

RESEARCH ARTICLE

Estimating regional timber supply and forest carbon sequestration under shared socioeconomic pathways: A case study of Maine, USA

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Abstract

This study provides a regional model framework to evaluate timber supply and carbon impacts of environmental and socioeconomic change in Maine, USA. We construct alternative future narratives that vary economic growth, forest management, and environmental policies and then conduct econometric analysis to project forest area and timber supply over the next 80 years under five shared socioeconomic pathways (SSPs). Forest area changes from 2020–2100 ranged from a 11% decline in SSP3 (regional rivalry) to 0.2% for SSP1 (sustainability). Maine's forest carbon stocks and timber supply can still mutually increase before 2070 for all pathways, largely due to improvements in forest management, growth, and yield. Overall timber supply is projected to increase by 0.21–0.51% per annum, with supply expanding faster for pathways with higher timber price growth. Total forest carbon stocks (ecosystem and products) are projected to increase 0.40–0.64%/yr for similar reasons. Sensitivity analysis indicated the key drivers most likely to affect Maine's forest sector are timber prices, population change, personal income, land value, and conservation land area. This study offers valuable insight on possible methods about region-specific socioeconomic assessments.

1. Introduction

Forests are major contributors to the terrestrial carbon sink, absorbing or emitting CO₂ emissions through actions such as afforestation, deforestation, fire, and harvesting [1–3]. The US carbon storage in forests offset roughly 11% of national greenhouse gas (GHG) emissions from all sectors, which makes forest an effective force in climate change mitigation [4]. In Maine, USA, forest can remove more than 50% of GHG emissions [5]. However, in the period 1990–2015, the global forest area fell by 129 million hectares, 3% of forestland loss [6]. The conversion from forests into agricultural land or urban/other lands emits huge amounts of greenhouse gases, inevitably increasing soil erosion and water quality degradation [7]. Forest land use change, as driven by population growth and urbanization, is expected to continue

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under a range of socioeconomic and policy conditions [8]. In the US, Stein et al. [9] pointed out that over 57 million acres of rural forestland could experience substantial development pressures from 2000 to 2030 [9]. The 2010 RPA Assessment also predicted an estimated 4%–8% of forestland loss by 2060 in the US with the expansion of urban and developed areas [10]. Cook-Patton et al. [11] identified 51.6 Mha of reforestation area available in the US, yielding 314 MTCO₂yr⁻¹ in annual mitigation. Natural regeneration has been considered as a low-cost alternative to active tree planting and often provides high returns on investment in terms of multiple ecological outcomes [12]. Agroforestry has been more adopted by farmers, as it has more soil organic carbon than sole forestry or agriculture system [13].

Many uncertainties, such as socioeconomic, policy and technological development, could affect the climate change mitigation potential of the forest [14, 15]. Policy instruments that eliminate penalties or create incentives, ranging from tax benefits to cost-share assistance and payments to the sale of carbon credits, are often used to encourage landowners to maintain their forestland. Forest management strategies can increase forest resilience and carbon storage, different forest types can influence the carbon and nutrients in forest soils, with soils in softwood stands typically accumulating relatively more carbon [16]. New technology and bioenergy policy can shape forest products demand (e.g., pulplogs, sawlogs and biomass), which also affect GHG fluxes based on their emission profile associated with their production and use [17–20]. To reduce future vulnerability and enhance climate resilience, as well as adaption to climate change, we need to project the possible futures of the forest sector at multiple scales. These projections should rely on evolving biophysical conditions, as well as socioeconomic factors that can strongly influence patterns of forest cover, carbon, and timber harvests over the next century.

The Shared Socioeconomic Pathways (SSPs) provide a future socioeconomic framework and have been widely used to explore how the future world evolves [8, 21]. The SSPs were five alternative future socioeconomic narratives, including sustainable development, middle-of-road development, regional rivalry, inequality, and fossil-fuel development [8]. There is a wide range of applications of the SSP framework on the forest sector, such as developing global land use changes or forest area under future socioeconomic futures [22], estimating bioenergy supply [15, 23], projecting forest land based GHG flux [24, 25] and carbon stored in harvested wood products [26]. The application of future SSP frameworks on national or subnational trends is able to reflect local unique situations, such as climate adaptation practices, community resilience and sustainable development [8, 27]. Meanwhile, maintaining consistency is a primary challenge when downscaling the global SSPs or constructing bottom-up SSPs [28].

The state of Maine is a regional leader in climate policy. In 2019, Maine enacted legislation to reduce its carbon emissions by 45% below 1990 emissions levels by 2030, by 80% by 2050 and be carbon neutral by 2045 [29]. To reach the state's GHG reduction targets, more economically feasible programs are necessary, especially for small landowners. Along with the tightened reliance on forests to mitigate GHG emissions, the state also faces a historically high demand for forest products, including biomass. Policymakers and industry leaders are also focused on designing incentives to increase forest carbon stocks while also balancing the desire for a sustainable flow of timber to support forest-dependent communities. With future increasing population and economic growth, the traditional forest products consumption is projected to increase or potentially decrease depending on a variety of factors [30, 31]. Further, bioenergy consumption is also expected to change with more stringent GHG emissions targets [17].

Previous studies have found that the increasing importance of carbon sequestration will likely lengthen rotation lengths, defer or reduce harvests, and influence the mix of wood products [32–34]. The potential reduction in timber harvest and revenue will impair the forest

related economic growth in rural communities and might result in potential leakage of carbon and timber supply as harvests shift to other regions of the globe in response to local policies. Thus, this study uses a systematic dynamic forest sector modeling approach to understand how regional forest area, carbon stocks, and timber harvests evolve under a range of alternative future pathways. The SSPs developed for this paper use existing data and study-specific narratives and parameters to depict a wide range of conditions. We model different futures using SSPs to evaluate the balance or tradeoffs between forest area, carbon stocks, and timber harvests in a predominantly naturally regenerated forest with various management regimes. To do this, we first develop five Maine forest sector socioeconomic narratives that are aligned with the global qualitative SSP narratives literature. Forest area and wood harvest drivers were then estimated using logistic regression. After, the SSP narratives were translated into detailed quantitative scenarios on the forest sector, and these economic models were then run for each of the SSPs to model potential impacts under various socioeconomic pathways out to 2100. Results of the dynamic model and analysis were then utilized to evaluate the key drivers and opportunities to jointly maintain or enhance Maine's forest carbon stocks and timber supply.

2. Materials and methods

2.1. Study area

Our research study area is based on a state-level analysis of Maine, USA, a heavily forested and harvested area located in the northeastern part of country. Maine contains an estimated over 7 million ha of forest land covering 89.1% of the land area in the state [35]. Maine's forests lie in a transitional zone between the eastern deciduous forest to the south and the boreal forest to the north, with diversity of forest types, any climate-induced changes to forests will undoubtedly occur faster and more visibly than elsewhere. The combination effect of Maine's prolific seeding by native tree species, climate and overstory tree diversity explain the abundance and composition of natural regeneration rarely found in other regions. Forests are the foundation of Maine's natural resource-based economy for its forest product industry accounts for nearly 4.2% of the state's gross domestic product [36]. The state's vast forestland plays a vital role in mitigating and offsetting carbon emissions, the existing forest stock and harvested wood products sequester more than 12 million tons of carbon dioxide equivalent per year (MtCO_{2e}/yr), or more than 70% of the state's gross GHG emissions from 2012–2017 [4, 5]. Maine's forest industry has recently faced significant changes and there is high uncertainty about how the sector will evolve in the future. According to the 2016 National Land Cover Database (NLCD), Maine lost about 2,000 ha/yr in forestland and 1.1 Mt of CO_{2e} emissions each year between 1990 and 2009 [14].

2.2. Model structure and workflow

Forest sector models generally include forest area change, timber harvest and forest stock [37]. Empirical estimation methods, such as logistic regression, have been used to model land use change with drivers based on historic data [38]. Past studies have applied logistical regression in landowners' land use decisions including forest, agriculture and urban/developed land [38–41], deforestation analysis [42, 43] and forest plantations [44]. Harvest volume has also been estimated by econometric models, which express as a function of stumpage price, forest stock, forest ownership types, biophysical variables and other social economic variables [45–47]. The empirical models of timber supply developed for this study consist of three components, a land use change model, a harvest choice model, and alternative future scenarios based on five SSPs.

2.3. SSP development

Global level SSPs have been developed to shape alternative socioeconomic development trends over this century. The process of developing the SSPs in our regional forest sector model is driven by the general principles of global SSPs and the local characteristics of Maine. As O’Neill et al. [21] mentioned, the extended SSPs would be able to incorporate more detailed information for particular sectors or regions (e.g., Frame et al., [27]). This analysis assumes five alternative scenarios, modeled based on SSPs narratives, which shape the possible evolution of socioeconomic futures and potential challenges to mitigation and adaptation to climate change. Daigneault et al. [15] extended the details for five SSP narratives for the global forest sector, major socioeconomic elements including economic growth, wood product demand, land use regulation, and technology development, which are summarized in Fig 1. SSP1 shifts towards a sustainable development, facing low socio-economic challenges to adaptation and mitigation, denoted by higher GDP growth and strong land-use regulations. SSP2 follows a middle-of-the road development that does not shift much from historical patterns, showing moderate GDP and technology growth. SSP3 is characterized as a regional rivalry that focuses on more local/regional issues and competitiveness, facing high socio-economic challenges to adaptation and mitigation, denoted by slow or decaying GDP growth and weak land-use regulations in Fig 1. SSP4 describes the inequality development of regional disparities, with varied GDP growth by regions based on their development level. SSP5 assumes rapid development due to continued reliance on fossil fuels and advanced technologies. Details of each SSP narrative are provided in Supplemental Material.

2.4. Land use model

Empirical models of land-use change have long been used in environmental and resource economics for policy analysis of the effects of land-use change on the forest land base, including analyses of urban sprawl and ecosystem services. For example, Agarwal et al. [38] reviewed 19 land use models across different spatial, resolution and extent, based on a meta-analysis of 136 articles that included applications of logistic, regression, and econometric models. Research indicates that the area base model [49], the multinomial logit model [50], and the logit model [51] can all illuminate factors that affect human decision making at either plot- or county-level scales.

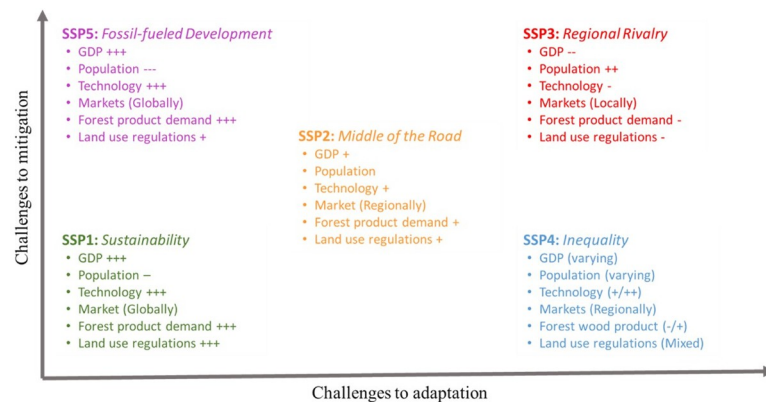


Fig 1. Five shared socioeconomic pathways (SSPs) for the global forest sector. Developed from [21, 48]. +/- indicate degree of change from current (2020) conditions, “+”, “++”, “+++” denoted low, moderate, and high degree.

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Due to its robustness and ease of application, this study utilizes the logit model to estimate forest area change. Forest cover differences are assumed to depend on the relative income per capita of the countries on both sides of the border, while their growth rates are dependent on income per capita, population growth, and rural population density [52]. In many prior analyses, the land cover categories were reduced to two inclusive categories (forest and non-forest). For this analysis, land use decision making is a probability function depending on socioeconomic and/or biophysical variables beyond population variables without feedback from the environment to the choice function.

We consider the area changes in land use from forestland to all other lands from 2003 to 2018 at county-level as the dependent variable. Previous land use or forestland area analyses often employ aggregate data, such as county-level [40, 41, 53]. The county-level forestland area data from US Forest Service's Forest Inventory and Analysis (FIA) National Program was aggregated and used to compute the forestland shares (the proportion of land use in forest uses) within each county. Drivers of land transformations are usually caused by economic growth, population and personal income levels [54, 55]. Population growth and income have complex relationships with forestland conversion. High population growth with high income levels can increase the land demand for residential use and accelerate the land conversion from forest area to agricultural area in response to rising demand for food, while also encouraging forestland retention or forest plantation by increasing demand for wood products and non-market ecosystem services [56]. We also add other two additional drivers, landowner types and wood product prices, as landowners can affect forest parcelization through management and investment practices, while stumpage prices are used as a proxy for timberland returns.

Our land use change model assesses the relative significance of six explanatory variables (i.e., population density, personal median income, biomass price, sawlog price, pulpwood price, and public ownership) on forest area change during the period 2003 to 2018 and estimates the impact of alternative future scenarios on county-level forest area shares. Following the theory of land use change [40], the share of forest land in i th county at time t is specified as the logistic regression model (LRM) of a linear combination of a vector of explanatory variables $X(t, i)$ and a vector of unknown parameters, β :

$$p(t, i) = \frac{\exp(\beta'X(t, i))}{1 + \exp(\beta'X(t, i))} \quad (1)$$

Where $p(t, i)$ is the expected share of land in timber use in county i at time t , the panel data $X(t, i)$ includes population density, personal income per capita, wood product prices (sawlogs, pulplogs, biomass) and public ownership proportion. The transformation of the logistic function yields a linear model:

$$\text{logit}(p(t, i)) = \ln \frac{p(t, i)}{1 - p(t, i)} \quad (2)$$

Hence, generating the error-components structure,

$$\text{logit}(p(t, i)) = \beta_0 + \beta_1 * \text{PopulationDensity} + \beta_2 * \text{LnPerCapitaIncome} + \beta_3 * \text{PriceSawlog} + \beta_4 * \text{PricePulplog} + \beta_5 * \text{PriceBiomass} + \beta_6 * \text{PublicOwnership} + \mu_i + \varepsilon_{it}$$

$$\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$$

$$\mu_i \sim N(0, \sigma_\mu^2) \quad (3)$$

The error components (μ_i, ε_{it}) are expected to vary with time and county, μ_i and ε_{it} are uncorrelated for all i and t . This function is fitted by the maximum likelihood approach, defining a random-effects model, and accounts for potential cross-correlation among multiple time-series observations of developed land within individual counties.

2.5. Harvest probability model

As the contradictory demand for both forest products and carbon sequestration from standing forest in the future, it is important to estimate the potential range of harvest volume and carbon stocks. We use a binary response function to estimate the likelihood that forestland owners will harvest trees. The analysis is based on a stand-level harvest choice model [47], where the dependent variable is classified as two options (no activity or harvest), and harvests can consist of three specific wood classes (sawlogs, pulplogs, or low diameter). The statistical model is developed on a 5-year time step from 2002 to 2016, using FIA data from over 9,000 observations plots in Maine. Growing stock volume functions were calculated by regression analysis of no harvest activity plot records. Timber supply is aggregated through interpolation of the predicted individual stand harvest decisions and corresponding harvest intensities to account for all 7 million ha of forested area in Maine. We used the same drivers as [47] to determine the relationship between harvesting, environmental, and socioeconomic factors.

The harvest choice model is parameterized using a combination of plot- and region-specific characteristics such as stand type, site location, stumpage price, and other key factors. This equation can be mathematically expressed as:

$$\begin{aligned} \text{logit}(p'(t, i)) = & \beta_0 + \beta_1 * \text{PriceSaw}_{\text{county}} + \beta_2 * \text{PricePulp}_{\text{county}} + \beta_3 * \text{LagBio} + \beta_4 * \text{Growth}_{p,s} + \beta_5 \\ & * \text{Mills}_{p,s} + \beta_6 * \text{LandValue} + \beta_7 * \text{HighwayDist} + \beta_8 * \text{Conservation} + \beta_9 \\ & * \text{Elevation} + \mu_i + \varepsilon_{it} \end{aligned} \quad (4)$$

where *PriceSaw*, *PricePulp* and *PriceBiomass* are sawlog and pulplog stumpage prices (\$/ton), *LagBio* is the amount of standing biomass on the stand in the previous period (ton ha⁻¹ yr⁻¹), *Growth* is the potential biomass growth between two periods (ton ha⁻¹ yr⁻¹) without harvesting, *Mills* is the number of mills within a specific buffer around the plot, *LandValue* is the assessed forestland value (\$ ha⁻¹), *HighwayDist* is the distance from the plot to a primary highway (km), *Conservation* is an indicator variable describing the category of plot ownership status (0 = non-conservation; 1 = public conservation; 2 = private conservation), and *Elevation* is the elevation of the plot (m).

2.6. Forest carbon

This analysis estimated the amount of carbon in Maine's forest growing stock and harvested wood products (HWPs). Aboveground carbon (AGC) stocks were estimated assuming that carbon comprised 50% of aboveground biomass (AGB), which are obtained from FIA. Part of harvested wood carbon is stored in products and contributes to long-term carbon storage. Based on Smith et al. [57], we assume that an average of 32%, 22%, and 0% of C, respectively contained in harvested sawlogs, pulplogs, and woody biomass is stored in wood products and landfills after 100 years. Based on 2016 harvest levels [58], this equates to about 24% of the total harvested C being stored in HWPs over 100 years.

2.7. Data

Historical records provide the general parameterization of the model following the descriptive SSP narratives (Fig 2). The historical county level population and personal income (relative to

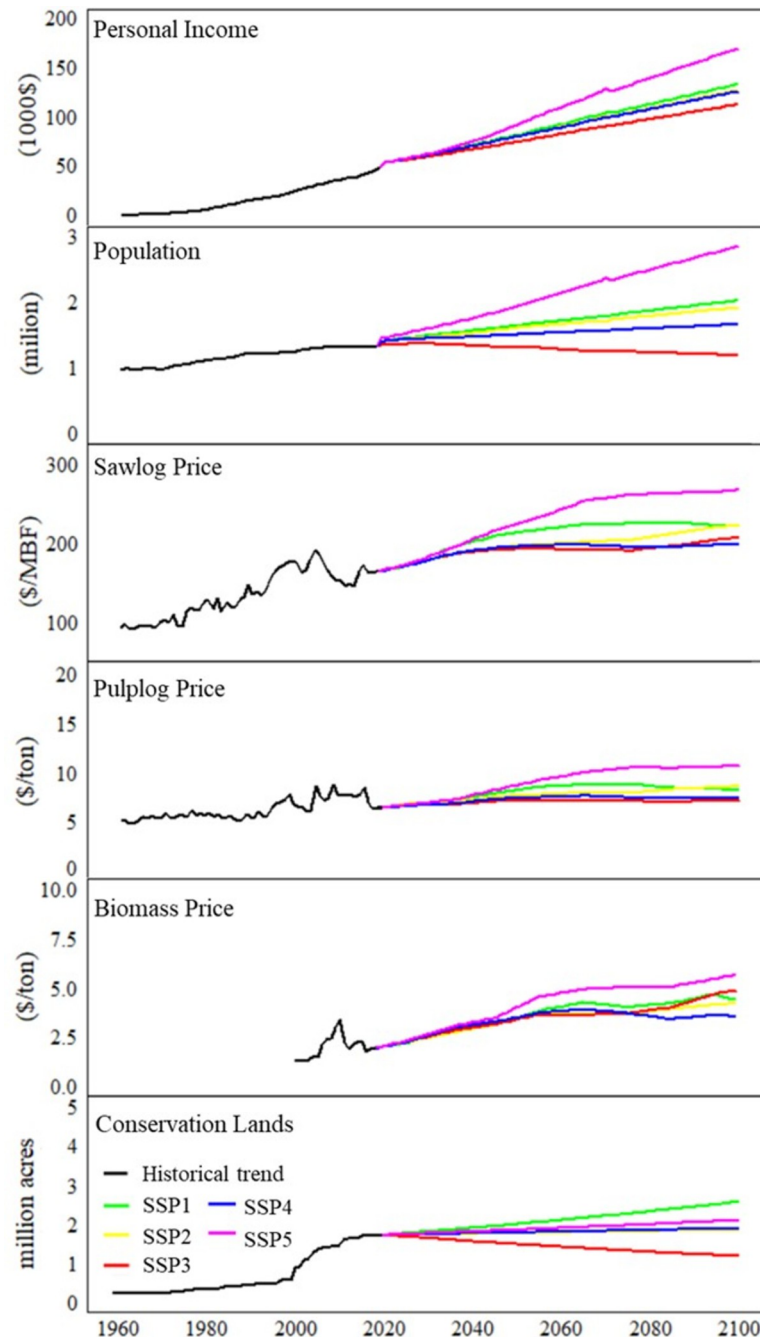


Fig 2. Historical records (black lines) and projections (colored lines) of Maine's personal income per capita, population, stumpage prices, and conservation land area under five SSPs.

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2009 USD) from 1959 to 2018 are obtained from U.S. Bureau of the Census and U.S. Bureau of Economic Analysis. Historical wood prices are obtained from 1959–2009 Maine Forest Service stumpage prices reports (Fig 2, black line). Landowner types from FIA data are aggregated at the county-level. To project future forest shares in response to possible socioeconomic developments, drivers of SSP scenarios are integrated into the logistic model framework to estimate future scenarios of forestland. The price projections of different wood types (sawlogs, pulplogs

and biomass) were from [59], who projected stumpage prices under SSP scenarios from 2015 to 2100 using three global forest sector models. We use the percentage changes in these price series to project stumpage price changes for Maine forests given participation in the global market (Fig 2, colored lines). Population and personal income projections were from [60], who project the future population and income at county scale by 5-year increments from 2015 to 2070. All data are interpolated from 2070 to 2100 using compound growth rate formulas.

Conservation and land ownership have shifted considerably over the past two decades. In 2000, only 7% of Maine's land was conserved, and most conservation lands were mostly publicly owned. By 2020, about 21% of Maine's land was conserved, and more than half of them were held privately in the form of fees or easements ([61]; Fig 2 and S1 Fig). Projections in SSP2 showed that 24% of total forestland is assumed as conservation land by the end of century, which follows the historical trend. Conservation lands tend to shrink to only 14% of total forest land in SSP3 and expand highest to 34% in SSP1 by 2100 in Fig 2. SSP4 has a similar amount of conservation area to SSP2 but has a greater spatial location disparity as most conservation land expands on the southern region.

Transportation cost is represented as the distance from individual FIA plots to the nearest highways, and is set as constant in SSP3, assuming not many innovative technologies and infrastructure improvements. By 2100, road distance is decreased 40% in SSP5, followed by 25% in SSP1 compared to the year 2016. Road distance change is also spatially uneven in SSP4, with most reductions located in the southern region. The number of saw and pulp mills within a 50 km radius buffer served as a proxy for local demand, and the numbers are not changed in SSP2, and decreased by 30% in SSP3 by the end of century compared to 2016. SSP5 shows both high demand for sawlogs and pulplogs that increased by 40%, SSP1 also assumes increased wood demand but more in sawlogs with a 40% increase in sawmill numbers and only a 20% increase in pulpmill numbers. Forest value reveals the opportunity cost for development. It is assumed to be the highest in SSP5 (increased by 40% in 2100 from 2016) and the lowest in SSP3 (decreased by 10% in 2100 from 2016).

2.8. Model calibration and validation

The stepwise method was used to select the best set of the minimum number of predictor variables with smallest Akaike Information Criterion (AIC) index. Likelihood ratio tests were then used to test for the significance of all factors by comparing the full model to the same model without the tested term. The random-effects model explained a significantly greater amount of variance indicating the random-effects model was better when compared fixed-effects model.

3. Results

3.1. Model estimates

The coefficients result from the forest area model and harvest probability model are summarized in Tables 1 and 2. The mixed-effects logit forest share model passed the global fit test and results generally corresponded with prior studies of the correlative associations between socioeconomic factors and change in the share of forest area. The estimated coefficients from the forest area model also have the generally expected signs (Table 1). Most product prices related terms were statistically significant and positive, and all but the biomass coefficient was statistically significant at the 99% confidence interval. Table 2 summarizes the expected signs and the estimated coefficients of the explanatory variables, standard errors, and their statistical significance for the RE harvesting models. Results indicate that timber prices, growth volume and site characteristics had a statistically significant effect on timber harvesting preferences. As expected, landowners are more willing to harvest trees from their forestland when timber

Table 1. Maine forest area model estimates and fit statistics.

Independent Variables	β /(S.E.)
Population Density	-2.090*** (0.303)
ln(Personal Income per Capita)	-1.850*** (0.144)
Public Ownership	3.182*** (0.823)
Pulplogs Price	0.050*** (0.016)
Sawlogs Price	0.008*** (0.001)
Biomass Price	0.058 (0.040)
Constant	-6.452*** (0.624)
Observations	240
LR test	$\chi^2 = 324$ (<0.001)
Goodness of fit	
Log Likelihood	-2,944
Akaike Inf. Crit.	5,906
Bayesian Inf. Crit.	5,938

Note

*p<0.1

**p<0.05

***p<0.01.

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price is higher, while the biomass price had no statistically effect on harvesting preference for low diameter.

3.2. SSP projections

3.2.1. Forest area. Economic and demographic changes in SSP1-5 (Fig 3), indicates that growing population and income drive the conversion of forestland to development, thereby leading to shrinking trends in forestland area, especially after 2070. With the highest wood product prices, SSP1 projected net forest expansion by about total 11,910 ha from 2020 to 2100. Forestland in SSP2 closely followed the historical trends, decreasing at a rate of 4,274 ha per annum. Most forestland is lost in SSP3 and SSP4 (9,653 and 8,531 ha yr⁻¹), driven by the relatively low value of wood products with lesser interest in the societal and environmental values of forests.

3.2.2. Timber harvest. Timber harvests are projected to rise by 1.2–1.5 times from 2020 to 2100 (0.21–0.51% yr⁻¹) under all scenarios (Fig 4). SSP5 (fossil-fueled) projects the largest harvest volume increases before 2070 (0.89% yr⁻¹), partially due to rapid economic growth and increasing population. High harvest frequency and intensity limit subsequent annual net growth of growing stock, while slowing wood demand and a shrinking forest area leads to a decline in harvest volume after 2070. SSP1 (sustainability) timber harvest follows a similar trend as in SSP5, increasing at a rate of 0.74% yr⁻¹ before 2070, but then decreasing. A large proportion of the reduction in the scenario resulted from less low-diameter timber harvests. Timber harvests in SSP2 initially rise moderately and continue to rise to 2100, at a rate of 0.51% yr⁻¹, with all three timber classes experiencing consistent gains over the century. SSP3 and 4 experience the lowest changes in harvest, driven by declines in population and slower economic development. As a result, harvests occur at a rate of 0.30%–0.36% yr⁻¹.

3.2.3. Forest carbon stocks. Although Maine's forests are projected to face increasing harvesting over the next 80 years, overall net tree growth under all SSPs results in increases in total aboveground carbon (AGC) stocks (Fig 5). The simulated AGC in SSP2 accumulated at

Table 2. Harvest choice model estimates and fit statistics.

Independent Variables	Sawlogs	Pulpwood	Low diameter
	β /S.E.	β /S.E.	β /S.E.
Sawlogs Price	0.007*** (0.002)	0.005*** (0.002)	-0.013*** (0.002)
Pulplogs Price	0.034*** (0.013)	0.066* (0.038)	0.387** (0.171)
Biomass Price			-0.085 (0.178)
Forest Growth	0.346*** (0.017)	0.118*** (0.006)	-0.560*** (0.016)
Private Conservation = 1	-0.114*** (0.024)	-0.098*** (0.020)	-1.836** (0.755)
Public Conservation = 1	-1.201*** (0.037)	-1.150*** (0.032)	-6.774*** (2.202)
Mills	0.015*** (0.003)	0.025*** (0.002)	0.033*** (0.002)
Land value	-0.121*** (0.024)	0.297*** (0.077)	-1.205** (0.513)
Distance	-0.021 (0.017)	0.011 (0.031)	-0.0004*** (0.0001)
Elevation	0.537*** (0.073)	0.572*** (0.069)	1.048*** (0.068)
Coastal	-0.113*** (0.040)	-1.509*** (0.187)	-2.591 (1.650)
Constant	-4.753*** (0.258)	-4.905*** (0.396)	5.370** (2.213)
Observations	6,117	6,117	6,117
Log Likelihood	-45,864	-64,110	-62,835
Akaike Inf. Crit.	91,754	128,248	125,708
Bayesian Inf. Crit.	91,841	128,342	125,836

Note

*p<0.1

**p<0.05

***p<0.01.

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the average rate of 1.26 million metric tons of carbon per year (MMTC yr⁻¹), or 0.49% yr⁻¹. This estimate is slightly less than the historical accumulation rate of 0.55% yr⁻¹ [4]. AGC is estimated to accrue at a slower pace in SSP1 and SSP5 (0.18 to 0.70 yr⁻¹), as net growth is reduced with higher harvest rates, especially in the middle of the century.

The harvested wood product (HWP) carbon pool increases across the different SSPs in similar trends as wood harvests. SSP1 and SSP5 have the highest level of carbon stored within HWPs, as the high economic growth and free trade drive the highest level of roundwood consumption (i.e., sawlogs and pulplogs). Even though we assume C in the low-diameter wood products is emitted immediately when harvested, the amount of carbon stored within HWPs continue to rise steadily due to declining low-diameter harvests.

Total forest sector carbon (AG + HWP) stocks rise by 1.4–1.7 times by from 2020 to 2100 (0.40–0.64% yr⁻¹) under all scenarios. SSP1 and SSP5 have a noticeable increase in overall

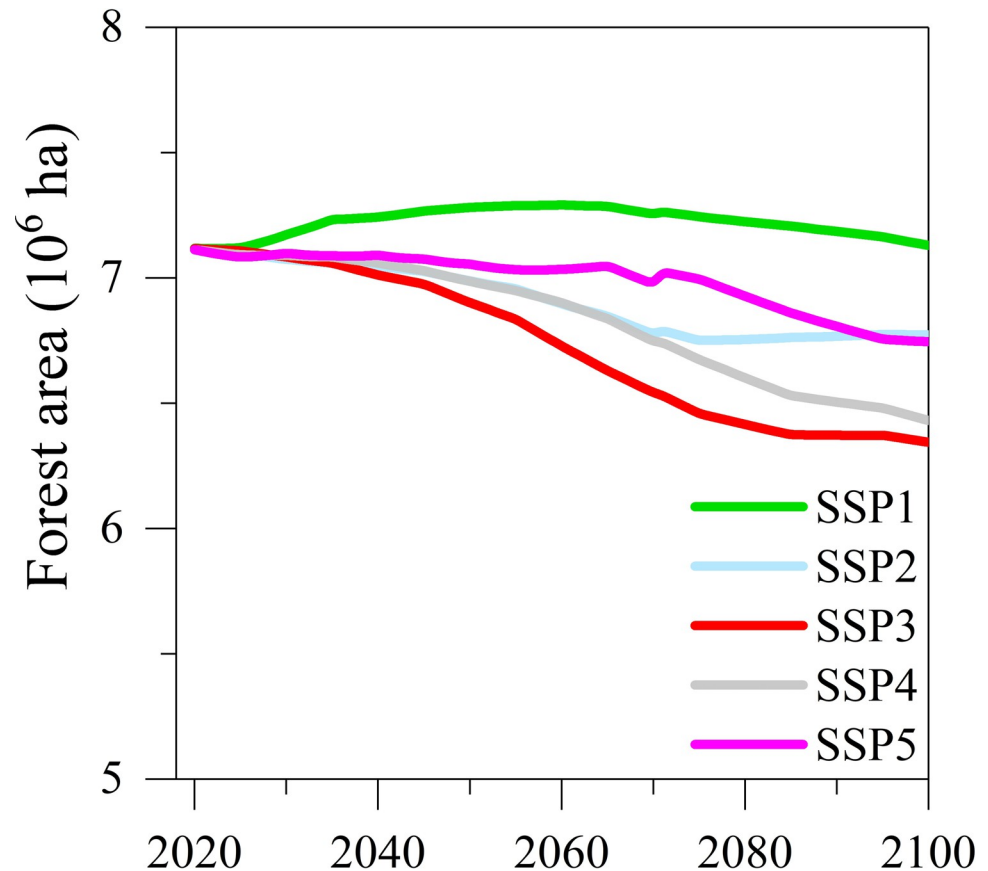


Fig 3. Projected Maine forest area (million ha) under different shared socioeconomic pathways (SSPs), 2020–2100.

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carbon stored due to the relatively high amount of HWP C. SSP1 yields the highest amount of total carbon stock, with a net gain of 184 MMTC from 2020 to 2100 (2.3 MMTC yr^{-1}), as a result of forestland expansion, productivity improvements, and moderately high timber harvests. SSP3 is estimated to have the lowest increase in total carbon stock, averaging 1.3 MMTC yr^{-1} . This low growth in total C is mainly driven by forestland loss.

3.3. Sensitivity analysis

Maine's forest area, harvest, and forest carbon stocks all varied substantially from 2020 to 2100 across the different SSPs examined. Because the estimates for each SSP were based on a range of assumptions, we performed a sensitivity analysis to isolate the effects of key parameter changes on forest area and timber supply.

Timber product prices made the highest contributions to the wide variation in projected forest area (average 6% more area before 2050, and 22% more after) and was followed by personal income (average 5.5% less area before 2050 and 15% less after), while population contribute only 1% of the variation to the forest area change (Fig 6, top and Fig 7, top). The high wood product prices raise land values, thereby encouraging landowners to invest in forest management and retain forestland. In addition, the promotion of renewable energy could also encourage investment in industrial plantations [62]. Both population and personal income

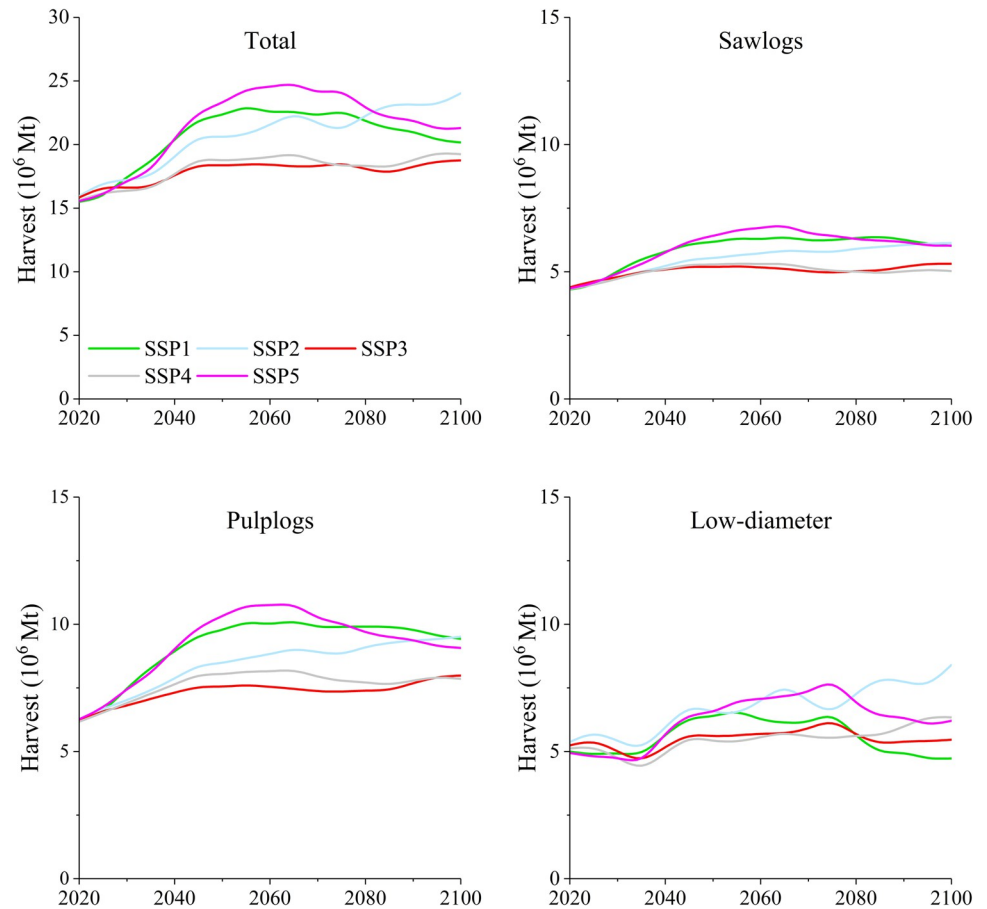


Fig 4. Total Maine timber harvest volume by timber product type and SSP scenario.

<https://doi.org/10.1371/journal.pclm.0000018.g004>

had a weak negative influence on forest area, as increases in these indicators could shift demand toward urban and developed uses [54].

Timber prices also had a strong influence on key model estimates, followed by forestland value (Fig 6, middle and bottom). Holding timber prices constant over the 80-year simulation period reduced the variability in timber harvests both within and across SSPs. Scenarios with high wood price growth (SSP 1,2, and 5) experienced a harvest increase of 10% or more

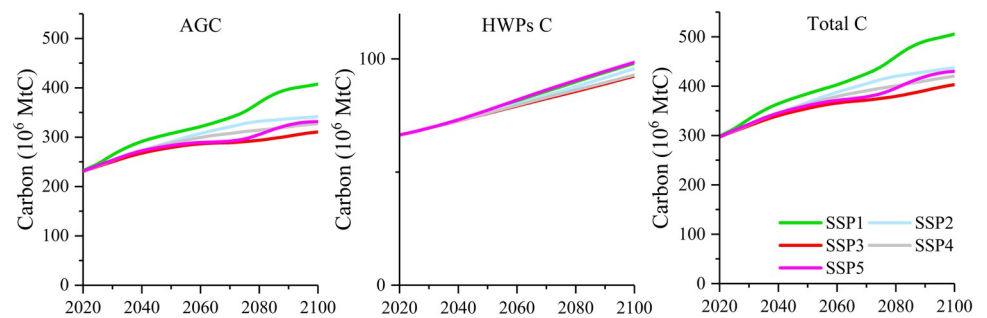


Fig 5. Projected forest carbon stocks (above-ground carbon, carbon stored in HWPs and total carbon stocks) under baseline and SSPs.

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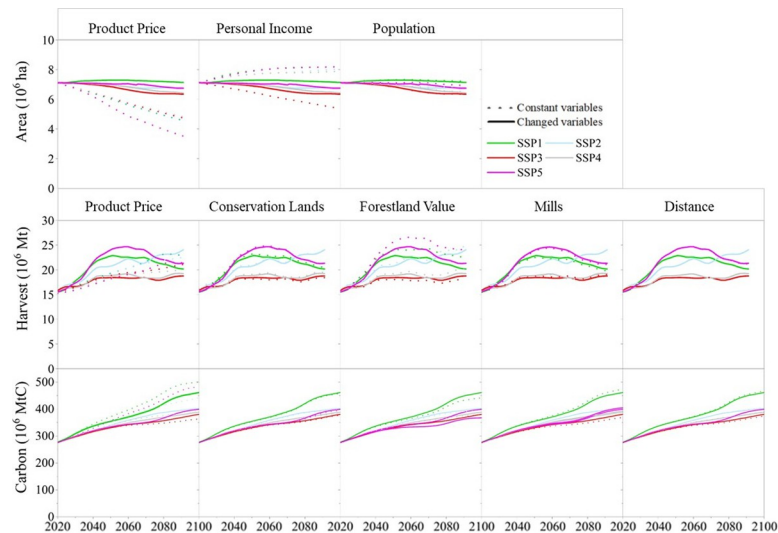


Fig 6. Annual forest area (million ha), timber harvest volume (MMT yr⁻¹) and total carbon storage (MMTC) under different shared socioeconomic pathways (SSPs), 2020–2100. Solid lines denote simulations with changed variables (i.e., our core assumptions) and dashed lines denote simulations with values held constant.

<https://doi.org/10.1371/journal.pclm.0000018.g006>

relative to when prices do not change over time (Fig 7). As a result, total forest carbon (including AG and HWP) could decline by as much as 16% in the last half of the century because of the high price growth assumptions, with highest declines occurring in SSP5 (-16%), followed by SSP1 (-9%) and SSP2 (-7%).

Holding forestland value constant over the simulation period has a relatively small impact on model results until the second half of the century, when increases in forestland value drive a higher proportion of landowners to manage their land for multiple objectives, not just timber harvest. As a result, overall timber harvesting is reduced by 2–10% in all but the regional-rivalry SSP3 scenario (+4%) where forestland values are assumed to have minimal change over time. As a result, Maine's forest carbon stocks could change by 1–5% based on how much forestland values are assumed to change over time.

Including the effect of conservation land designation in our analysis had a slightly negative effect on harvest activity, which declines by 1%–2% across all but SSP3, which experiences the opposite effect (+1%) because of the original assumption that conservation land area would decline under that scenario. Increasing conservation land area did increase total forest carbon stocks for four of the five SSPs, but only slightly on average (+0.6%).

Other modeled factors such as the number of mills in a 50 km radius and the distance from the forest to the nearest road had minor impacts on forest harvest and carbon stock estimates. It is assumed that road networks would improve more in SSP1 and SSP5, which also means lower transportation and harvest cost, encouraging more harvests (+0.2%) and leading to less carbon sequestration (-1%) relative to holding this factor constant over time. Mill numbers have similar effects, such that that increased mill capacity encourages more timber harvest in SSP1 and SSP5 (+1.6%), resulting in a 1–2% reduction in carbon stocks in SSP5 and 1, respectively.

4. Discussion

Forestland area in Maine is projected to increase only in SSP1 and shrink in the other SSPs examined. The estimated reduction in forest land is consistent with previous studies and

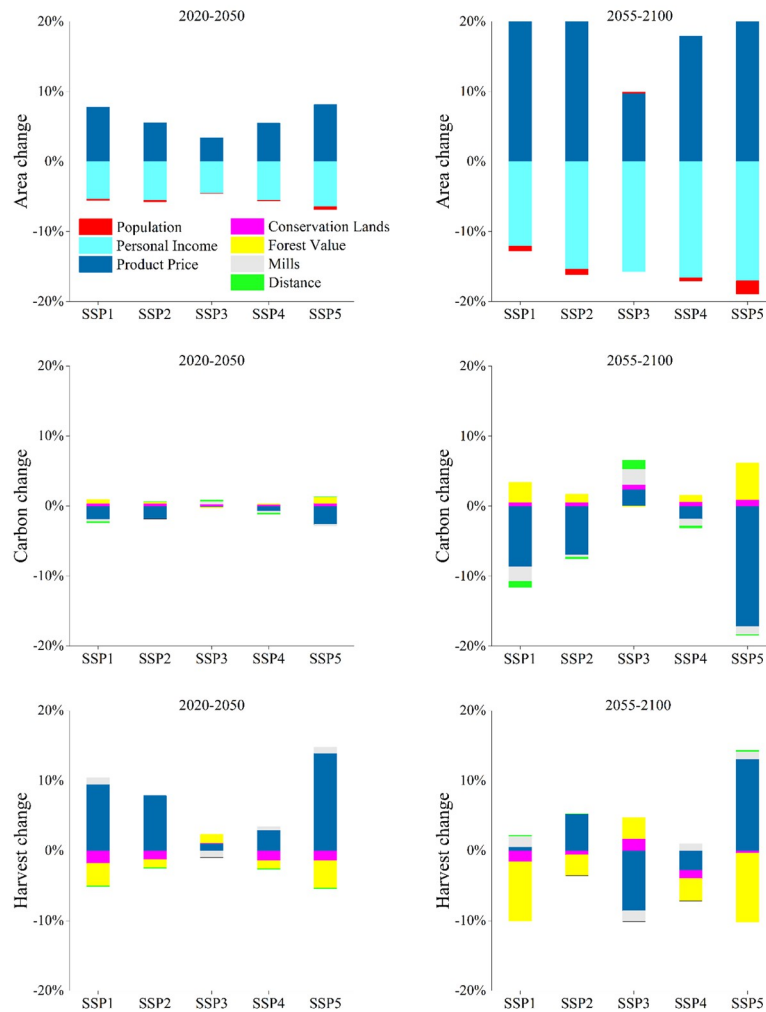


Fig 7. Mean influence individual parameters assumption on forest area, timber harvesting and carbon storage estimates across SSPs.

<https://doi.org/10.1371/journal.pclm.0000018.g007>

historical records [53]. Both sawlog and pulpwood prices have the largest contributions to forest area change and timber supply variation, while the biomass price does not. The non-statistically significant effect of biomass price on forest area can be explained by the low value and utility of the biomass market. Previous studies found that even with higher biomass prices, the supply of forestland owners' participation in biomass harvesting is quite low. For example, Markowski-Lindsay et al. [63] applied logistic regression to study Massachusetts non-industrial private forest landowners' harvesting preferences and found a low likelihood of biomass harvesting and inelastic supply with respect to price. In addition, Aguilar et al. [64] also found woody biomass harvesting is mainly determined by timber revenue instead of biomass price. One reason for this might be the low economic viability of bioelectricity plants and other uses for biomass in the state since Maine has experienced significant market losses for both low-grade wood and harvest residues in the last decade. The relatively inexpensive natural gas has also pushed little economic return of biomass to the landowner. According to the Maine Forest Service, biomass represented 16%-23% of the statewide timber harvest from 2016 to 2019, but less than 3%-5% of the stumpage revenue to landowners. Thus, policies and incentives

targeting biomass prices will have low efficiency effects to improve biomass supply and increase their utilization. Therefore, it is likely better to focus on strategies to improve an integrated harvest system such as commercial timber harvests where woody biomass is also harvested rather than target specific timber products. Even though the sensitivity analysis found the forestland changes are driven primarily by timber prices with much lower associations with changes in income and population, we also note the need to evaluate the spatial structure of this change, particularly in a state like Maine given its distinct geography and clustered population density. For example, inefficient patterns of human settlement are resulting in the loss of significant forest acreage to development in southern and central Maine. The increasing population might lead to the increasing of parcelization, which may strongly result in more inactive forest management by landowners.

Simulations display that forest carbon and timber can mutually increase in Maine before 2070 under a range of SSPs. Timber harvests increase stability and carbon storage accumulated following previous trends highlighted in SSP2. When compared to SSP2, greater shifts in socioeconomic conditions (regulations, population, income, technologies, etc.) result in more dramatic trends in SSP1 and SSP5, and thus lead to the expected increases in both timber harvests and carbon accumulations. While after 2070, timber harvests decreased, and carbon storage increased in this scenario, largely due to the stagnant product prices and longer rotations that reduced harvest intensities, thereby leaving more carbon in the forest. Facing declining population, slower economic development with decreased wood consumption demands (i.e., SSP3 and SSP4), the timber harvest increases more slowly. However, these pathways also experience larger declines in forest area, so carbon stocks also increase slowly. This finding is consistent with other analyses, as Daigneault et al. [30] and Popp et al. [65] also found that global carbon stocks in SSP3 were low due to land use change and low investment. Further, conversions of forest land to other uses are often the largest source of emissions within the land use, land-use change, and forestry GHG accounting sector [4].

Improving forest management or designating more forests as conservation could increase forest carbon stocks, while only slightly reducing timber harvest. Our sensitivity analysis found that high forestland valuation, which influences how forests are managed for multiple objectives, could result in an 8.4% harvest reduction in SSP1 and 10% in SSP5, thereby increasing carbon stocks by 4.5% and 8.6%, respectively. However, increasing the forest area under conservation in most SSPs reduce timber harvests by 1–2%, while increasing total carbon stocks by 0.6%. Rising wood demand (and prices) have the largest contribution to the increase in timber harvest before 2050 for SSPs 1, 2, and 5, thereby resulting in a relative reduction in carbon stocks. While our analysis illustrates the logical tradeoffs between timber and carbon, the overall findings indicate that managing forests for carbon storage can still be largely complementary with timber production, as consistently increasing wood prices also incentivizes more intensive forest management and most importantly, keeping forests as forests.

Most SSPs narratives are developed on global pathways, limiting insights at national- and regional-levels. National- and local-scale scenarios cannot necessarily be produced by simply downscaling global or regional scenarios because local elements could overwhelm the effect of global parameters [66]. Some studies have developed SSPs on a regional-level by examining stories of regional development and land use, while linking to regional assumptions of the SSPs. For example, Daigneault [48] linked the Global Timber Model (GTM) with a national economic land use model to develop a detailed assessment of how the forest sector in New Zealand could evolve under the five SSPs, while Ausseil et al. [66] also integrated a global economic trade model at the national-level with landscape models to conduct a site-specific assessment in a lowland environment of New Zealand. Likewise, Palazzo et al. [67] downscaled global partial equilibrium models results for forestlands converted to agriculture lands, while

Hu et al. [45] built a national statistical approach to study possible developments of the forestry sectors under the five SSPs and their products at a Norwegian-level. Given the large spatial scale of these various prior studies, there is still a real need to develop modeling frameworks applicable to smaller scales like individual states examined in this analysis. As our analysis assumes that climate and other natural effects on forests remain constant over time, a future extension of this work should incorporate the effects of climate change (e.g., insects, floods, heat waves or storms) on timber, carbon, and other ecosystem services given the expected shifts and sensitivity to these factors [68]. Other possible extensions of our framework include modeling intermediate wood products in more detail, quantifying the impact at the forest type or species scale, increasing the number of forest carbon pools to track (e.g., soil and dead-wood), and expanding the pathways and analysis to also include agriculture and other natural and working lands.

5. Conclusions

This study provides a modeling framework that translates qualitative SSP narratives representing plausible alternative futures into a region-scale quantitative forest sector analysis using Maine, USA as an applied example. The approach utilizes a land use model and harvest choice model rooted in the historical dataset yet modified and extrapolated to 2100 by different SSP narratives based on key aspects (e.g., stumpage prices, conservation land area, distance to highway, regional mill demand). Several iterations of the model were conducted to estimate Maine's forest area, timber supply and forest carbon stock under different socioeconomic scenarios. Between 2020 and 2100, forest area expanded only in SSP1, adding by 11,910 hectares, while it decreased in other four scenarios, with a maximum loss of 9,653 ha yr⁻¹. Timber harvests and carbon stocks increase in all scenarios, with timber harvests projected to rise by 1.2–1.5 times and carbon stocks projected to rise by 1.4–1.7 times. The results show that forest carbon and timber in Maine can mutually increase by 2070 under a range of SSPs.

Overall, the regional model framework developed in this analysis could emphasize local issues and is suitable for being applied to other sectors (e.g., agriculture) and regions. This approach can help to establish a bridge between global scenarios and more detailed analysis for individual sectors that may have relative importance in a localized context. In this study, this approach was used to assess how changes in socio-economic conditions (e.g., wood prices, population, income) could affect land use and timber supply. These specific land use sector pathways and timber supply pathways could allow policymakers to examine barriers and opportunities for potential climate change strategies.

Supporting information

S1 File. Shared Socioeconomic Pathway (SSP) narratives.
(PDF)

S1 Fig. North and south regions of Maine with spatial locations of conservation lands as of 2018 by ownership. The base map and Conserved Lands data were obtained from the Maine Department of Marine Resources [69].
(TIF)

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Project administration: Adam Daigneault.

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Supervision: Adam Daigneault.

Validation: Jianheng Zhao, Adam Daigneault.

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Writing – original draft: Jianheng Zhao.

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