opportunity costs. We calculate opportunity cost weights by analyzing development pressure at the pixel level, where each pixel's forest conversion rate—estimated as the anticipated shift from forest to urban land use—serves as an index for local development pressure. These weights range from zero (no development pressure) to one (full development pressure), with higher weights assigned to areas facing greater likelihoods of conversion. This approach provides flexibility in estimating opportunity costs based on localized economic pressures. Our findings indicate that incorporating opportunity costs significantly affects forest carbon supply dynamics, with higher development pressures leading to increased costs and reduced potential for carbon storage. By applying weighted opportunity costs, however, the financial burden is moderated, supporting a balance between carbon storage goals and economic considerations. These findings suggest that forest conservation programs would benefit from regionally adjusted incentives, especially in development-prone areas where high opportunity costs might deter landowners from participating. By prioritizing regions with critical carbon storage potential and high conversion risk, conservation policies could maximize environmental impact and economic efficiency across the Appalachian landscape. This approach offers a pathway for conservation policies that support carbon sequestration objectives while acknowledging economic trade-offs.

1. Introduction

As urgency to tackle climate change grows, diverse remedies have been proposed. One cost-effective solution that has developed in recent years involves carbon storage in agriculture and forestry (Terasaki Hart et al., 2023; U.S. Department of Agriculture, 2023). In this context, carbon storage in forestry specifically has become an important focal point since forests have a large and cost-effective carbon storage capacity relative to other carbon storage solutions (Austin et al., 2020; Ontl et al., 2020).

Despite the emergence of forest-based carbon initiatives, including both carbon offsets and carbon credits (Kaarakka et al., 2023; Zhang, 2005), there are various methodological, socio-economic, and implementation challenges constraining the further development of forest-based carbon storage programs (Pan et al., 2022). These challenges have been extensively documented in forest science literature, particularly in relation to carbon sequestration methodologies, payment schemes, and landowner participation incentives (Engel et al., 2008; Lubowski et al., 2006). Carbon offsets refer to actions that compensate for emissions by reducing or capturing carbon in one place to balance emissions produced elsewhere, whereas carbon credits are tradable permits representing a verified quantity of carbon reduction that can be bought and sold in compliance or voluntary markets (Hamrick and Gallant, 2017).

One fundamental aspect is that conventional market mechanisms often overlook the intrinsic value of forest carbon storage, resulting in what is commonly referred to as market failure. For example, when landowners convert forests to agriculture or urban uses due to higher short-term profits, the market fails to account for lost carbon storage benefits, incentivizing unsustainable land use. This oversight has prompted an increased focus on assessing forest carbon supply through payment for ecosystem services (PES) (Frey et al., 2021; Cho et al., 2020; Liu et al., 2019), with the potential for expanded use of carbon market mechanisms in the future (Tanger et al., 2023; World Bank, 2023; Webb,

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2021).

Given the recognized challenges of market failure—where the full value of forest carbon storage is not reflected in market transactions, leading to underinvestment in conservation— it is crucial to understand how the economics of forest use and conservation can be accurately measured and promoted (Cubbage et al., 2022). Studies in forest economics have emphasized the role of dynamic cost models in addressing these failures, particularly in adapting conservation strategies to region-specific conditions (Kline and Alig, 2005; Sohngen and Mendelsohn, 2003). For example, forest landowners may choose profitable land uses like agriculture or development over conservation, as markets fail to compensate for the broader climate benefits of carbon storage. Various tools and methodologies have been employed in evaluating the benefits that forests provide in terms of carbon sequestration. The benefits of forest carbon storage and the associated costs of preserving these benefits can be illustrated by the concept of return on investment (ROI), a metric commonly used to assess the supply relationship of forest carbon storage.

Typically, the benefits of forest carbon storage in ROI metric estimation for evaluating forest carbon supply are assessed using carbon simulators such as Terrestrial Ecosystem Modeling (TEM) and the Forest Vegetation Simulator (FVS) (Dixon, 2002; Raich et al., 1991). While these approaches operate on distinct assumptions and mechanisms, leading to slightly varied benefit measures, their shared objective in measurement is presumed. Therefore, the selection of one simulator over another is generally not a contentious issue, emphasizing its sensitivity as a matter of preference rather than a fundamental dispute. This is primarily because each estimator, despite its unique methodological framework, aims to provide reliable estimates of carbon storage capabilities.

Conversely, the choice of cost measure in ROI metric estimation for evaluating forest carbon supply can differ significantly based on an individual's perspective on the value of ecosystem services related to carbon provisioning. Within the framework of PES, some may restrict the costs to explicit expenses linked to forgoing returns from forest uses, particularly timber harvests (Nikolakis and Innes, 2017), while others may expand costs to include both explicit expenses and the opportunity cost associated with forgoing potential gains from alternative uses of forestry, such as urban development (Liu et al., 2022). The gap between these viewpoints is significant, as these expenses can vary greatly across different locations and may not be related or even be positively correlated.

This disparity reveals that regions with high opportunity costs, such as those near urban areas, face different financial pressures than more remote areas with limited alternative land-use potential. As a result, forest carbon programs need tailored cost measures that reflect local economic contexts, since uniform approaches may fail to account for the diverse economic trade-offs across regions. By recognizing these variations, policymakers can design PES programs that more effectively balance conservation incentives with local economic realities, ultimately promoting broader feasibility and adoption of forest carbon storage strategies.

Moreover, this divergence in cost perspectives can lead to markedly different forest carbon supply relationships (Engel et al., 2008). For example, the opportunity cost of urban development, which may far exceed the explicit cost of timber harvest, could result in urban development returns dominating the cost measure (Irwin and Bockstael, 2007). Conversely, focusing solely on explicit costs would ignore the significant urban development pressures in certain areas, leading to notable differences in forest carbon supply projections. These distinctions underscore the need for carefully tailored approaches that consider both types of costs to capture the full spectrum of economic drivers impacting forest conservation.

While theoretically, the inclusion of both explicit and opportunity costs in valuing ecosystem services for their supply relationship is preferable since it provides a more comprehensive assessment of economic value, practical applications have primarily limited themselves to assessing explicit costs only. For example, the Conservation Reserve Program (CRP) exemplifies this trend in its approach to providing PES to private landowners in exchange for temporarily withdrawing environmentally sensitive land from agricultural production. The determination of payment rates in CRP agreements is exclusively based on the land's agricultural productivity, directly tied to explicit costs (Claassen et al., 2008). However, this practice explicitly excludes the consideration of opportunity costs in computing CRP rental rates as a means to balance between encouraging conservation and avoiding competition with land renters (Baker and Galik, 2009).

Despite the prevailing use of PES without factoring in opportunity costs in conservation practices, the potential to include these costs in future PES mechanisms is quite conceivable. This foresight becomes critical when evaluating the cost of supplying forest carbon storage in areas near metropolitan regions with high demand for real estate development, as opposed to costs in remote areas where such demand is virtually absent. Specifically, the need for a distinct treatment of the cost measure by incorporating opportunity costs between these contrasting scenarios is likely to become more apparent. This is especially true if there is a substantial demand for forest carbon storage in proximity to metropolitan areas as opposed to remote areas – a scenario that seems quite plausible.

Including opportunity costs is anticipated to alter the basis of evaluating forest carbon storage supply based solely on explicit costs. There is a growing body of literature that explores these mechanisms. This growing research investigates the consequences of integrating opportunity costs and shows how their inclusion results in variations in optimal solutions for PES supply when comparing the contrasting cost assumptions (Börner et al., 2017). Nevertheless, a drawback in the expanding literature is the tendency for modeling to be binary, with studies either including or excluding the consideration of opportunity cost across the study area. For instance, Cho et al. (2021) explored how the cost of conservation investment, with and without inclusion of the opportunity cost of protected areas, yields different solutions in a multi-objective optimization framework at the county level in the Central and Southern Appalachian Region of the United States. While such studies comparing optimal spatial conservation targets with and without opportunity costs offer valuable insights into potential improvements for future PES mechanisms, the all-or-nothing approach poses practical challenges. Forestland in remote locations face virtually no opportunity cost from urban development, while those near metropolitan areas, with high potential for urban expansion, require tailored consideration based on their urban development pressures.

This variation in urban development pressures necessitates a more strategic approach to managing forest carbon storage supply, especially those located between areas facing minimal and maximum development pressure. Given the range of development pressures, forestland that lie between minimal and maximum development pressure necessitate a distinct approach regarding the consideration of opportunity cost of urban development. It is essential, therefore, to adapt the application of the cost measure to reflect a spectrum that spans solely from explicit costs to a comprehensive inclusion of both explicit and opportunity costs, along with variations in between. This refined adjustment in the cost analysis framework allows us to better understand and respond to the intricate dynamics of forest carbon storage supply amidst urban expansion pressures.

Our objective is to examine the evolution of spatial targets and supply dynamics for forest carbon in the Central and Southern Appalachian Region of the United States, transitioning from a focus solely on explicit costs to incorporating both explicit and opportunity costs. This shift reflects the complexities of development pressures within our cost assumptions. In this context, we define opportunity costs as the potential returns landowners forgo when forestland is conserved rather than converted to urban development, which is the alternative land use considered in our model. Our analysis considers a pair of opportunity cost assumptions: full opportunity costs and weighted opportunity costs.

Full opportunity costs assume the highest development pressure across all areas, representing the maximum potential economic gains from urban development, with a uniform weight of 1 (or 100 %) applied across all pixels. This scenario assumes that all forestland faces high development pressure, maximizing opportunity costs uniformly across the study area. Weighted opportunity costs, in contrast, allow for flexibility by adjusting the opportunity cost weight according to the intensity of development pressure at each pixel, derived from forest-to-urban conversion rates. To calculate these rates, we use the difference between urban and forest returns in the forest change model, applying each year's estimated difference to the model's parameters while holding other variables constant to capture pixel-level development pressure. This weighted approach calculates each pixel's weight by comparing its conversion rate to a maximum threshold rate determined by the distribution of forest conversion rates across the region, enabling us to capture spatial differentiation in development pressures that vary with proximity to one or more urban areas. The resulting weights range from zero (no development pressure) to one (full development pressure), offering a detailed consideration of opportunity costs that aligns with varying local economic contexts across different locations.

Our results highlight the crucial importance of incorporating both explicit and opportunity costs in optimizing cost efficiency. Consequently, this plays a significant role in developing strategies for forest carbon supply in the face of diverse development threats. We show that an increase or decrease in forest carbon supply is significantly affected by three cost assumptions: only explicit costs considered, the inclusion of full opportunity costs, and the latter adjusted by varying levels of development pressure. By integrating these different assumptions, we acknowledge that not all regions face the same economic pressures and provide a scalable framework to apply opportunity costs proportionate to local development risks.

This weighted approach provides a quantitative foundation for adjusting the consideration of opportunity costs, ensuring that our assessment of forestland carbon supply accurately reflects the potential of urban development. By allowing a flexible and targeted application of cost measures to specific degrees of development pressure across different forestland areas, we enhance our strategies for managing forest carbon. As we refine our methodology using weighted opportunity costs, we further explore how these adjustments impact a broader strategy for forest carbon management. Understanding the interplay between cost assumptions and their effects on forest carbon supply dynamics is crucial for optimizing management approaches in response to varying development pressures.

2. Method

The cost assumptions—using explicit costs alone and combining both explicit and opportunity costs—are applied separately in single-variable optimization to facilitate optimal spatial targeting of pixels. This approach helps derive specific forest carbon supply relationships for each scenario. In the weighted opportunity costs approach, weights are defined to adjust opportunity costs based on the varying levels of development pressure across regions, capturing the expected influence of urban development on forestland conversion. By scaling opportunity costs according to projected forest conversion rates at the pixel level, the model reflects the economic pressures driving land-use decisions more accurately, enabling more realistic forest carbon supply estimates.

Building on this approach, the three-stage framework begins by constructing a land use model based on historical data. This model identifies the relationship between returns and forestland use, focusing on the differential between forest and urban returns as the primary driver of forest land conversion. This differential reflects the opportunity cost of maintaining land as forest rather than converting it to urban use.

In the second stage, projected return data is applied to the model's parameters to estimate forest conversion rates at the level of individual 10 km by 10 km pixels. This allows for forecasting areas most likely to be converted to urban use and highlights regions under increased development pressure. The projected forest conversion rate at the pixel level is then used to apply weighted adjustments to opportunity costs, ensuring that areas with higher development pressure have appropriately scaled opportunity costs in the model.

In the final stage, supply curves for forest carbon storage are generated under the three cost assumptions. These curves incorporate the weighted opportunity costs based on projected forest conversion rates, allowing for an accurate estimation of costs at different levels of development pressure. By comparing scenarios with and without these weighted opportunity costs, we illustrate their impact on the feasibility and efficiency of forest carbon supply.

The following subsections provide a detailed overview of each stage of the three-stage model, organized as follows: *2.1. Forest land use model, 2.2. Forest conversion rate, and 2.3. Forest carbon supply*.

2.1. Forest land use model

The estimation of forest conversion rates, used to weight opportunity costs in deriving carbon supply curves, is conducted through a pixel-level forestland use model. This model assumes that each 100 km^2 (10 km by 10 km) pixel, containing both forestland and non-forestland, represents a distinct ownership unit. Each pixel is considered to be owned by a private landowner who is risk-neutral, aims to maximize utility, and acts as a price-taker in the market. The private landowner is hypothesized to maximize returns by determining the degree of forestland conversion, which can range from none to the full extent of the existing forestland, converting it into urban area for development purposes over a specified timeframe.

To empirically evaluate this hypothesis, we define the ratio of private forest area in the final year of each of the three five-year intervals examined (namely, 2001–2006, 2006–2011, and 2011–2016, with the periods aligned to coincide with the National Land Cover Database (NLCD) cycles) to its area in the initial year of each interval as an indicator of forest conversion change. This conversion rate is hypothesized to be influenced by the net difference between forest return and urban return in the first year of the corresponding period.

To operationalize this pixel-level approach, we identify private forest areas by consolidating classifications of evergreen, deciduous, and mixed forests from the National Land Cover Database (NLCD), which has a resolution of 30 m by 30 m (Dewitz, 2023). This consolidation enables us to compute the total forestland within each 10 km by 10 km pixel for the NLCD periods. Forestland under permanent protection, which is ineligible for inclusion in the forest carbon supply relationship, is excluded. This exclusion applies to areas protected by both government and non-governmental organizations, as identified in the Protected Areas Database of the United States (PAD-US) by the U.S. Geological Survey (USGS) Gap Analysis Project (GAP) (2022).

A key variable in the land use model is the historical forest return, estimated using the Soil Expectation Value (SEV) method. For estimating urban return, we use the annualized median assessed land value as a proxy, following a methodology similar to Lubowski et al. (2006) (see Figs. S1 and S2 in the Supplementary Material for the spatial distributions of historical forest and urban return estimates).

In addition to the primary measure, other variables are included to control for external factors that may affect forest conversion rates, referred to as "other relevant variables." These controls help isolate the impact of the return disparity, emphasizing the contrast between the opportunity cost of not converting forestland to urban use—the most beneficial alternative use of the land—and the explicit cost of maintaining it as forestland. The relevant variables include geophysical characteristics, such as average slope and elevation, estimated using the Zonal Statistics tool in ArcGIS 10.1 (ESRI, 2012) and a Digital Elevation Model (DEM) provided by the U.S. Geological Survey (USGS) (2013). These geophysical factors are included due to their documented influence on the costs of converting forestland (Nelson and Geoghegan, 2002).

Additionally, the model includes state dummy variables to account for regional differences in forestland conversion rates across AL, GA, NC, SC, KY, VA, and WV, with TN serving as the reference state. Ecoregion dummy variables account for variations in forestland conversion across different ecoregions, representing the Central Appalachian Forest and Cumberlands/Southern Ridge and Valley ecoregions, with the Southern Blue Ridge ecoregion as the reference, based on ecological classification by the U.S. Environmental Protection Agency (EPA). Time-period dummy variables capture temporal changes in forestland conversion for the 2006–2011 and 2011–2016 periods, using 2001–2006 as the reference period. Table 1 provides a description of all variables used in the model.

2.2. Forest conversion rate

By applying parameters for the difference between urban and forest returns from the forest change model, along with projected future returns detailed in Table 1, we estimate the anticipated rate of forest conversion over a future timeframe extending from 2016 to 2050. This period begins with the most recent historical data available and extends to 2050, aligning with the global target for achieving carbon neutrality as stipulated in the Paris Agreement (UNFCCC, 2024).

To project forestland in 2050, we apply each year's estimated difference between forest and urban returns to the corresponding parameter in the forest change model, holding all other variables constant. We then calculate the forest conversion rate at each pixel by subtracting the projected forestland in 2050 from the estimated forestland in 2016, divided by the estimated forestland in 2016. This pixel-level conversion rate represents the likelihood or intensity of forest-to-urban conversion over the study period, allowing us to assess development pressure at each location. This rate is then used as a basis for determining the relative weight assigned to opportunity costs in our cost estimates, with higher conversion rates corresponding to higher weights.

To compute weights for opportunity costs, we used a pair of cost scenarios: weighted cost and full cost. In the full cost scenario, opportunity costs are assumed to reflect the maximum potential economic return from urban development, and we apply a weight of 1 (or 100 %) uniformly across all pixels. This scenario assumes that all forestland faces high development pressure, thereby maximizing opportunity costs across the entire study area.

In contrast, the weighted cost scenario assigns variable weights based on localized development pressures, derived from the previously calculated forest conversion rates. Here, each pixel's forest conversion rate directly informs the opportunity cost weight by reflecting the intensity of development pressure. To establish these weights, we analyze the frequency distribution of forest conversion rates to identify a plausible maximum conversion rate, which serves as a threshold for significant conversions. A specific percentage of this maximum rate is set as a cutoff to exclude outliers and focus on meaningful conversions rather than minor fluctuations. For each pixel, the percentage of its forest conversion rate relative to this maximum threshold represents the weight assigned to opportunity costs. This approach allows us to scale opportunity costs in proportion to actual development pressures across different locations, assigning higher weights to areas with greater forest-to-urban conversion rates and lower weights to areas with minimal conversion risk.

These forest conversion estimates are essential for assigning appropriate weights to opportunity costs when deriving supply curves under various cost scenarios in the following stage. Thus, while the full cost scenario applies a fixed weight of 1 for all pixels, the weighted cost scenario varies opportunity costs across pixels, ensuring that our analysis captures the spatial variability in development pressures and reflects local economic contexts in opportunity cost estimation.

Table 1
Parameter estimates for all variables used in the forest land use model (n = 7002).

Variable	Parameter Estimates (Std Error)
Constant	−0.017* (0.002)
Economic variable	
Forest return relative to urban return ($/ha) (× 0.0001)	0.104* (0.016)
Geophysical variables	
Average elevation (meter) (× 0.0001)	−0.066* (0.024)
Average slope (degree) (× 0.001)	0.156 (0.115)
Cumberlands and Southern Ridge and Valley ecoregion (binary)	−0.002* (0.001)
Central Appalachian Forest ecoregion (binary)	−0.001 (0.001)
Alabama (binary)	0.003 (0.002)
Georgia (binary)	−0.003 (0.002)
North Carolina (binary)	0.002 (0.001)
South Carolina (binary)	0.002 (0.004)
Kentucky (binary)	−0.002* (0.001)
Virginia (binary)	−0.001 (0.001)
West Virginia (binary)	−0.004* (0.001)
Time variables	
2006–2011 period (binary)	0.024* (0.001)
2011–2016 period (binary)	0.032* (0.001)
F-test statistic	56.260*
Adjusted R-square	0.107

Note: * denotes significance at the 5 % level or better. Dependent variable is the natural log of change in forest share (Ratio of forested area in the last year to forested area in the first year of the period (i.e., 2001–2006, 2006–2011 and 2011–2016).

2.3. Forest carbon supply

The single-objective optimization (Eq. 1) is set up to maximize the cost efficiency of forest carbon credits using private forestland area eligible for protection (F_i), forest carbon sequestration rate per unit of forest area (c_i), and cost for protecting forest carbon storage per unit of forest are (R_i) at each pixel i along with total target carbon storage to set up the optimization as following:

$$O = Min\sum_{i=1}^{n} R_i X_i, \tag{1}$$

subject to

$$\sum C_i X_i \le B$$

$$C_i = c_i \times F_i,$$

$$X_i \in [0, 1],$$

where O is the total target minimum cost for supplying forest carbon storage, R_i denotes the projected 2050 costs. The cost data for protecting forest carbon storage is applied in three ways: (1) forest returns considered as explicit costs only, (2) a combination of forest returns and urban returns, and (3) a combination of forest returns and weighted urban returns. The weighting in the third approach is based on the forest conversion percentage relative to the maximum rate, as discussed in the previous subsection. These costs are annualized with a 5 % discount rate for pixel i across n pixels. X_i is the decision variable for pixel i, C_i represents the pixel-specific total forest carbon storage, calculated by multiplying c_i by F_i, and B is the total target forest carbon storage supply, which varies in increments of 5 %, ranging from 5 % to 100 % of the total forest carbon storage in eligible private forestland within the study area in 2016. The decision variable X_i is a continuous number between 0 and 1, where 0 signifies no investment in the pixel and 1 indicates investment needed to protect all eligible private forestland in the pixel. This optimization procedure identifies total target minimum costs (O) at different total target storage (B) thresholds.

The USDA Forest Inventory and Analysis (FIA) forest carbon dataset, analyzed by Wilson et al. (2013), provides the data on the forest carbon sequestration rate per unit of forest area (c_i), used to calculate the pixel-specific total forest carbon storage (C_i) (Refer to Fig. S3 in the Supplementary Material for total carbon storage per hectare). This dataset quantifies the carbon stock in tonnes per hectare, with a resolution of 250 m, and focuses on carbon equivalents rather than carbon dioxide equivalents, in line with the EPA's 2005 conversion standard where one carbon equivalent is deemed to be 3.67 units of carbon dioxide equivalent. This approach enables a targeted analysis of carbon metrics. Our comprehensive evaluation of forest carbon, based on data from the national forest inventory, covers carbon present in live trees both above and below the ground, the remains of fallen trees, the surface of the forest floor, the soil's organic carbon, standing but dead trees, and the undergrowth, including both its terrestrial and subterranean elements. In mapping the total carbon stocks at a pixel level throughout the contiguous U.S., the USDA-FIA method applies a nearest neighbor imputation technique, as described by Wilson et al. (2013), effectively addressing gaps in the data by using values from the nearest available data points in the dataset.

This optimization is methodically conducted 20 times at varying total target storage (B) thresholds for each cost assumption. In each iteration, the overall target for carbon storage is adjusted, serving as a pivotal constraint. Within this focused optimization framework, the objective is to minimize the total costs associated with attaining predetermined forest carbon storage levels. Consequently, we identify the most efficient allocations for pixels, treating each as an individual decision unit, and ascertain their specific contributions to forest carbon supply by systematically increasing the total carbon storage goal. Using the optimal solutions, we map out the spatial distribution of pixels designated for forest carbon supply under different budget scenarios for each of the three ROI metric versions. We then plot the annual aggregate forest carbon storage from optimally selected pixels on the x-axis against the annual cost per tonne of forest carbon storage on the y-axis for every budget scenario and under each of the three cost assumptions. By linking these data points across different budget scenarios, we construct a detailed supply curve for forest carbon storage corresponding to each of the three cost scenarios.

3. Empirical results

3.1. Forest conversion rate

Table 1's pixel-level forest change model parameter estimates show a moderate fit with an adjusted R^2 value of 0.107, indicating the model explains approximately 10.7 % of the variance in forest area change over time. The model's validity is highlighted by a significant F-statistic (56.260). Notably, the coefficient for this parameter indicates that an annual increase of $1 per hectare in forest returns relative to urban returns contributes to an average increase of 0.00104 % in forestland share over a 5-year period, based on data from 2001 to 2016. This equates to an annual increase in forestland share of approximately 0.00021 %. This finding is significant in that it suggests increasing forest return relative to urban return could serve as an incentive to support forest carbon storage.

By integrating projected forest returns relative to urban returns in 2050 into the parameters of the forest change model, we estimate the forest coverage for each pixel in that year, while holding all other variables constant. We subsequently compare these projections with the forest coverage of each pixel in 2016, allowing us to assess the percentage of change (either loss or gain) of each pixel in forest coverage based on projected returns 35 years into the future. The analysis of the frequency distribution for the forest conversion change over this period reveals that a significant portion of pixels—approximately 72.4 %—are expected to experience a reduction in forest share within a range of 0.01–95.8 % (see Panel A in Fig. 1).

To evaluate the impact of urban development on forests through incorporating opportunity costs weights, we set a 25 % conversion rate as the ceiling for projected decrease over the analysis period. This threshold is informed by the distribution of forest change estimates, ensuring that our model remains within plausible bounds (see Panel A in Fig. 1). We retain this 25 % ceiling because a limited number of pixels (13 out of 2334) exceed this rate, suggesting that such high conversion rates represent exceptional cases rather than typical forest conversion dynamics. By treating these higher conversion rates as outliers, we set a realistic model boundary that avoids skewing results and maintains the integrity of our analysis.

The frequency distribution of percentage of forest conversion relative to this threshold (referred to as "weight on opportunity cost") is shown in Panel B of Fig. 1. The figure indicates that 27.6 % of pixels are assigned a 0 % weight on opportunity cost. Low weights on opportunity cost are prevalent, appearing in a majority of pixels (for example, 54.7 % of pixels) with a positive weight less than 0.20. In contrast, a smaller subset of pixels (for example, 17.8 % of pixels) have a weight of 0.20 or

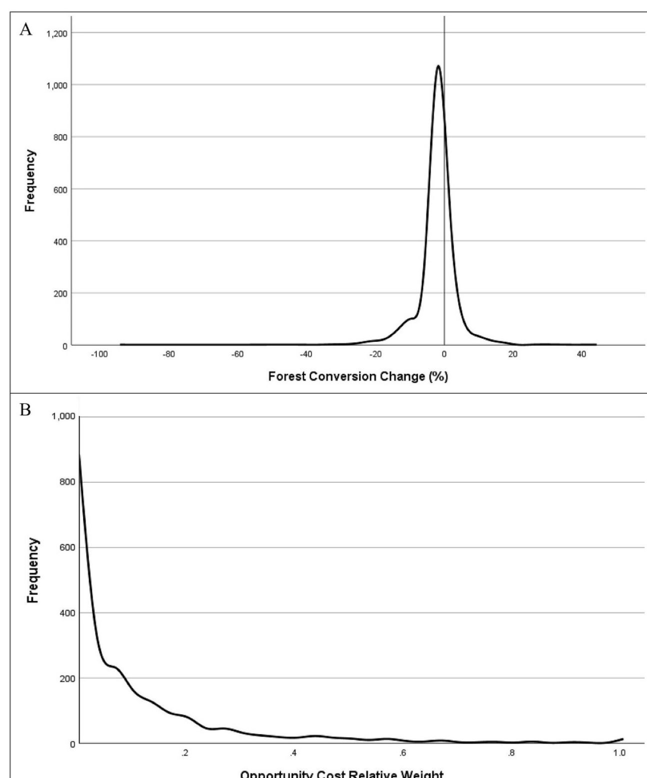

Fig. 1. Frequency distribution of forest conversion changes from 2016 to 2050 based on pixel-level land use model (Panel A) and frequency distribution of the proportion of forest conversion relative to a defined threshold (referred to as "weight on opportunity cost") (Panel B).

higher, indicating higher opportunity costs associated with forest conversion in these areas.

Panels A and B in Fig. 2 depict the spatial distribution of the forest conversion rate and the corresponding weights on opportunity cost derived from it. Panel A in Fig. 2 shows that while most of the pixels (67.1 %) are expected to experience some degree of forest cover loss based on projected urban and forest returns, the intensity of this loss varies. The figure highlights that a higher ratio of pixels in the study area covering Tennessee, Alabama, Georgia, and Kentucky are expected to experience more significant forest loss compared to other states depicted. In Tennessee and Alabama, a notable concentration of forest loss of 5 % or more is evident, particularly in the regions around Knoxville and Chattanooga, TN, and Birmingham, AL. This loss is concentrated in major cities with populations over 100,000 along the interstate highways in the southern part of the map. These patterns may be influenced by urban expansion in metropolitan area and development of second homes in the mountainous regions. Panel B of Fig. 2 illustrates the spatial distribution of weights on opportunity cost, aligning with the spatial distribution of forest conversion rates shown in Panel A of Fig. 2. Higher weights are assigned to those pixels in Panel B of Fig. 2 that exhibit high conversion rates as depicted in Panel A of Fig. 2.

Fig. 3 depicts the annual carbon cost per unit of forest carbon supply

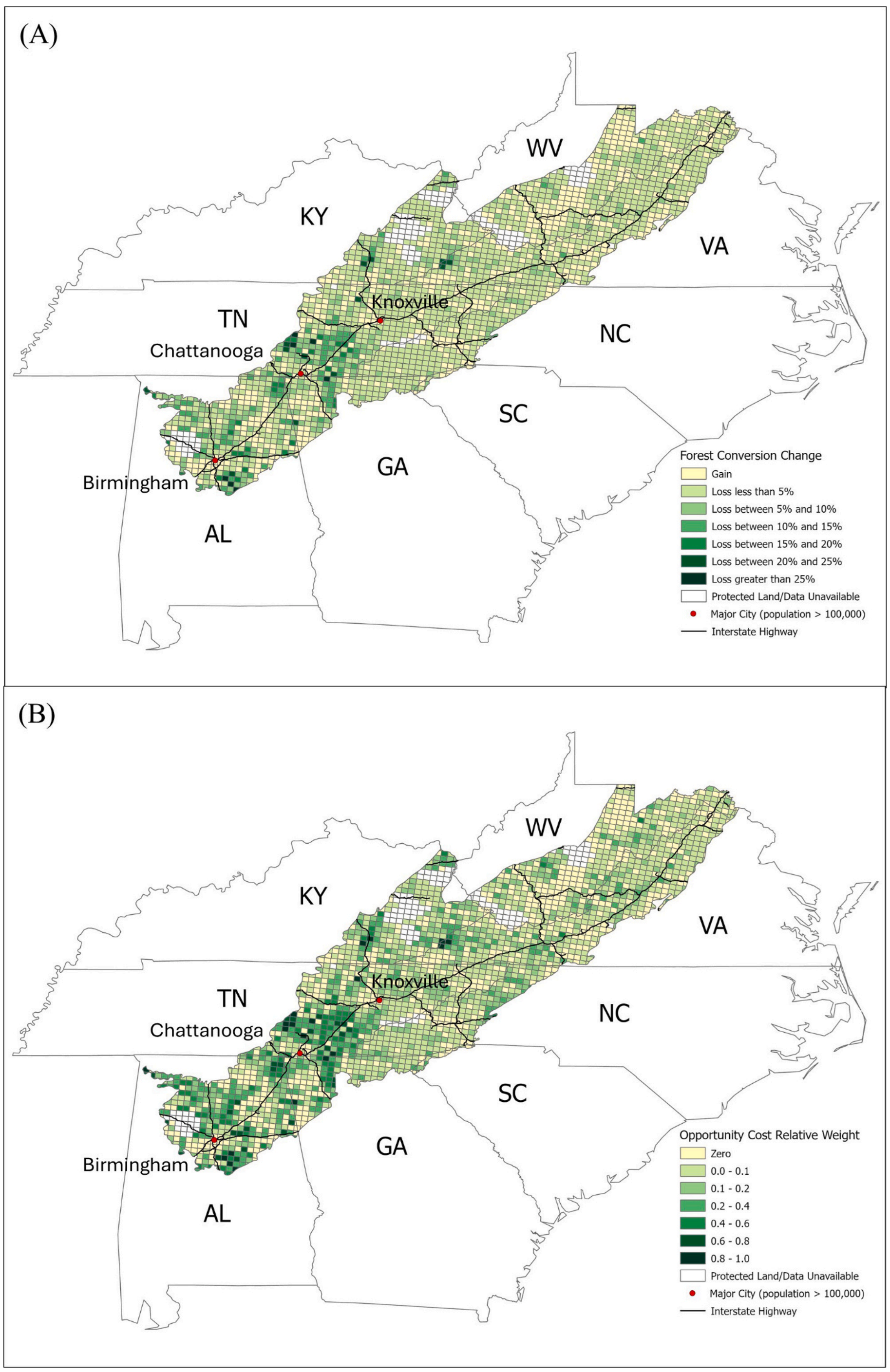

Fig. 2. Spatial distribution of the forest conversion rate from 2016 to 2050 based on a pixel level land use model (Panel A) and the corresponding spatial distribution of opportunity cost weight (Panel B).

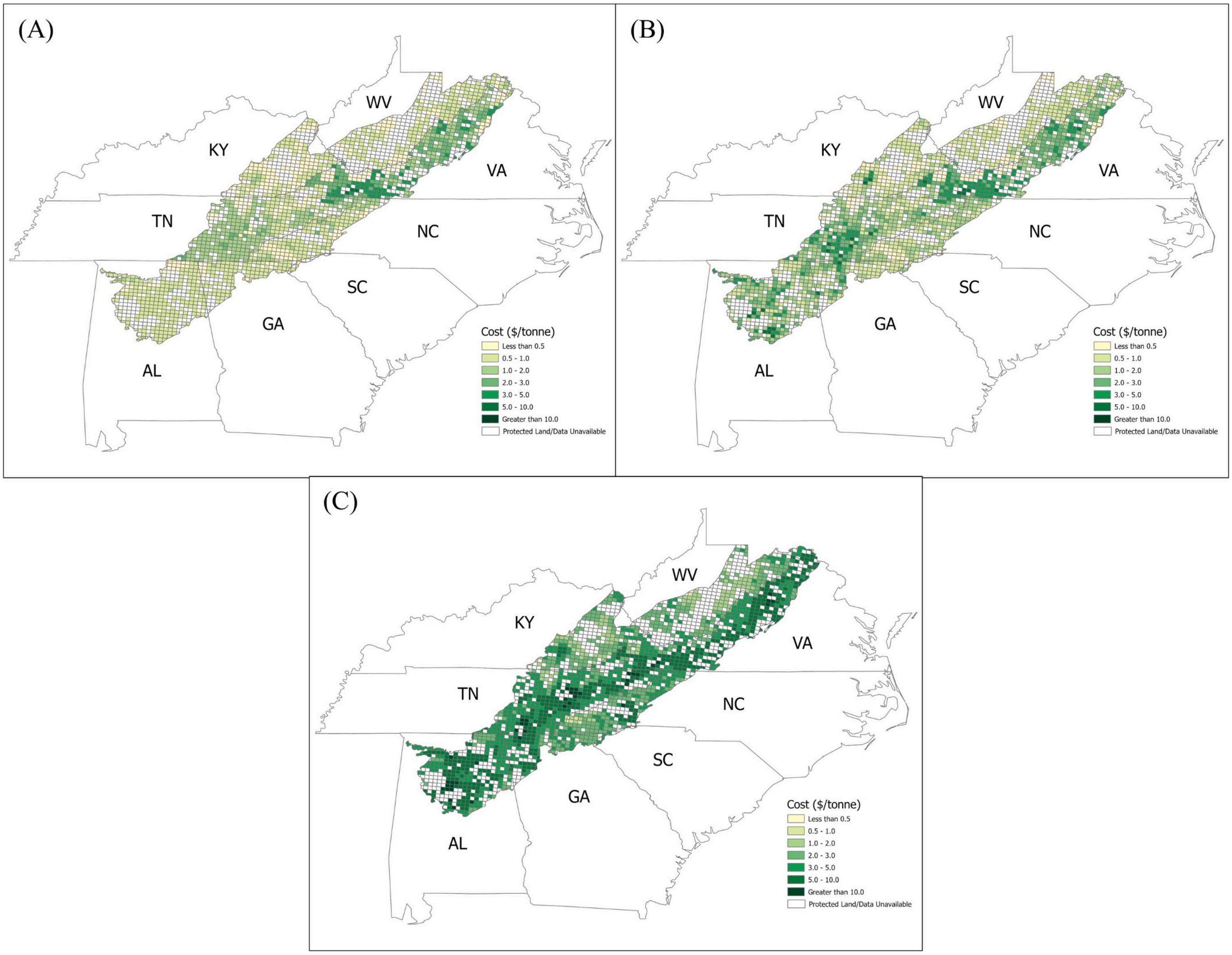

Fig. 3. Annual carbon storage costs ($/ha) under various cost assumptions: explicit costs only (Panel A), explicit plus weighted opportunity costs (Panel B), and explicit plus full opportunity costs (Panel C).

($/tonne/year) under three distinct cost assumptions: explicit costs only, explicit plus weighted opportunity costs, and explicit plus full opportunity costs, as presented in Panels A, B, and C respectively. In Panel A, most regions in Virginia and some areas in Tennessee have costs exceeding $2/t/year due to high soil expectation values reflecting strong timber market performance. Panel B, which includes weighted opportunity costs, shows an increase in high-cost pixels (exceeding $3/t/year) in regions with significant forest cover loss, particularly in Tennessee, Alabama, Georgia, and Kentucky, as shown in Panel A in Fig. 2. These higher weights for opportunity costs recognize the potential economic losses from foregone urban development (around major cities) in favor of forest carbon sequestration. Panel C, which combines explicit and full opportunity costs, reveals that a significant portion of the study area (over 66.7 % of eligible areas) incurs costs exceeding $3/t/year.

3.2. Forest carbon supply

Fig. 4 presents supply curves for forest carbon storage based on different cost assumptions, illustrating the impact of integrating opportunity costs. Across all storage levels, the addition of weighted opportunity costs results in only a marginal cost increase compared to the explicit costs only case. However, the inclusion of full opportunity costs causes a much more significant rise, widening the cost gap considerably as the carbon storage levels increase. For example, at a total carbon storage level of 450 million tonnes, the annual explicit cost per tonne stored is $0.72. When weighted opportunity costs are included, this annual cost increases to $1.04 per tonne, representing a moderate increase of 44.6 %. This comparison highlights how the per-tonne annualized costs shift under different cost assumptions, even when evaluating the same total storage level. In contrast, at a total carbon storage level of 450 million tonnes, incorporating full opportunity costs elevates the annual cost per tonne stored to $3.30, representing a substantial increase of 217.18 %. This comparison illustrates that while adding weighted opportunity costs slightly increases the annualized cost per tonne from the baseline of explicit costs, this increase remains more manageable compared to the significant rise observed when full opportunity costs are included.

In Fig. 5, Row A, which considers explicit costs only, the increase from 25 % to 75 % of total carbon storage reveals initial concentrated pockets in Tennessee's eastern regions, northern Alabama, northern Georgia, eastern Kentucky, and the western areas of both North and South Carolina, along with a moderate concentration in central West Virginia as optimal forest carbon storage targets. As carbon targets increase, there is an evident expansion: eastern Tennessee's central and western areas become more involved, Alabama's storage spreads southward, northern Georgia's coverage extends to its central and southern regions, and eastern Kentucky sees westward expansion. Both western portions of the Carolinas begin to include more of their eastern

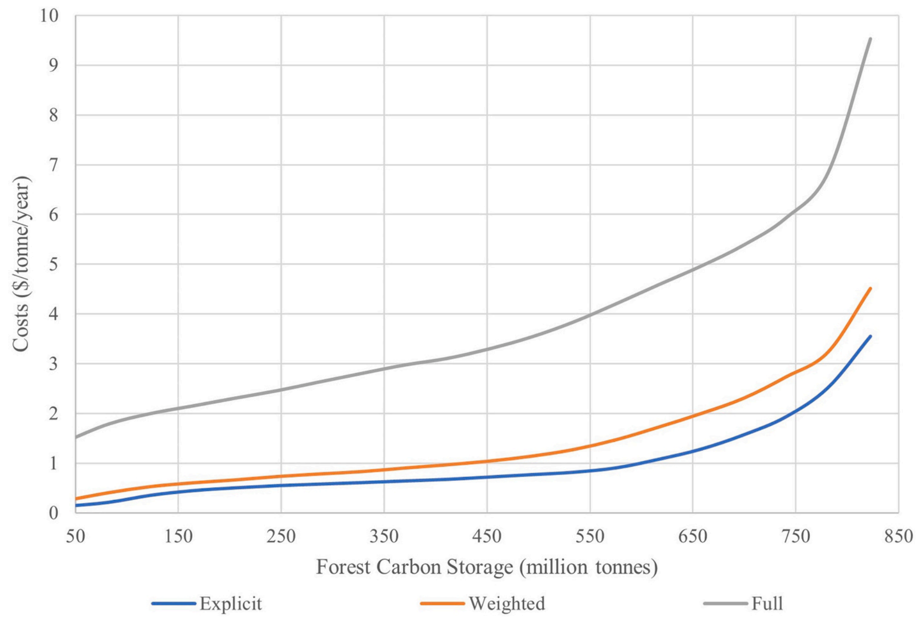

Fig. 4. Supply curves for forest carbon storage based on three cost assumptions (“Explicit” refers to explicit costs only, “Weighted” includes explicit plus weighted opportunity costs, and “Full” encompasses explicit plus full opportunity costs).

Fig. 5. Spatial distribution of optimal carbon storage (million tonnes) at different thresholds of total carbon storage (25 %, 50 %, 75 %) by different cost assumptions (A: explicit costs only; B: explicit plus weighted opportunity costs; C: explicit plus full opportunity costs).

territories. West Virginia's contribution stretches from its center to the northern and southern regions.

In Fig. 5, Row B, considering explicit plus weighted opportunity costs, the spatial distribution of carbon storage differs from Row A's explicit costs alone, altering the priority areas slightly. Regions in eastern Tennessee, northern Alabama, northern Georgia, and eastern Kentucky that were optimal at lower costs may show a reduced emphasis, while other regions may emerge as more cost-effective due to the inclusion of potential land-use returns. West Virginia shows a central concentration shift, and the Carolinas' western regions maintain their significance but may exhibit changed intensity.

In Fig. 5, Row C reveals a selective spatial distribution of carbon storage under the explicit plus full opportunity costs scenario. The regions identified for carbon storage are a bit more limited, reflecting a more restrictive economic viability when full opportunity costs are included. Unlike the extensive spatial expansion observed in the lower-cost scenarios of Rows A and B, the increase from 25 % to 75 % of total carbon storage in Row C does not show a comparable expansion, indicating that many regions viable under explicit or weighted opportunity costs become economically unfeasible when full costs are accounted for.

Table 2 summarizes the varied impact of different cost assumptions on total costs, carbon storage, and forest area across states for optimal forest carbon storage supply at three carbon storage thresholds. It also highlights the percentage changes from explicit to weighted and full opportunity costs, effectively providing a state-level summary of Fig. 5. States such as Alabama and Georgia see significant changes in costs and storage under full cost accounting at the 25 % threshold, with Alabama experiencing a 28 % reduction in costs under weighted costs and a 57 % reduction under full costs, accompanied by a 45 % and 91 % drop in carbon storage, respectively. Similarly, Georgia sees costs increase by 40 % under weighted costs and 90 % under full costs, while carbon storage decreases by 14 % and 71 %, respectively, hinting at the varying viability of forest carbon storage with full opportunity costs. Kentucky's significant costs increase without a corresponding rise in storage suggests a higher economic impact for carbon sequestration. North Carolina shows an upturn in costs and storage, possibly indicating more expensive sequestration methods. South Carolina's minimal carbon storage at full costs points to the potential economic infeasibility of carbon sequestration in the extreme western portion of the state, while Tennessee and Virginia's case reflect a decrease in economic efficiency for carbon storage investments. West Virginia's sharp cost rise at full opportunity costs raises concerns over the economic sustainability of forest carbon storage.

Shifting from the 25 % to the 50 % total carbon storage threshold, Table 2 indicates significant changes in cost dynamics across the states. Alabama and Georgia face increased total costs with reduced carbon storage efficiency, suggesting escalating costs for additional storage. Kentucky and North Carolina show a capability to meet higher storage demands, albeit with substantial cost increases, reflecting potential for greater carbon sequestration but at a steeper price. South Carolina exhibits a slight rise in costs despite low storage increments, hinting at limited sequestration potential. Tennessee and Virginia encounter rising costs with moderate storage gains, suggesting a complex cost-storage relationship. West Virginia stands out with marked increases in both costs and storage, indicating a readiness for larger sequestration efforts, though with significant financial implications.

Table 2

Summary of the impact of different cost assumptions on total costs, carbon storage, and forest area across states for optimal forest carbon storage supply at three carbon storage thresholds (Explicit, Weighted, Full), providing a state-level summary of Fig. 5.

State	Total Costs					Total Carbon Storage					Total Forest Area				
	Exp ($m)	Weighted ($m, Δ%)		Full ($m, Δ%)		Exp (m ton)	Weighted (m ton, Δ%)		Full (m ton, Δ%)		Exp (m ha)	Weighted (m ha, Δ%)		Full (m ha, Δ%)	
25 % of Total Carbon Storage Threshold															
AL	8.29	5.98	−28	3.53	−57	18.28	10.11	−45	1.63	−91	0.16	0.09	−44	0.02	−88
GA	3.54	4.95	+40	6.72	+90	7.94	8.32	+5	2.93	−63	0.07	0.06	−14	0.02	−71
KY	24.07	28.53	+19	127.52	+430	68.11	58.22	−15	65.32	−4	0.59	0.50	−15	0.56	−5
NC	5.53	11.17	+102	28.03	+407	18.72	22.76	+22	14.92	−20	0.14	0.16	+14	0.10	−29
SC	0.46	0.35	−24	0.00	−100	0.92	0.63	−32	0.00	−100	0.01	0.01	+0	0.00	−100
TN	3.51	5.96	+70	18.71	+433	17.10	15.06	−12	9.94	−42	0.16	0.14	−13	0.08	−50
VA	2.71	5.94	+119	13.32	+392	18.19	17.42	−4	6.55	−64	0.15	0.14	−7	0.05	−67
WV	19.05	37.25	+96	200.40	+952	56.30	73.11	+30	104.33	+85	0.39	0.50	+28	0.72	+85
Sum	67.16	100.13	+49	398.23	+453	205.56	205.56	+0	205.56	+0	1.67	1.60	−4	1.55	−7
50 % of Total Carbon Storage Threshold															
AL	41.44	22.20	−46	43.27	+4	72.17	29.11	−60	16.22	−78	0.75	0.29	−61	0.14	−81
GA	17.54	16.13	−8	48.34	+176	30.89	21.75	−30	17.51	−43	0.28	0.18	−36	0.13	−54
KY	44.78	60.53	+35	224.66	+402	103.11	96.48	−6	101.37	−2	0.90	0.84	−7	0.88	−2
NC	17.13	38.10	+122	185.33	+982	37.59	54.33	+45	70.60	+88	0.27	0.39	+44	0.51	+89
SC	0.61	0.41	−33	2.70	+343	1.21	0.72	−40	0.89	−26	0.01	0.01	+0	0.01	+0
TN	7.24	17.75	+145	85.23	+1077	22.83	28.63	+25	32.42	+42	0.21	0.25	+19	0.27	+29
VA	3.46	10.46	+202	61.17	+1668	19.37	22.63	+17	23.08	+19	0.16	0.18	+13	0.18	+13
WV	59.96	107.26	+79	322.23	+437	124.03	157.53	+27	149.10	+20	0.87	1.12	+29	1.06	+22
Sum	192.16	272.84	+42	972.93	+406	411.11	411.11	+0	411.11	+0	3.45	3.27	−5	3.19	−8
75 % of Total Carbon Storage Threshold															
AL	60.12	67.38	+12	156.11	+160	96.34	62.98	−35	44.56	−54	1.07	0.67	−37	0.46	−57
GA	25.95	30.77	+19	98.77	+281	41.50	33.64	−19	30.57	−26	0.40	0.30	−25	0.26	−35
KY	54.07	80.95	+50	267.96	+396	114.48	113.33	−1	113.00	−1	1.02	1.00	−2	1.00	−2
NC	66.82	93.62	+40	260.56	+290	93.95	98.86	+5	90.39	−4	0.69	0.73	+6	0.67	−3
SC	0.61	0.92	+51	3.68	+503	1.21	1.21	+0	1.18	−2	0.01	0.01	+0	0.01	+0
TN	51.42	103.45	+101	329.40	+541	68.22	88.61	+30	97.40	+43	0.61	0.79	+30	0.86	+41
VA	11.70	46.48	+297	263.11	+2149	29.41	46.81	+59	71.61	+143	0.24	0.37	+54	0.56	+133
WV	97.59	122.47	+25	393.80	+304	171.65	171.31	+0	168.09	−2	1.24	1.24	+0	1.21	−2
Sum	368.28	546.04	+48	1773.39	+382	616.67	616.67	+0	616.67	+0	5.28	5.12	−3	5.04	−5

Note: "Exp" refers to explicit costs only, "Weighted" includes explicit plus weighted opportunity costs, and "Full" encompasses explicit plus full opportunity costs; $m refers to million dollars, m ton refers to million tonnes, m ha refers to million hectares; Δ% refers to % change compared to explicit only assumption.

Transitioning from the 50 % to the 75 % total carbon storage threshold demonstrates a further evolution in the economic landscape of forest carbon sequestration across the states, as shown in Table 2. Alabama shows a substantial rise in costs, yet it also reveals a considerable increase in carbon storage, indicating a greater but more costly capacity for sequestration. Georgia, with increased costs and carbon storage, suggests that it can still scale up sequestration efforts, although this comes at a higher expense. Kentucky maintains a consistent carbon storage level despite rising costs, revealing a potential plateau in sequestration efficiency. North Carolina's costs surge dramatically at this higher threshold, which, alongside a significant boost in carbon storage, points to a possible intensification of sequestration activities. South Carolina, with minimal changes across the board, implies a steady yet limited sequestration capacity. Tennessee and Virginia both face pronounced cost increments with corresponding increases in carbon storage, whereas West Virginia's figures imply a readiness to significantly expand sequestration despite escalating costs.

One key observation is that the total forest area (across all states combined) decreases when shifting from explicit to weighted and full accounting, with a 4 % reduction under weighted costs and a 7 % reduction under full costs at the 25 % carbon storage threshold. Similarly, at the 50 % threshold, total forest area declines by 5 % under weighted costs and 8 % under full costs, while at the 75 % threshold, the decreases are 3 % and 5 %, respectively. These shifts reflect the inclusion of full opportunity costs adjusted for varying levels of development pressure. This reduction, particularly notable in the 75 % threshold case with a 0.24 million-acre difference, occurs because the full accounting model incorporates the full impact of urban development pressure in the forest conversion model, significantly shrinking the forest area. The implication of this reduction is crucial: as full opportunity costs narrow the feasible areas for forest carbon storage, regions with high development pressure may be effectively excluded from carbon sequestration strategies. This shift indicates that while a larger forest area appears economically viable under explicit cost assumptions, factoring in opportunity costs reveals that only specific regions remain feasible for sustainable sequestration efforts. This underscores the need for targeted policy interventions in regions with lower development pressures to maximize the efficiency and sustainability of forest carbon storage.

Further highlighting the influence of cost assumptions, we see a substantial increase in total costs for the same level of forest carbon storage when shifting from explicit to weighted opportunity costs. Costs rise by 42–49 % and then escalate dramatically to full opportunity costs by 225–298 % across the 25 %, 50 %, and 75 % carbon storage thresholds. This cost escalation reinforces the growing economic demands as opportunity costs and development pressures are incorporated, emphasizing the financial implications of these constraints.

The combined analysis presented in Fig. 5 and Table 2 underscores the significant impact of incorporating different cost assumptions on the spatial distribution and economic viability of forest carbon storage across various states, the inclusion of weighted and full opportunity costs increasingly restricts these areas, highlighting the economic trade-offs involved. States such as Alabama and Georgia show reduced viability under full cost accounting, while Kentucky and North Carolina face higher costs without proportional increases in storage. The findings suggest that regions initially identified as cost-effective may become economically unfeasible when comprehensive land-use returns are considered, raising critical considerations for policymakers regarding the balance between carbon sequestration goals with economic sustainability.

4. Discussion

We demonstrate how incorporating both explicit and opportunity costs influences the evolution of spatial targets and supply dynamics for forest carbon, aligning with our study's aim to examine these shifts under varying degrees of development pressure. In line with the Paris Climate Agreement, our study supports the broader goal of emission reductions by addressing the economic dimensions of forest carbon storage in the Central and Southern Appalachian region. The integration of opportunity costs in conservation assessments, as shown in our study, allows for more realistic policy design that aligns economic incentives with emissions reduction goals, thereby enhancing contributions to the U.S. Nationally Determined Contributions (U.S. Nationally Determined Contribution (NDC), 2021) framework. By tailoring opportunity costs to the unique economic contexts of this area, our analysis provides actionable guidance for carbon storage policies that contribute to achieving the NDCs and reinforce global climate action objectives. The Paris Agreement calls for net-zero carbon emissions globally by 2050, and our findings suggest that forest conservation in this region could be instrumental in meeting this target. Forests in the Central and Southern Appalachian region serve as significant carbon sinks, and their preservation and management can directly support both national and global climate objectives.

The role of cost assumptions is crucial in shaping the outcomes of forest carbon management strategies. By altering the weight assigned to opportunity costs, our model captures the differing economic landscapes across regions, highlighting the importance of local development pressures in forest conservation decisions. Explicit costs alone provide a limited view, while incorporating opportunity costs—especially in regions with high development pressure—yields a truer reflection of the trade-offs faced by landowners. This layered approach illustrates how different cost assumptions directly influence the spatial distribution and extent of forest conservation efforts.

Such distinctions in cost assumptions carry significant implications for policy and land management strategies. For instance, under the explicit costs scenario (Panel A in Fig. 3), regions with robust timber markets, such as Virginia and parts of Tennessee, may require targeted financial incentives to support forest carbon projects. Previous studies have also highlighted how differences in timber market performance influence conservation policy design, underscoring the need for context-specific strategies (Galik and Jackson, 2009; Prestemon and Wear, 2000).

Meanwhile, applying weighted opportunity costs (Panel B) highlights the need to address urban development pressures in areas with notable forest cover loss, including Tennessee, Alabama, Georgia, and Kentucky, where policy must carefully balance development and carbon conservation. Finally, the full opportunity costs scenario (Panel C) suggests that a one-size-fits-all approach may be unworkable due to widespread high costs, making flexible, region-specific policies essential to address the distinct economic contexts and opportunity costs in each area.

These results emphasize the powerful role of cost assumptions in shaping conservation strategies, as different cost structures yield markedly different outcomes. Moreover, the findings align with broader themes in forest economics literature, which call for integrating spatial and economic variability in ecosystem service assessments to ensure effective conservation outcomes (Lubowski et al., 2006; Nelson et al., 2009). By factoring in opportunity costs, especially in high-development areas, we capture a more realistic economic landscape that accounts for the complex trade-offs landowners face. This insight is particularly relevant in regions where urbanization inflates land values, directly influencing forest carbon supply dynamics. Thus, our study suggests that incorporating opportunity costs into conservation planning not only refines local actions but also aligns them with broader goals, contributing to cumulative progress toward global carbon neutrality. Targeted conservation in high-pressure regions can offset emissions from other areas, supporting both regional and national goals under the Paris Agreement.

However, while this focus on opportunity costs provides valuable insights, our model does not include transaction costs, such as monitoring, enforcement, and administrative expenses, due to data limitations. Specifically, our return data is only available at the county level, which lacks the precision needed to capture transaction cost variability across pixels. Such costs can vary considerably based on factors like land accessibility, local development pressures, and regulatory requirements—factors that differ widely across smaller spatial scales. Including transaction costs would require detailed, site-specific data to avoid inconsistencies. Estimating these costs based on county averages would likely reduce the precision of our model's cost estimates and introduce inaccuracies, ultimately affecting the reliability of our forest carbon supply projections.

Even without factoring in transaction costs, our model offers actionable insights for tailoring conservation strategies by adjusting opportunity costs to reflect local economic pressures. In regions across Tennessee, Alabama, Georgia, and Kentucky, where urban development pressure is high, assigning a higher weight to opportunity costs allows for a more realistic evaluation of the economic trade-offs between forest conservation and alternative land uses, such as urban development. By incorporating higher opportunity costs in these high-demand areas, the model reflects the actual financial pressures landowners face when choosing between conservation and development. This approach helps policymakers and land managers assess conservation's economic viability in places where forest preservation competes directly with profitable development options, making it possible to target financial incentives more effectively in areas where they are most needed.

Conversely, in regions with lower development pressure, applying a reduced or zero weight to opportunity costs can render conservation a naturally more competitive economic choice, potentially reducing the need for additional financial support. This regionally targeted strategy aligns forest carbon supply goals with local economic realities, promoting a cost-effective, region-specific approach to conservation that is adaptable to the varying pressures across the landscape.

To further refine this targeted approach, our weighted opportunity cost framework addresses the limitations of relying solely on explicit costs. By enabling dynamic adjustments of opportunity cost weights based on regional development pressures, this framework provides flexibility and adaptability to changing local conditions. This flexibility allows for more informed, region-specific conservation decisions that consider both environmental and economic priorities, offering a comprehensive view of trade-offs in land use changes and supporting sustainable, adaptive conservation practices.

The effectiveness of incorporating weighted opportunity costs is evident in the moderate cost increase observed—less than 50 %, compared to over 200 % with full opportunity costs. This manageable increase reflects the framework's balance between accurate economic representation and cost feasibility. By examining how different opportunity cost weights influence forest carbon supply, our analysis highlights the critical role of cost assumptions in achieving a practical balance between conservation goals and economic constraints. This balanced approach is likely to attract support from policymakers and stakeholders who seek both environmental benefits and economic viability.

In addition, this balanced approach also helps attract support from policymakers and stakeholders who consider both conservation benefits and economic impacts, including the trade-offs with economic development. By recognizing the economic pressures that landowners face from alternative land uses, such as urban expansion or agricultural development, this framework provides a realistic assessment of the costs associated with forest carbon management. It enables a strategy that aligns conservation goals with economic realities, offering a feasible path forward that respects both sustainability objectives and development needs.

Furthermore, the gradual integration of weighted opportunity costs can act as a stepping stone toward eventually incorporating full opportunity costs. Beginning with a moderate adjustment helps stakeholders adapt to potential financial impacts, easing the transition into more comprehensive cost structures. This incremental approach allows conservation planning to evolve with economic changes, ensuring that forest carbon strategies remain both ecologically and economically sustainable over time.

An example of where this approach could prove beneficial is in programs like the CRP. By incorporating weighted opportunity costs, these programs could become significantly more appealing to landowners, especially those with high-value land who may hesitate to forego profitable agricultural or development uses. Traditional CRP compensations often overlook the economic sacrifices tied to opportunity costs, but a weighted approach could better account for these, creating a more balanced incentive structure that aligns conservation goals with landowner interests.

In refining our analysis, another methodological consideration is the approach to measuring forest area changes over time. While one might consider using averages of forest area across each period as an alternative approach, this method also presents limitations that could obscure valuable insights. Averages tend to smooth out variations at the beginning and end of each period, potentially masking critical shifts in forest-to-urban conversion, which often respond sharply to economic conditions or policy changes within each interval. In contrast, using the final-to-initial year ratio aligns directly with the NLCD data structure, which provides forest cover data only for the first and last years of each period. This alignment avoids assuming a uniform rate of change across each interval and captures a more accurate picture of cumulative development pressures over time. By relying on final-to-initial ratios, we retain distinct changes that occur at key points within each period, allowing for clearer insights into forest resilience or susceptibility to conversion—insights that averaging would likely dilute. This approach also better reflects our hypothesis, emphasizing the cumulative impacts of economic drivers, such as forest and urban returns, on land-use decisions over time.

Another important consideration in our modeling framework is pixel size, which directly influences the resolution and accuracy of spatial data. While the 10 km by 10 km pixel size provides a realistic view of forestland at the regional level, a finer spatial scale could potentially improve precision in assessing localized development pressures and conservation opportunities. However, this resolution choice is constrained by the availability of forest and urban return data—a key explanatory variable in our forest land use model—which is only accessible at the county level. Using county-level return data at a finer resolution presents challenges, as return values are uniform across each county. Consequently, each smaller pixel within a county would carry the same return values, resulting in limited statistical significance and redundancy, as smaller-scale observations with identical values fail to provide meaningful differentiation. These alignment limitations between land use and economic return data are common in economic land use models (Castro et al., 2018).

The choice of a 10 km by 10 km pixel size offers several advantages within the given constraints. This scale enhances computational feasibility, allowing efficient processing of large datasets, while also aligning with a practical level for capturing regional land-use dynamics. It avoids excessive noise that can arise from insufficiently varied data at finer resolutions. At smaller scales, such as 1 km by 1 km, the model tends to generate an artificially high number of observations that fail to accurately reflect actual changes in development pressure, thereby reducing both the model's goodness of fit and predictive accuracy. By contrast, the 10 km by 10 km scale strikes a balance between spatial precision and data coherence, enabling a robust and reliable forecast of forest conversion under urban development pressure. Supplementary results using a spatially finer (1 km by 1 km) are presented in Table S1 for comparison. As anticipated, the adjusted R-squared, which measures the model's goodness of fit, dropped significantly—from 10.7 % to 1.3 %—representing an 87 % decline.

Another key consideration is the forest land use model's assumption that each pixel functions as an independent ownership unit. In reality, forestland ownership may span multiple pixels, and a landowner with holdings across several adjacent or non-adjacent pixels might approach land conversion decisions differently. Rather than viewing each pixel in isolation, they might consider the combined returns and development pressures across their entire property. This broader ownership structure would allow landowners to substitute or balance conversion activities, potentially converting only a portion of their holdings or prioritizing conversion in areas with higher urban returns. Thus, while the model assumes independent decision-making at the pixel level, it does not capture the potential for strategic allocation of land use changes across a larger ownership area. Such ownership patterns could result in a more complex decision process, reflecting joint optimization of returns across multiple pixels.

To address this, future work could enhance the model by incorporating parcel-level land use decisions, which would allow for a more realistic representation of forestland ownership dynamics. By considering parcels as the decision-making unit rather than individual pixels, the model could capture interactions across pixels under shared ownership, enabling landowners to strategically manage conversion activities across their holdings. Such an approach would allow for joint optimization of returns, where landowners could weigh development pressures and environmental conditions across multiple pixels to maximize overall property returns. This enhancement would provide a more detailed understanding of how ownership structure influences land conversion decisions, particularly in areas facing varied urban pressures or environmental constraints. Integrating this parcel-level perspective could lead to more accurate predictions of land use change patterns and support more effective policy design for sustainable land management.

In addition to these proposed enhancements, our study acknowledges certain limitations tied to existing modeling assumptions. For example, we assume static economic conditions, which could be refined by introducing dynamic variables that reflect market price fluctuations, regional economic growth rates, and shifting land-use demands. The model also currently uses consistent rotation lengths across all regions without accounting for local variations in forestry practices; customizing rotation lengths based on regional forestry management data would improve accuracy by aligning with local practices. Moreover, the assumption of consistent ecosystem service values over time does not fully capture the variability in ecological and economic interactions. Future models could apply temporal adjustments to ecosystem service values or introduce scenario-based forecasting to better account for potential shifts under different climate and policy conditions. These modifications would enhance the model's ability to reflect the dynamic nature of economic and ecological interactions, offering a closer approximation to real-world complexities.

Given these considerations, our study underscores the potential of integrating weighted opportunity costs in forest carbon management to support a balanced, region-specific conservation approach. Yet, limitations related to pixel size, static assumptions, and potential economic fluctuations emphasize the need for ongoing refinement. Future research can address these limitations by incorporating dynamic economic models and finer spatial data, thereby enhancing the model's accuracy and practical application. Such advancements would ultimately promote sustainable and economically justified land use practices across diverse landscapes.

5. Conclusion

Our study highlights the importance of creating tailored incentives for forest-based carbon offset and credit markets that align with the diverse economic conditions found across the Central and Southern Appalachian region. By integrating both explicit and opportunity costs, policymakers can develop flexible, region-specific programs that effectively encourage forest conservation in areas facing varying levels of development pressure, thereby maximizing the impact of conservation investments.

In regions with high development pressure, such as areas near expanding urban centers, carbon offset incentives can be designed to reflect higher opportunity costs. This approach captures the substantial economic trade-offs that landowners face when opting for conservation over more profitable options like urban development or agriculture. By incorporating these opportunity costs, policymakers can make forest-based offsets financially competitive with alternative land uses, positioning conservation as a viable option in areas where land values and development pressures are elevated.

Conversely, in regions with lower development pressures where land values are stable, forest-based offset incentives can focus primarily on explicit conservation costs, rather than high opportunity costs. This distinction allows conservation programs to efficiently allocate resources by promoting forest conservation in lower-growth areas at a reduced cost, reserving higher payments for regions where landowners would forgo substantial financial returns by choosing conservation over development.

A flexible, weighted approach to opportunity costs within forest-based carbon offset markets offers a balanced and scalable incentive structure that reflects the diverse economic landscapes across Central and Southern Appalachia. In high-development regions, offset payments can be adjusted upward to provide returns that sufficiently compensate landowners for potential income from development activities. In less economically pressured areas, incentives can be tailored to emphasize direct conservation costs, thus supporting sustainable forestry without unnecessary resource allocation.

By adapting forest-based offset incentives to local economic conditions, these markets can achieve greater conservation impact across Central and Southern Appalachia, ensuring that forest carbon storage remains an attractive option for landowners regardless of regional development dynamics. This regionally sensitive approach fosters a sustainable balance between conservation and economic opportunity, making forest conservation both feasible and competitive across diverse Appalachian landscapes and enhancing the long-term success of carbon storage initiatives.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT-4 in order to improve the clarity, grammar, and coherence of the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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CRediT authorship contribution statement

Seong-Hoon Cho: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Conceptualization. **James C. Mingie:** Writing – review & editing, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors do not have any competing interests, financial or non-financial, to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.forpol.2025.103450.

Data availability

Data will be made available on request.

References

Austin, K.G., Baker, J.S., Sohngen, B.L., Wade, C.M., Daigneault, A., Ohrel, S.B., Bean, A., 2020. The economic costs of planting, preserving, and managing the world's forests to mitigate climate change. Nat. Commun. 11 (1), 5946.

Baker, J.S., Galik, C.S., 2009. Policy options for the conservation reserve program in a low-carbon economy. In: Climate Change Policy Partnership. Duke University, Durham, NC, 27p.

Börner, J., Baylis, K., Corbera, E., Ezzine-de-Blas, D., Honey-Rosés, J., Persson, U.M., Wunder, S., 2017. The effectiveness of payments for environmental services. World Dev. 96, 359–374.

Castro, L.M., Härtl, F., Ochoa, S., et al., 2018. Integrated bio-economic models as tools to support land-use decision making: a review of potential and limitations. J. Bioecon. 20, 183–211.

Cho, S., Ayara, A.B., Lambert, D.M., Clark, C.D., Chen, G., Hayes, D.J., Sharma, B.P., 2020. Deriving site-specific and time-varying supply curves for forest carbon storage. J. Environ. Plan. Manag. 63 (12), 2144–2162.

Cho, S., Lee, Y.G., Zhu, G., 2021. Understanding how opportunity cost affects multi-objective conservation investment in the Central and Southern Appalachian Region (USA). Environ. Conserv. 48 (3), 192–199.

Claassen, R., Cattaneo, A., Johansson, R., 2008. Cost-effective design of agri-environmental payment programs: US experience in theory and practice. Ecol. Econ. 65 (4), 737–752.

Cubbage, F., Rubilar, R., Mac Donagh, P., Da Silva, B.K., Bussoni, A., Morales, V., Cubas-Baez, A., 2022. Comparative global timber investment costs, returns, and applications, 2020. J. Forest Bus. Res. 1 (1), 90–121.

Dewitz, J., 2023. National Land Cover Database (NLCD) 2021 Products: U.S. Geological Survey data release. https://doi.org/10.5066/P9JZ7AO3.

Dixon, G.E., 2002. Essential FVS: A User's Guide to the Forest Vegetation Simulator. Internal Rep. U. S. Department of Agriculture, Forest Service, Forest Management Service Center, Fort Collins, CO, 226p. (Revised: February 16, 2024).

Engel, S., Pagiola, S., Wunder, S., 2008. Designing payments for environmental services in theory and practice: An overview of the issues. Ecol. Econ. 65 (4), 663–674.

ESRI, 2012. ArcGIS Help 10.1: Spatial Analyst Toolsets, ArcGIS Resources. Retrieved June 21, 2024, from. http://www.esri.com/.

Frey, G.E., Kallayanamitra, C., Wilkens, P., James, N.A., 2021. Payments for forest-based ecosystem services in the United States: Magnitudes and trends. Ecosyst. Serv. 52 (101), 377.

Galik, C.S., Jackson, R.B., 2009. Risks to forest carbon offset projects in a changing climate. For. Ecol. Manag. 257 (11), 2209–2216.

Hamrick, K., Gallant, M., 2017. Unlocking Potential: State of the Voluntary Carbon Markets 2017. Forest Trends' Ecosystem Marketplace.

Irwin, E.G., Bockstael, N.E., 2007. The evolution of urban sprawl: Evidence of spatial heterogeneity and increasing land fragmentation. Proc. Natl. Acad. Sci. 104 (52), 20672–20677.

Kaarakka, L., Rothey, J., Dee, L.E., 2023. Managing forests for carbon–status of the forest carbon offset markets in the United States. PLOS Clim. 2 (7), e0000158.

Kline, J.D., Alig, R.J., 2005. Forestland development and private forestry with examples from Oregon (USA). Forest Policy Econ. 7 (5), 709–720.

Liu, X., Cho, S.H., Hayes, D.J., Armsworth, P.R., 2019. Potential efficiency gains in payment programs from resolving spatial and temporal heterogeneity in the cost of supplying forest carbon. J. Environ. Manag. 250 (109), 421.

Liu, X., Cho, S.H., Chen, G., Hayes, D., English, B., Armsworth, P.R., 2022. Does a trade-off exist between economic and environmental impacts of forest carbon payment programs? Sustain. Sci. 17 (5), 2031–2047.

Lubowski, R.N., Plantinga, A.J., Stavins, R.N., 2006. Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function. J. Environ. Econ. Manag. 51 (2), 135–152.

Nelson, G.C., Geoghegan, J., 2002. Deforestation and land use change: sparse data environments. Agric. Econ. 27 (3), 201–216.

Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, D., Shaw, M., 2009. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. Front. Ecol. Environ. 7 (1), 4–11.

Nikolakis, W., Innes, J.L., 2017. Evaluating incentive-based programs to support forest ecosystem services. Environ. Conserv. 44 (1), 1–4.

Ontl, T.A., Janowiak, M.K., Swanston, C.W., Daley, J., Handler, S., Cornett, M., Patch, N., 2020. Forest management for carbon sequestration and climate adaptation. J. For. 118 (1), 86–101.

Pan, C., Shrestha, A., Innes, J.L., Zhou, G., Li, N., Li, J., Wang, G., 2022. Key challenges and approaches to addressing barriers in forest carbon offset projects. J. For. Res. 33 (4), 1109–1122.

Prestemon, J.P., Wear, D.N., 2000. Linking harvest choices to timber supply. For. Sci. 46 (3), 377–389.

Raich, J.W., Rastetter, E.B., Melillo, J.M., Kicklighter, D.W., Steudler, P.A., Peterson, B. J., Vorosmarty, C.J., 1991. Potential net primary productivity in South America: application of a global model. Ecol. Appl. 1 (4), 399–429.

Sohngen, B., Mendelsohn, R., 2003. An optimal control model of forest carbon sequestration. Am. J. Agric. Econ. 85 (2), 448–457.

Tanger, S.M., Da Silva, B.K., Polinko, A.D., McConnell, T.E., McDill, M.E., 2023. Estimating stand-level carbon supply curves for loblolly pine and Douglas-fir plantations. J. For. 121 (2), 125–134.

Terasaki Hart, D.E., Yeo, S., Almaraz, M., Beillouin, D., Cardinael, R., Garcia, E., Cook-Patton, S.C., 2023. Priority science can accelerate agroforestry as a natural climate solution. Nat. Clim. Chang. 13 (11), 1179–1190.

U.S. Department of Agriculture, 2023. Report to Congress: A general assessment of the role of agriculture and forestry in U.S. carbon markets. Retrieved June 21, 2024, from. https://www.usda.gov/sites/default/files/documents/USDA-General-Assessment-of-the-Role-of-Agriculture-and-Forestry-in-US-Carbon-Markets.pdf.

U.S. Geological Survey (USGS), 2013. USGS Data Tools. Retrieved June 21, 2024, from. https://www.usgs.gov/educational-resources/usgs-data-tools.

U.S. Geological Survey (USGS) Gap Analysis Project (GAP), 2022. Protected Areas Database of the United States (PAD-US) 3.0. U.S. Geological Survey data release.

U.S. Nationally Determined Contribution (NDC), 2021. Reducing Greenhouse Gases in the United States: A 2030 Emission Target. Retrieved November 17, 2024, from. https://unfccc.int/sites/default/files/NDC/2022-06/United%20States%20NDC%20April%2021%202021%20Final.pdf.

United Nations Framework Convention on Climate Change (UNFCCC), 2024. Key Aspects of the Paris Agreement. Retrieved June 21, 2024, from. https://unfccc.int/most-requested/key-aspects-of-the-paris-agreement.

Webb, C., 2021. Making carbon markets work for faster climate action. Nat. Conserv. Retrieved June 21, 2024, from https://www.nature.org/en-us/what-we-do/our-insights/perspectives/carbon-markets-for-faster-climate-action/.

Wilson, B.T., Woodall, C.W., Griffith, D.M., 2013. Imputing forest carbon stock estimates from inventory plots to a nationally continuous coverage. Carbon Balance Manag. 8 (1), 1–15.

World Bank, 2023. State and trends of carbon pricing 2023. http://hdl.handle.net/10986/39796. License: CC BY 3.0 IGO.

Zhang, Y., 2005. Multiple-use forestry vs. forestland-use specialization revisited. Forest Policy Econ. 7 (2), 143–156.