

## Climate and socioeconomic impacts on Maine's forests under alternative future pathways

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### ABSTRACT

This study investigates the combined effects of climate and socioeconomic change on fiber supply and forest carbon in Maine, USA, for broad alternative futures. We conduct an econometric analysis to project forest resource use over the next 80 years under a range of shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs). Results show that continued forest successional dynamics – without any harvesting – contribute the most to Maine's aboveground carbon (AGC) accumulation, with 2100 AGC potentially increasing by 140% compared to 2020. On this basis, climate change could result in 2.44–2.64 times greater AGC in 2100 compared to today. Harvest activities are major drivers of forest C dynamics, resulting in 2100 AGC being only 16% >2020. Socioeconomic factors (SSPs) had much larger effects on total harvest and carbon stocks than climate change (RCPs). Harvest volume were projected to increase by 9–29% between 2020 and 2100 for favorable socioeconomic development scenarios (SSP1/SSP2/SSP5) and decrease by 3–29% for unfavorable socioeconomic development scenarios (SSP3/SSP4). Overall, Maine's forest C pools were projected to increase by end-century for RCPs x SSP1/SSP2. This study offers valuable insight on possible methods for region-specific socioeconomic and climate change assessments, particularly in areas with extensive and diverse working forests with mixed ownership.

### 1. Introduction

Forests are a critical component of the global carbon cycle because they take up and store carbon in vegetation biomass (Fahey et al., 2010). In the United States, net forest sequestration reached 173 Tg C per year, offsetting about 10% of greenhouse gas (GHG) emissions from transportation and energy sectors (Wear and Coulston, 2015). In 2022, the estimated carbon dioxide equivalent (CO<sub>2</sub>e) sink derived from land use, land-use change, and forestry (LULUCF) activities was estimated to be 754 million metric tons (EPA, 2023). Ongoing global warming is projected to significantly affect carbon uptake and release rates in forest ecosystems, either by directly modifying photosynthesis and ecosystem respiration or by indirectly introducing disturbances such as fire, storm, and insect outbreaks (Chen et al., 2019; Wei et al., 2018), although overall impacts can vary by region, forest type, and management response (Favero et al., 2021).

Timber harvesting, the major human introduced forest disturbance, can laterally remove the carbon from forest ecosystems and either immediately release it into the atmosphere or store it within harvested wood products (HWPs) —such as paper, furniture, and construction materials—thereby constituting an additional forest carbon pool. By using historical records, Johnston and Radeloff (2019) revealed that the carbon sequestered within global end-use HWPs represented a net sink of 90 Tg C in 2015. Similarly, Zhang et al. (2020) found that the average annual carbon sink in global end-use HWPs was 122 Tg C during the period of 1992–2015, accounting for 3.2– 6.1% of the annual carbon sink within the global forest sector (2400 ± 400 Tg C per year) (Pan et al., 2011). In addition, Eggers (2002) reported that carbon stored in the HWP pool constituted 13% in Australia, 8% in Finland, 13% in Germany, 8% in Norway, and 26% in Portugal across the entire forestry sector and all wood products. Smith and Heath (2008) updated this fraction to 10% in the USA, while Dewar and Cannell (1992) reported a

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high 33% in the UK. Further, active forest management can enhance the growth rate and carbon sequestration in standing forests, thereby offsetting some of the impacts of natural and anthropogenic disturbance (Daigneault et al., 2022).

Numerous factors, including climate change, forest management strategies, utilization standards, and socioeconomic variables can substantially influence both the carbon stored in standing forest and the HWP carbon pool (Johnston and Radeloff, 2019; Li et al., 2022). Climate change can threaten the function and productivity of forest ecosystems; for example, higher temperatures may reduce photosynthesis and timber yield within tropical forest ecosystems. However, within boreal forest ecosystems, warmer temperatures might enhance photosynthesis and prolong the growing season, thus bolstering timber output (Kirilenko and Sedjo, 2007). In water-deficient forest ecosystems, heightened precipitation can stimulate timber production, while a wetter climate can inhibit photosynthesis and impede tree growth in water-sufficient regions ecosystems (Husen et al., 2017). In addition, modeling studies indicate that increasing concentrations of atmospheric CO<sub>2</sub> are likely to drive modifications in forest ecosystems and could potentially boost the rate of tree growth through the carbon fertilization effect; there are also several factors that have the potential to limit this effect, including nutrient and water availability, ozone pollution, and tree species, age, and size (Janowiak et al., 2018).

The rapid development of the global economy in parallel with the boom of population over the past four decades has accelerated the demand for wood products, leading to a considerable expansion of the HWP carbon pool (Li et al., 2022; Zhao et al., 2022b). Churkina et al. (2020) pointed that the demand for wood products can be directly promoted by the increasing population. Concurrently, urbanization processes have driven an increased need for timber, which is used in constructing buildings and making furniture (Mishra et al., 2022). Higher household income is also typically associated with greater demand for forest products (Sohngen et al., 1999; Trømborg et al., 2000). In addition, Brack (2018) identified a positive correlation between the quality and durability of wood products consumed and household income. This association contributes to a reduced carbon outflow rate by extending the lifespan of wood product use. Although paper products are generally of shorter service life, the high demand for these products can form a sizable quick-turnover carbon pool. Therefore, incorporating these socioeconomic influences is necessary to predict the dynamics of the HWPs carbon pool.

Several studies have incorporated ecological and economic factors to evaluate the impacts of climate change and harvest behavior on forest growth, carbon, and timber supply using a range of analytical methods applied at the stand (e.g., Mei et al., 2019) regional (e.g., Beach et al., 2015), and global (e.g., Golub et al., 2022) scale. Ecological-economic modeling approaches to quantify climate and socioeconomic impacts to the forest sector include integrated assessment (e.g., Tavoni et al., 2007), global (e.g., Buongiorno, 2015; Favero et al., 2021) and regional (e.g., Baker et al., 2023; Solberg et al., 2003) dynamic optimization, stochastic dynamic (e.g., Siebel-McKenna et al., 2020), and econometric methods (e.g., Haynes et al., 2007; Wear et al., 2013). Many forest sector analyses incorporate the impact of climate change through changes in forest yield functions (e.g., Perez-Garcia et al., 2002), while some also account for potential disturbance and stock effects through biome shifts and forest dieback (e.g., Tian et al., 2016). Approaches also vary in how the markets and agents in the models respond to economic and ecological shocks, with some holding prices constant (e.g., Hanewinkel et al., 2013) while others including endogenous price responses to changes in supply and demand (e.g., Favero et al., 2018). Nearly all studies account for adaptation via changes in forest management, including adjusting harvest timing and intensity (Rose, 2014). As a

result of the differences in the models, scenarios, and input data employed, the estimated impacts of climate and socioeconomic change on the forest sector are highly variable (Aaheim et al., 2011).

The RCP-SSP scenario framework has been developed and used to model the effects of socioeconomic development and climate change on global harvesting and carbon storage (Ebi et al., 2014; Favero et al., 2017; Kriegler et al., 2012; O'Neill et al., 2014). The Shared Socioeconomic Pathways (SSPs) are five alternative socioeconomic trajectories, namely sustainable development, middle-of-the-road development, regional rivalry, inequality, and fossil-fuel development (Riahi et al., 2017). The Representative Concentration Pathways (RCPs) represent greenhouse gas concentration trajectories that encompass a broad range of climatic outcomes, from lower (RCP 2.6) to higher (RCP 8.5) CO<sub>2</sub> concentrations.

Maine's forest ecosystem is characterized as a transitional ecotone, composed of a broad mixture of boreal forest and central hardwood species that are highly sensitive to climate change. Janowiak et al. (2018) conducted an assessment of forest vulnerability in the Northeast USA and found that a warmer climate may hinder the growth of northern and boreal tree species (e.g., spruce-fir), while other species (e.g., hardwoods and pine-oak forests) may benefit from this change. Boulanger et al. (2017) also found that these boreal tree species display lower growth rates under warming conditions. Given the important role of the forest industry in Maine, USA, a quantitative understanding of the impacts of climate change and socioeconomic change on Maine's forest resource is essential.

In this study, we synergize forest sector modeling with climate and economic projections to explore and assess the impacts of climate-induced changes on statewide forest resource uses and carbon storage in Maine. We use an alternative futures framework to evaluate the effects of various socioeconomic and climate drivers on the region's forests, modeling a total of 20 RCP-SSP scenarios. This integrated modeling approach quantifies the extent to which various drivers can affect Maine's forest sector through to 2100. Decision- and policymakers in the Northeast US and other forested regions can use this framework to help direct the sector towards a desired pathway and societal outcomes.

## 2. Materials and methods

### 2.1. Study area

This study is a state-level analysis for Maine, USA, which has a forested area of >7 million ha and the highest forest cover rate in the country, at nearly 90% (Butler, 2018). Much of the forest is uneven aged and comprised of multiple species. Natural regeneration constitutes 97.9% of stand renewal, while plantations contribute a mere 2.1% (Brissette, 1996; McWilliams, 2005). About 141,000 ha were harvested in 2020, with over 91% managed through partial harvesting methods, encompassing both partial and shelterwood harvests (Maine Forest Service, 2020).

Maine's forest is a critical terrestrial carbon storage pool and sequesters over 70% of the annual GHGs in Maine, with about than 10 million metric tons of CO<sub>2</sub> equivalent (MtCO<sub>2</sub>e) sequestered annually in standing forests and another 1.6 MtCO<sub>2</sub>e/yr stored in the harvested wood products carbon pool (Bai et al., 2020; Domke et al., 2020; Li et al., 2022). In addition, the forest products industry is a critical component of the economy in Maine, contributing more than \$8 billion/yr in economic output, which is 4% of the state's gross domestic product (Bailey and Green, 2021). Maine's area designated as conservation increased from about 5% in the 1980s to >20% today (Irland, 2018; Zhao et al., 2020), but about 85% of that area is still working forest with regular logging activities (MLTN, 2017). However, Maine's forests are still

facing development pressures, and decreasing at a rate of about 2000 ha per year (Daigneault et al., 2021). In addition, the state's climate is becoming warmer and drier in the growing season (EPA, 2016; Frumhoff et al., 2007), which could reduce forest productivity by directly reducing tree growth and mortality or indirectly introducing disturbances including insect outbreaks, drought, and storms.

## 2.2. Integrated forest sector model

The empirical models of timber supply developed for this study consist of three components: a forest landscape model, a land use change model, and harvest choice models. Forest sector models generally include forest area change, timber removals and standing volumes (Turner et al., 2006). Empirical estimation methods have been used to model land use change with drivers based on historic data (Agarwal et al., 2002). Harvest volume has also been estimated using econometric models, which express volume as a function of stumpage price, forest stock, forest ownership types, biophysical variables, and socioeconomic variables (Hu et al., 2018; Polyakov et al., 2010; Zhao et al., 2020).

The development of five SSPs (1–5) for the Maine forest sector are described in Zhao et al. (2022a) and the five climate change (RCPs baseline - 8.5 W/m<sup>2</sup>) effects on forest yields are simulated in LANDIS-II. Fig. 1 depicts how we integrated climate change and socioeconomic projections with our forest growth, land use allocation, and harvest choice models.

## 2.3. Forest growth simulation

To estimate the climate change effects on forest growth, we used a spatially explicit forest landscape modeling framework, LANDIS-II v7.0 (Scheller et al., 2007; Wei and Larsen, 2018), together with the PnET-Succession extension v3.4 (de Brujin et al., 2014). LANDIS-II is a well-known forest landscape model (FLM) that has already been applied in a variety of climate change research. It is designed to simulate broad-scale (>105 ha) forest landscape dynamics with different simulation extensions in user-defined time step (>1 year) (Scheller and Mladenoff, 2007; Wei and Larsen, 2019), including succession, competition, cohort growth, biomass accumulation, insect disturbance, carbon fluxes, and impacts of climate change (Dymond et al., 2016). The model allows landscape conditions and forest dynamics to be parameterized using empirical data that reflect historical conditions. The PnET-Succession extension implements succession in each grid cell with cohorts defined by age ranges and including biomass per cohort. LANDIS-II and its PnET-Succession extension require information on the study area landscape, tree species coverage, forest stand age, tree species parameters, disturbance information, and weather. It can simulate cohort biomass changes due to climate change as each cohort regenerates, ages, and dies. The model also simulates the annual net primary productivity (ANPP) and aboveground biomass (AGB), which can then be quantified as aboveground carbon (AGC) stocks.

Climate data including monthly maximum and minimum temperatures as well as monthly precipitation come from USGS' Geo Data Portal.<sup>1</sup> Historic climate data are used to simulate tree biomass up to the model start time (2006) during model spin-up. The scenario period starts in 2006 and runs through 2100. Climate change in the baseline simulation is based on randomly assigning 55 years of observed climate (1950–2005). Future climate change data are outputs from the Hadley global environment model v2-earth system (HadGEM2) and the community climate system model v4.0 (CCSM4 model) participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5). Weather data input for the period from 2006 to 2100 was calculated using the percentage changes in temperature and precipitation from simulated weather data to ensure a smooth transition between the historical and

projected climate. According to these climate scenarios, the annual mean temperature in Maine would increase at a higher rate than in the past, warming by about 1.2 °C (RCP2.6) to 6.9 °C (RCP8.5) by 2100. The average annual precipitation is projected to increase at a rate of 1.12–3.18 mm per year, higher than the past 1.14 mm per year during 1950–2005, adding 106.68 mm (RCP2.6) to 299.72 mm (RCP8.5) by 2100. The core climate change impacts analysis assumed that CO<sub>2</sub> remained constant at 390 ppm out to 2100, but we relaxed this assumption as a sensitivity analysis.

The input landscape contains interacting cells with user-defined resolution, where an individual cell has homogeneous forest cover, light, and soil conditions (Scheller and Mladenoff, 2007). In our simulation, we used a 2700 × 2700 grid map to represent Maine's forest landscape, with the cell size within that landscape set at 100 × 100 m. The simulated forests included thirteen tree species, including American beech (*Fagus grandifolia*), balsam fir (*Abies balsamea*), black spruce (*Picea mariana*), red spruce (*Picea rubens*), white spruce (*Picea glauca*), yellow birch (*Betula alleghaniensis*), eastern hemlock (*Tsuga canadensis*), paper birch (*Betula papyrifera*), red maple (*Acer rubrum*), sugar maple (*Acer saccharum*), northern white cedar (*Thuja occidentalis*), eastern white pine (*Pinus strobus*), and yellow birch (*Betula alleghaniensis*). Tree species are represented in each grid cell as 5-year age cohorts, where forest composition and structure information in each cell were initialized using forest data obtained from US Forest Service Forest Inventory and Analysis (FIA). We then used a Python script to randomly generate stands on the landscape. The simulation time step in the PnET-Succession extension was also five years to be consistent with LANDIS-II.

## 2.4. Land use allocation and harvest choice simulation

Forest area change (i.e., land use allocation) was estimated by a probability function ( $p$ ) contingent on socioeconomic and/or biophysical variables. The detailed estimation and results of the forest area change are described in Zhao et al. (2022a). The harvesting intensity for three distinct wood classes  $c$  (sawlogs, pulplogs, or low-diameter) was determined using logistic functions of linear combinations of a vector of explanatory variables,  $X$ , and a vector of unknown parameters,  $\beta$ :

$$\log \left[ \frac{p(y_{it} = 1)}{1 - p(y_{it} = 1)} \right] = \vec{x}_{it} \beta + v_t \quad (1)$$

where  $Y_{ij}$  is the dichotomous response of plot  $i$  at time  $j$ ,  $\vec{x}_{ij}$  represents the covariate's preceding biomass, stand biomass and net growth, and  $v_t$  is the random subject distributed  $NID(0, \sigma_v^2)$ .

The harvest choice model for three wood classes was estimated by a conditional logit model, integrating forest management type-specific coefficients for discounted revenues, individual-specific coefficients for site characteristics and socioeconomic values. The corresponding probability distribution ( $P$ ) for selecting alternative  $j$  is articulated as:

$$P(y_{i,c} = j|x_i, Z_{i1}, \dots, Z_{im}) = \frac{\exp(\beta_j^T x_i + z_{ij}^T Y)}{\sum_{s=1}^m \exp(\beta_j^T x_i + z_{ij}^T Y)} \quad (2)$$

Where, the dependent variable  $y_{i,c}$  categorized into three options  $j$  (no activity, partial harvest, or full harvest), respecting to three specific wood classes  $c$  (sawlogs, pulplogs, or low-diameter). Parameters  $x_i$  denote individual-specific attributes, e.g., mill numbers, distance to the nearest road, land value, etc.  $\beta_j$  is the coefficient associated with the individual-specific attributes  $x_i$  for alternative  $j$ . Parameters  $z_{ij}$  represent choice-specific attributes, such as discounted revenue of forest management types,  $Y$  represents the observed values of the choice-specific attributes for alternative  $j$  and individual plot  $i$ .  $\beta_j^T$  and  $z_{ij}^T$  are the transposes of the coefficient vectors  $\beta_j$  and  $z_{ij}$ , respectively.  $\sum_{s=1}^m \exp(\beta_j^T x_i + z_{ij}^T Y)$  represents the summation over all the alternatives (no

<sup>1</sup> <https://cida.usgs.gov/gdp/>.

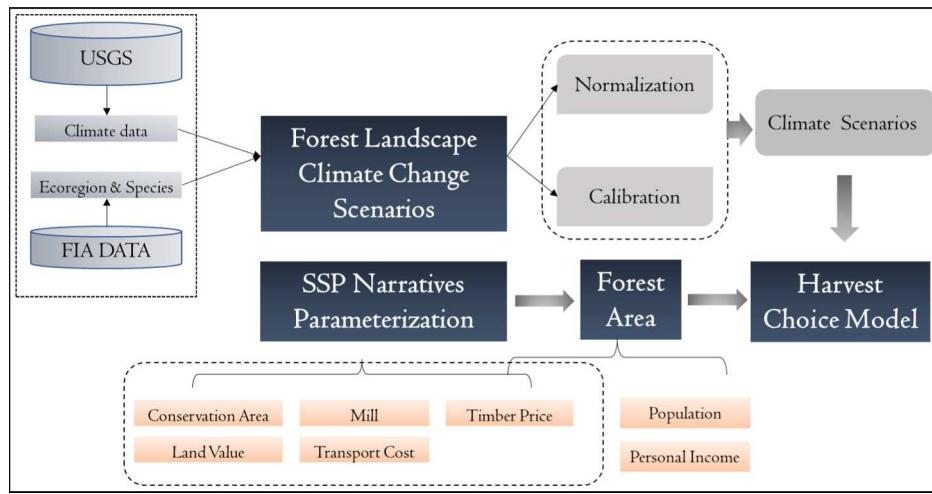


Fig. 1. Schematic diagram of data and models applied in this analysis.

activity, partial harvest, and full harvest) for a specific wood class  $c$ .

This empirical equation can be mathematically expressed as:

$$\text{logit}(p(i, c)) = \beta_0 + Y * \text{Revenue}_{\text{forestype}} + \beta_1 * \text{Biomass} + \beta_2 * \text{Biomass}^2 + \beta_3 * \text{Mills} + \beta_4 * \text{LandValue} + \beta_5 * \text{HighwayDist} + \beta_6 * \text{Conservation} + \varepsilon_i \quad (3)$$

where forest type revenue of three possible management decisions was calculated at the previous period and the end of the period. The growing stock volume functions for three wood products were determined by regression analysis of no harvest activity plot records. Timber supply was aggregated through interpolation of the predicted individual stand harvest decisions and corresponding harvest intensities to cover all 7 million ha of forested area in Maine. *Revenue* is the discounted revenue ( $\$/\text{ha}^{-1}$ ) of each forest type (e.g., spruce-fir), *Biomass* is the amount of standing biomass on the stand ( $\text{ton ha}^{-1} \text{yr}^{-1}$ ), *Mills* is the number of mills within a specific buffer around the plot, *LandValue* is the assessed forestland value ( $\$/\text{ha}^{-1}$ ), which accounts for the fair market value of timberland. *HighwayDist* is the distance from the plot to a primary highway (km), and *Conservation* is an indicator variable describing the category of plot ownership status (0 = non-conservation; 1 = public conservation; 2 = private conservation), noting that most conservation land in Maine is working forest and open to logging. As characteristics such as the distribution of private forestland ownership (e.g., industrial, small) and land use policy are likely to vary across the state, the model also includes county-level fixed effects. Table A1 provides more details and sources of key data for our harvest model.

The growing stocks were calibrated by the simulated aboveground biomass outputs from the LANDIS-II model; therefore, climate change would impact the harvest decisions by directly changing the discounted revenue and standing biomass. This approach allows us to project harvest volume under different climate scenarios while isolating the other effects such as changes in fiber prices and land ownership.

## 2.5. Scenario analysis

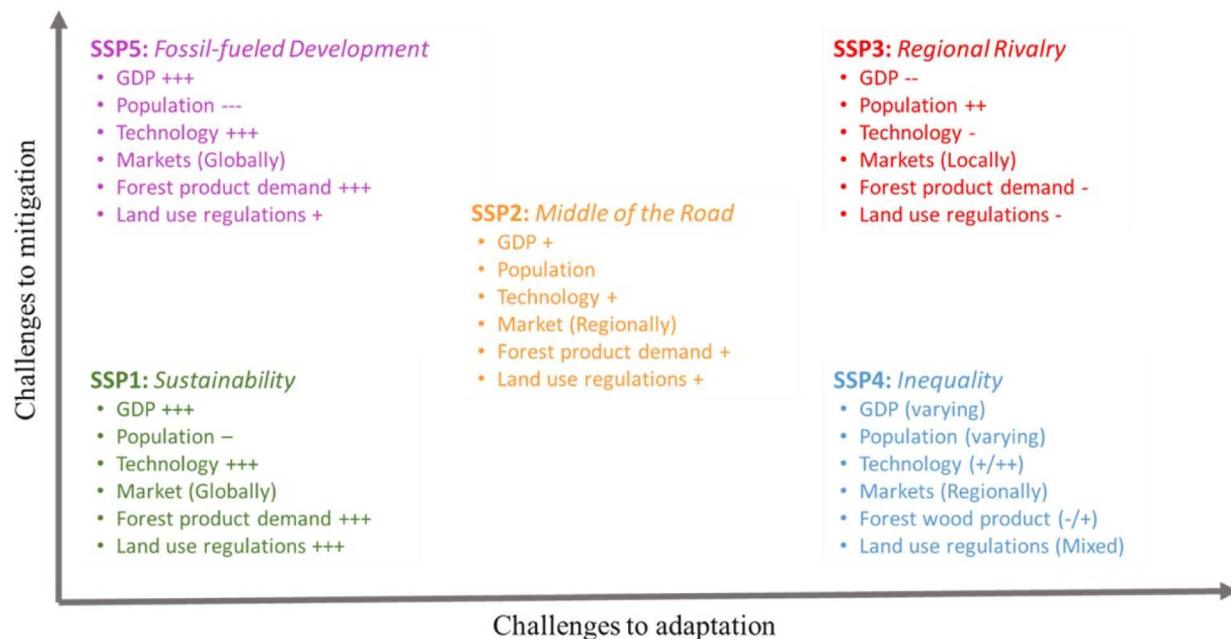
Our analysis employs the RCP-SSP framework, a scenario-based approach developed to explore and understand how socioeconomic factors interact with climate change and how different policy decisions and socioeconomic pathways may shape future climate outcomes (Riahi et al., 2017). This framework supports the examination of wide-ranging combinations of socioeconomic and climate variables and has been used extensively by the Intergovernmental Panel on Climate Change (IPCC) in its assessments (O'Neill et al., 2020). Our analysis uses a combination of

four climate change projections (RCP2.6, RCP4.5, RCP6.0, and RCP8.5) and five shared socioeconomic pathways (SSP 1–5) to model a total of 20

scenarios. We note that while some RCP-SSP combinations (e.g., RCP 8.5-SSP1, RCP 2.6-SSP3) are less likely than others (O'Neill et al., 2020), we opt to include all 20 scenarios in our analysis to present the full scope of impacts from climate and socioeconomic change that could occur in Maine's forests from 2020 to 2100.

Maine's forest SSP development was driven by the general principles of global forest SSPs (Daigneault et al., 2019), and tailored to fit the local characteristics of Maine, following Zhao et al. (2022a). SSP1 moves towards more sustainable development, with low challenges to adaptation and mitigation, denoted by high GDP growth and strong land-use regulations. SSP2 describes a middle-of-the-road development that largely follows historical patterns, showing moderate GDP and technology growth. SSP3 represents a regional rivalry that focuses more on local issues and experiences high adaptation and mitigation challenges, slow GDP growth, and weak land-use regulations. SSP4 follows an inequality development of regional disparities, with varied GDP growth by regions based on development levels. SSP5 assumes rapid economic development because of continued reliance on fossil fuels and advanced technologies. Key elements that vary across our SSP scenarios include economic growth, wood product demand, land use regulation, and technology development (Fig. 2). These variations are incorporated into our analysis by exogenously specifying changes in variables used to parameterize the land use allocation and harvest choice simulation models, including timber prices, land ownership, mill capacity, and land value. More details on our SSP development and parameterization are provided in Supplementary Material (Text S1) and Zhao et al. (2022a).

We model forest responses to baseline and climate change projections from two climate models (CCSM4 and HadGEM2), driven by low (RCP2.6), moderate (RCP 4.5, RCP 6.0), and high (RCP 8.5) emission scenarios. Each emission scenario was simulated three times using two climate models, namely CCSM4 and HadGEM2, for a total of 24 forest landscape climate change impacts scenarios. For each climate forcing scenario, we ran the LANDIS-II simulations with four replicates for 100 years at 5-year time steps starting in the year 2000. Natural disturbances and harvests were not included in these climate simulations, as the focus was on isolating the forest growth changes from anthropogenic forcing impacts, which we captured in the harvest choice



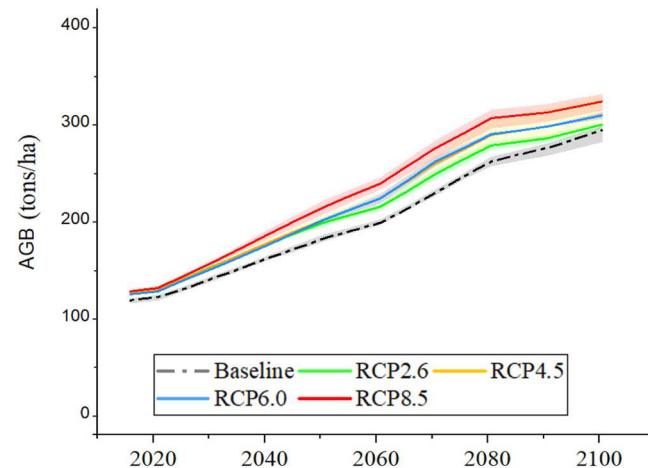
**Fig. 2.** Shared socioeconomic pathways (SSPs) featured in this analysis. +/- indicate degree of change from baseline (2020) conditions, “+”, “++”, “+++” denoted low, moderate, and high degree of change.

model. Model parameters for the LANDIS-II model were calibrated in the spin-up phase with historic climate data (1950–2005) as initial biomass grew up to the biomass reported in the FIA data. Calibrated baseline parameters were then run for the 2016–2100 period for all simulations. The stochastic variation among replicates was minor, so we used the mean value AGB comparisons and visual inspection of graphs to assess trends among RCPs. The model was primarily calibrated through the comparison of simulated results in the initial year (i.e., spin-up values) and the observed forest inventory data in 2016, more details on model validation and calibration are provided in Supplementary Material (Text S2).

## 2.6. Sensitivity analysis

Factors in our models were measured in different units, therefore their relative influences on results change cannot be directly compared based on their unit change. Thus, we used an elasticity-based methodology to measure how supply or carbon stocks respond to an increase in socioeconomic factors. The measure of the sensitivity of supply or carbon stocks to factors was calculated by dividing the percent change in their quantity by the percent change in each factor of interest. We recognize that the price elasticities of fiber supply often differ among various types of forest products (Tian et al., 2017), so we quantified the impacts across three distinct wood product grades (i.e., sawlogs, pulplogs, and low-diameter biomass) and estimated how these products respond to their own or cross-prices. Income and population were also evaluated, as they vary widely across the SSPs.

To understand the effect of increasing CO<sub>2</sub> levels on biomass growth, we rerun the LANDIS-II model for our study area with GHG concentrations following the projected increases under the different climate scenarios. we also conducted an additional sensitivity analysis to better understand the effect of increasing CO<sub>2</sub> levels on biomass growth across a wide range of future pathways. This involved rerunning the LANDIS-II model for our study area, taking into account GHG concentrations following the projected increases under the different climate scenarios. Following this, we compared the biomass change in climate change projections for a subset of scenarios, combining RCP 4.5, RCP 8.5, SSP1, and SSP3 under both increasing CO<sub>2</sub> fertilization and constant CO<sub>2</sub>



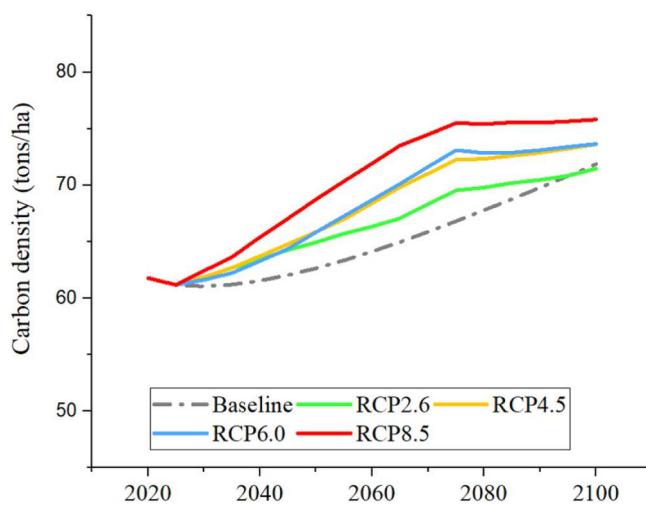
**Fig. 3.** Trends in total aboveground biomass (AGB; t ha<sup>-1</sup>) for all Maine forest species simulated under Baseline, RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 climate scenarios without harvesting.

fertilization assumptions. This comprehensive approach helped us to identify and quantify the impacts of rising CO<sub>2</sub> levels on harvesting and carbon storage under various possible future pathways.

## 3. Results

### 3.1. Climate change impacts

Without harvesting, forest ecosystems in Maine have the potential for a large and sustained increase in biomass stocks regardless of the climate change scenario. If left to grow under current climate conditions (Baseline), the simulated AGB is projected to increase by 2.04 tons ha<sup>-1</sup> yr<sup>-1</sup>, from 123 tons/ha in 2016 up to 295 tons/ha in 2100, a 140% gain over the 80-year simulation (Fig. 3). Climate change typically had a positive effect on Maine's forest biomass; the increment in AGB was



**Fig. 4.** Mean AGC density (tons/ha) with the continuation of historical harvest rates and under the Baseline climate and four climate change scenarios.

minor in the lowest emission scenario (RCP 2.6), with an average gain of 2.11 tons  $\text{ha}^{-1} \text{yr}^{-1}$  (144%), followed by the medium emission scenario (RCP 4.5 and RCP 6.0), with an average gain of 2.24 tons  $\text{ha}^{-1} \text{yr}^{-1}$  (152%). The largest biomass change occurred in the highest emission scenario (RCP8.5), increasing by an average of 2.40 tons  $\text{ha}^{-1} \text{yr}^{-1}$  (164%). Results indicate that biomass increases were largely driven by continued recovery dynamics from leaving the forest unharvested over the next 80-years, which would result in a 140% increase or about 1.1%  $\text{yr}^{-1}$ . In comparison, climate change only resulted in an additional 5–24% of biomass relative to the ‘Baseline’ climate conditions. Continued successional dynamics are also projected to drive forest AGB towards fast growing species, such as eastern white pine, red maple and sugar maple, regardless of the climate scenario (Fig. A.1). Compared to the Baseline climate simulation, climate change resulted in a greater AGB in all thirteen species but had minor effects on the relative species composition.

Assuming Maine’s forests continue to be harvested over time at historical rates (approx. 11 Mt. AGB  $\text{yr}^{-1}$ ) and the climate aligns with current trends, we estimate that the mean aboveground carbon density would accumulate at a rate of 0.19%  $\text{yr}^{-1}$  resulting in 16% additional AGC by 2100 (Fig. 4). Moderate climate change scenarios (RCP 4.5 and 6.0) with harvesting experience an increase in AGC of 0.22%  $\text{yr}^{-1}$ . The largest effects of climate on overall forest growth when harvests are accounted for is the high emission scenario (RCP 8.5) in which carbon density increased by 0.26%  $\text{yr}^{-1}$  or a total of 23% between 2020 and 2100. These results highlight that harvesting dynamics can have a noticeable influence on Maine’s forest carbon stocks when only accounting for the effects of climate change. In comparison, the coupled effects of climate and socioeconomic changes are more dramatic, as outlined in the following section.

### 3.2. Integrated forest sector model analysis

#### 3.2.1. Econometric model

In the harvest intensity model (Table 1), pulplog price and initial biomass of three wood classes were found to have a significant positive correlation with harvest intensity for all wood classes. Harvest intensity for low-diameter woods was also positively related to sawlog and biomass prices. Harvest intensity for sawlogs was positively related to sawlog growth but negatively related to pulplog growth.

Table 2 summarizes the estimated coefficients of the explanatory variables, standard errors, and their statistical significance for harvesting models. As expected, all coefficients for discounted revenue were positive (four out of six of these coefficients were statistically

**Table 1**  
Harvest intensity model estimates.

| Sawlog Parameters           | $\beta$ / (SE)        | Pulplog Parameters | $\beta$ / (SE)      | Low-diameter (LD) Parameters | $\beta$ / (SE)        |
|-----------------------------|-----------------------|--------------------|---------------------|------------------------------|-----------------------|
| Price_Pulp_T1               | 0.882***<br>(0.027)   | Price_Pulp_T1      | 0.723***<br>(0.019) | Price_Pulp_T1                | 0.124***<br>(0.023)   |
| Biomass_Pulp_T1             | 0.103***<br>(0.011)   | Biomass_Pulp_T1    | 0.141***<br>(0.002) | Biomass_Pulp_T1              | 0.133***<br>(0.002)   |
| Biomass_LD_T1               | 0.052***<br>(0.019)   | Biomass_LD_T1      | 0.019***<br>(0.001) | Price_LD_T1                  | 0.967***<br>(0.044)   |
| Biomass_Saw_T1 <sup>2</sup> | -0.001***<br>(0.0001) |                    |                     | Price_Saw_T2                 | 0.004***<br>(0.001)   |
| Sawlog_growth_Net           | 0.955***<br>(0.073)   |                    |                     | Price_LD_T2                  | 0.968***<br>(0.086)   |
| Pulp_growth_Net             | -0.111***<br>(0.012)  |                    |                     | LD_growth_Net                | 0.092***<br>(0.003)   |
| Constant                    | -24.046***<br>(0.441) |                    |                     |                              | -20.142***<br>(0.286) |
| Observations                | 6117                  |                    |                     |                              | -0.367                |
| Log Likelihood              | -12.867               |                    |                     |                              | 6117                  |
| Akaike Inf. Crit.           | 25,750                |                    |                     |                              | -20.909               |
| Bayesian Inf. Crit.         | 25,804                |                    |                     |                              | 41,835                |
|                             |                       |                    |                     |                              | 41,889                |

\*\*\* = significant at 0.01; \*\* = significant at 0.05; \* = significant at 0.10;

**Table 2**  
Harvest choice model estimates.

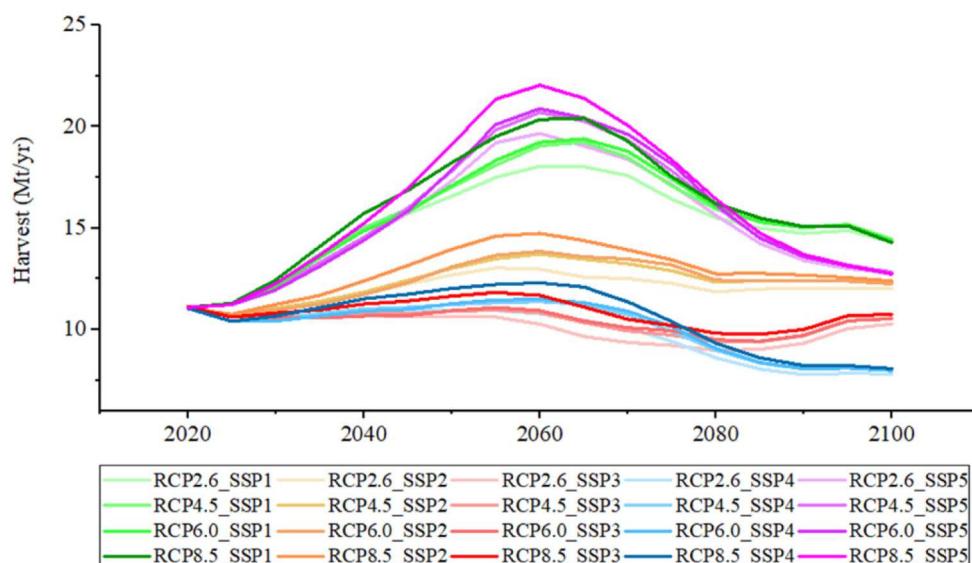
| Variables                      | Full harvest (clearcut)  | Partial harvest           |
|--------------------------------|--------------------------|---------------------------|
| Commercial Hardwoods Revenue   | 0.0009***<br>(0.0009)    |                           |
| Hemlock Revenue                | 0.0011*<br>(0.0002)      |                           |
| Other Softwood Revenue         | 0.0099<br>(0.0005)       |                           |
| Other Hardwood Revenue         | 0.0014**<br>(0.0002)     |                           |
| Spruce-fir Revenue             | 0.0012**<br>(0.0001)     |                           |
| Eastern White Pine Revenue     | 0.0010<br>(0.0001)       |                           |
| Biomass                        | 0.0089***<br>(0.0037)    | 0.0177***<br>(0.0023)     |
| Biomass <sup>2</sup>           | -0.00005***<br>(0.00001) | -0.00004***<br>(0.000007) |
| Mills                          | 0.0199<br>(0.0115)       | 0.0157<br>(0.0071)        |
| Conservation (private)         | -0.0292<br>(0.1745)      | 0.0449<br>(0.1273)        |
| Conservation (public)          | -1.0966***<br>(0.2834)   | -1.1017***<br>(0.2199)    |
| Highway Distance               | 6.7444<br>(7.4566)       | -1.4905<br>(6.5501)       |
| Land value                     | 0.0000001<br>0.000004    | -0.0000004**<br>0.000003  |
| Constant                       | -3.4073***<br>(0.2610)   | -3.5046***<br>(0.1908)    |
| Observations                   | 6117                     |                           |
| Log Likelihood                 | -3196.1                  |                           |
| LR Test                        | 332.703*** (df = 30)     |                           |
| McFadden pseudo-R <sup>2</sup> | 0.10                     |                           |

\*\*\* = significant at 0.01; \*\* = significant at 0.05; \* = significant at 0.10;

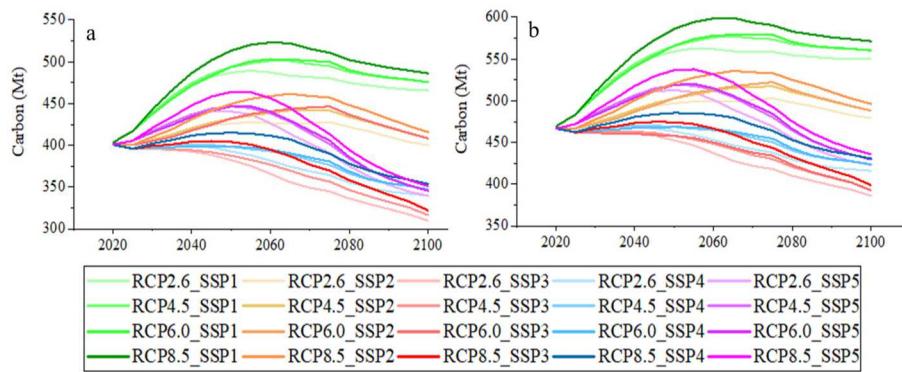
significant), indicating that the probabilities of choosing management for different forest types are positively related to their potential discounted revenue. We also found that biomass and conservation lands had a statistically significant effect on timber harvesting preferences. These estimates were then combined with the land use change model presented in Zhao et al. (2022a) to project the forest area, harvest level, and carbon stocks under the five shared socioeconomic pathways and four climate change scenarios.

### 3.2.2. Fiber production

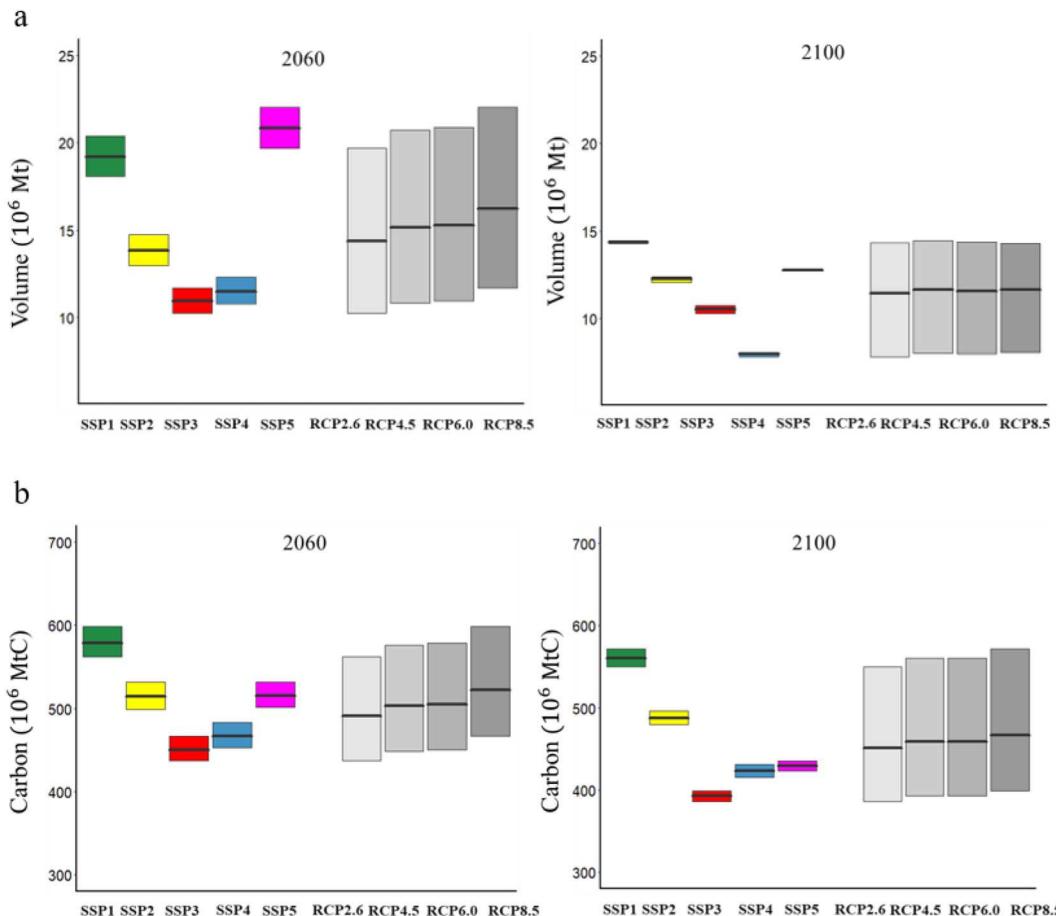
Harvests were projected to peak around 2060 in most scenarios, before declining at various rates up to 2100. This trend suggests that while socioeconomic and climate factors can significantly influence forest harvesting in the near-term, their impact gradually diminishes towards the end of the century. Specifically, forest harvests were highest in RCP8.5 x SSP5 scenario, nearly doubling by 2060 before seeing a modest increase of 15% by 2100. The RCP8.5 x SSP1 scenario follows a similar trajectory, with an 83% increase by 2060 and a 29% increase by 2100. While, RCPs x SSP3/SSP4 even show a reduction in harvests of



**Fig. 5.** Projected forest harvest volume (Mt/yr) under different SSP x RCP combinations.



**Fig. 6.** Maine forest a) aboveground carbon (AGC; Mt./yr) and b) AGC + harvested wood products (HWP; Mt./yr) carbon by SSP  $\times$  RCP scenario.



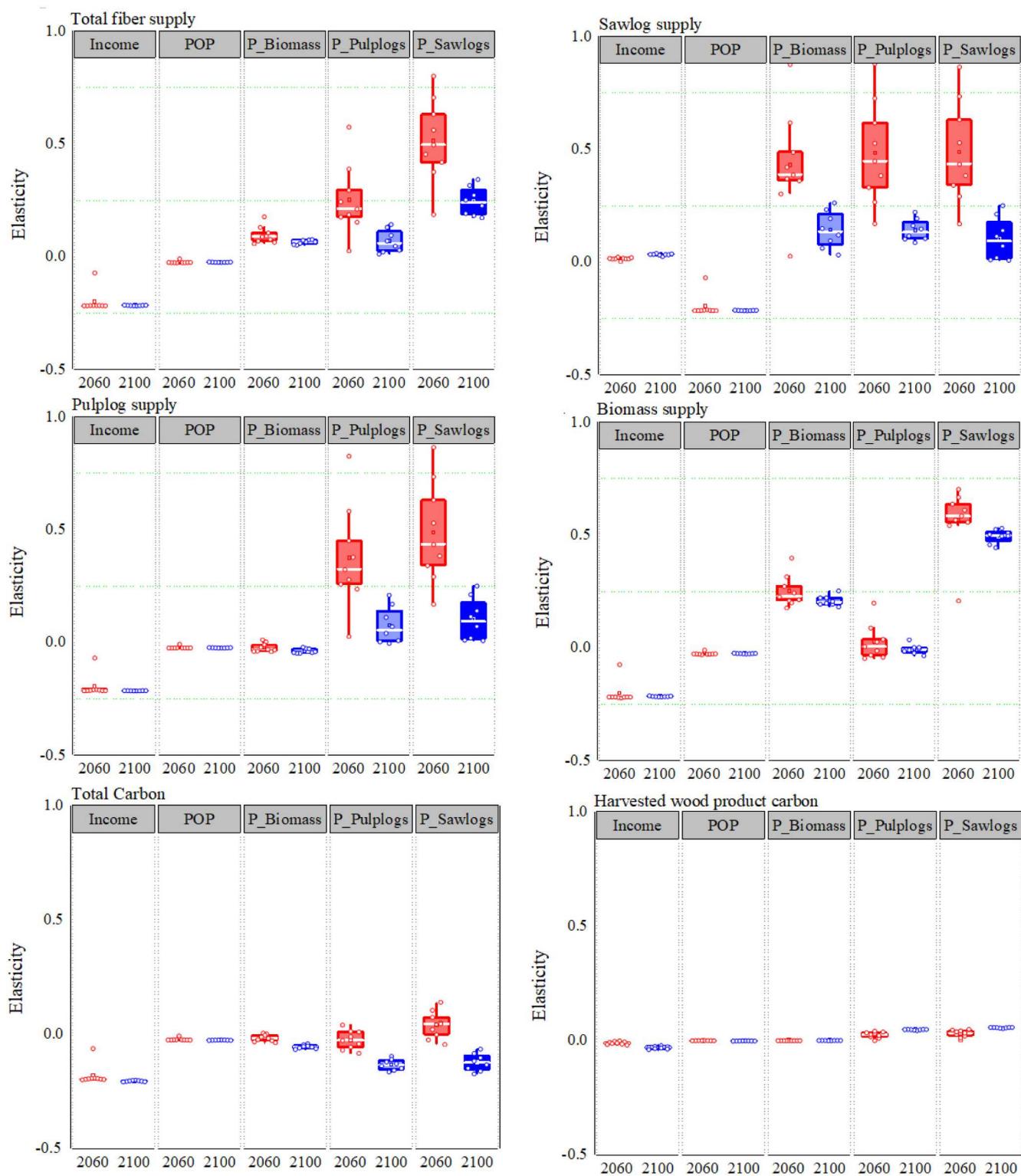
**Fig. 7.** Estimated range and mean values in total Maine a) timber harvest volume and b) forest carbon (HWP and AGC; Mt. C) by SSP and RCP scenarios between 2060 and 2100.

about 8–29% from 2020 to 2100 (Fig. 5).

The relative rank of the line color groups from upper dark to lower light indicated that a larger harvest was expected in scenarios with rapid warming and more climate change (RCP8.5) and a smaller harvest was expected in scenarios with the least amount of warming and limited climate change (RCP2.6). The distinct color clusters of SSPs highlighted that the largest variations among these 20 scenarios were due to SSPs assumptions (i.e., harvest trends are highly clustered around each SSP regardless of the RCP). This suggests that socioeconomic factors (as represented by the SSPs) might have a more substantial effect on future forest harvest trends than the rate of climate change (as represented by the RCPs).

In detail, harvests in SSPs were projected to increase 0.6%–1.6% per year by 2060 and 0.3%–0.7% per year by 2100 in SSP1/SSP2/SSP5 (Fig. 7a). In contrast, slight reductions in harvests were observed in SSP3 and SSP4. On the climate side, the annual increase rate for RCPs fell within a narrow range from 0.7%–1.0% per year by 2060, decreasing to around 0.1% per year by 2100. This further demonstrates that the socioeconomic factors may have a larger influence on forest harvest than climate change. The notable disparity in mean values observed among the SSP groups further demonstrate that the socioeconomic factors had larger effects on forest harvest than climate change did.

Finally, similar trends in harvests for sawlogs and pulplogs were found, with increased harvests in RCPs  $\times$  SSP1/SSP2/SSP5 scenarios and



**Fig. 8.** Box and whisker plot of estimated socioeconomic variables of elasticities of fiber supply and forest carbon stock dynamics. (Income = income per capita; POP = population density; P\_Biomass = biomass price; P\_Pulplogs = pulplogs price; P\_Sawlogs = sawlogs price).

decreased harvests in SSP3/SSP4. However, the trend for low-diameter harvests differed slightly, with the largest harvest by 2100 observed in RCPs x SSP3 and the only decrease in RCPs x SSP4.

### 3.2.3. Forest carbon

Based on these estimations, AGC peaks could be observed in 2050,

2060, or 2070, depending on the specific combination of SSPs and RCPs (Fig. 6). The most significant increase in carbon stocks was found in the RCPs x SSP1 scenarios, with peak annual rates rising by 0.47%–0.65% above the 2020 AGC levels by 2060. This was followed by RCPs x SSP2, which showed peak annual rates of 0.13%–0.27% more AGC by 2070. The RCPs x SSP5 scenarios peaked the earliest, in 2050, with AGC

**Table 3**Maine harvest and forest carbon stock estimates for CO<sub>2</sub> fertilization sensitivity analysis.

| Scenario                         | No CO <sub>2</sub> Fertilization |      |      | CO <sub>2</sub> Fertilization |      |      | % Change |      |       |
|----------------------------------|----------------------------------|------|------|-------------------------------|------|------|----------|------|-------|
|                                  | 2040                             | 2070 | 2100 | 2040                          | 2070 | 2100 | 2040     | 2070 | 2100  |
| <i>Total Harvest (Mt/yr)</i>     |                                  |      |      |                               |      |      |          |      |       |
| RCP4.5-SSP1                      | 15.0                             | 18.5 | 14.5 | 16.5                          | 18.6 | 14.4 | 10%      | 0.4% | -0.5% |
| RCP4.5-SSP2                      | 11.9                             | 13.3 | 12.3 | 13.0                          | 13.4 | 12.3 | 10%      | 1.2% | 0.2%  |
| RCP4.5-SSP3                      | 10.8                             | 9.9  | 10.6 | 11.8                          | 10.2 | 10.6 | 9%       | 2.7% | 0.6%  |
| RCP4.5-SSP4                      | 11.0                             | 10.7 | 8.0  | 12.0                          | 11.0 | 8.0  | 9%       | 2.3% | 0.3%  |
| RCP4.5-SSP5                      | 14.6                             | 19.3 | 12.8 | 16.0                          | 19.4 | 12.8 | 10%      | 0.5% | -0.5% |
| RCP8.5-SSP1                      | 15.7                             | 19.3 | 14.3 | 18.9                          | 20.4 | 14.7 | 20%      | 5.8% | 2.5%  |
| RCP8.5-SSP2                      | 12.4                             | 13.9 | 12.4 | 14.9                          | 15.2 | 12.9 | 20%      | 9.0% | 4.4%  |
| RCP8.5-SSP3                      | 11.3                             | 10.5 | 10.8 | 13.5                          | 11.9 | 11.4 | 20%      | 13%  | 5.8%  |
| RCP8.5-SSP4                      | 11.5                             | 11.4 | 8.1  | 13.8                          | 12.7 | 8.6  | 20%      | 12%  | 6.6%  |
| RCP8.5-SSP5                      | 15.2                             | 20.1 | 12.7 | 18.3                          | 21.0 | 13.0 | 20%      | 4.6% | 1.6%  |
| <i>Total Forest Carbon (MtC)</i> |                                  |      |      |                               |      |      |          |      |       |
| RCP4.5-SSP1                      | 544                              | 575  | 561  | 555                           | 583  | 565  | 2.1%     | 1.4% | 0.8%  |
| RCP4.5-SSP2                      | 490                              | 516  | 488  | 500                           | 524  | 492  | 2.2%     | 1.6% | 0.8%  |
| RCP4.5-SSP3                      | 463                              | 435  | 393  | 473                           | 442  | 396  | 2.2%     | 1.7% | 0.8%  |
| RCP4.5-SSP4                      | 470                              | 455  | 424  | 480                           | 463  | 427  | 2.2%     | 1.6% | 0.8%  |
| RCP4.5-SSP5                      | 507                              | 492  | 430  | 517                           | 497  | 432  | 2.0%     | 1.1% | 0.5%  |
| RCP8.5-SSP1                      | 556                              | 594  | 571  | 579                           | 621  | 592  | 4.0%     | 4.6% | 3.5%  |
| RCP8.5-SSP2                      | 500                              | 534  | 496  | 522                           | 559  | 513  | 4.2%     | 4.7% | 3.3%  |
| RCP8.5-SSP3                      | 473                              | 450  | 399  | 493                           | 473  | 412  | 4.3%     | 5.1% | 3.3%  |
| RCP8.5-SSP4                      | 481                              | 471  | 431  | 501                           | 494  | 446  | 4.3%     | 4.8% | 3.5%  |
| RCP8.5-SSP5                      | 518                              | 506  | 436  | 538                           | 524  | 448  | 3.9%     | 3.5% | 2.7%  |

increasing rates of 0.36%–0.49% per year. In contrast, RCPs x SSP3/SSP4 exhibited a different trend, with their carbon stocks starting at their highest in 2020 and continuously declining by average 0.18% per year for RCPs x SSP4 and 0.30% per year for RCPs x SSP3.

In detail, reductions in forest carbon were observed in RCPs x SSP3/SSP4 scenarios by 2060. By 2100, only RCPs x SSP1/SSP2 scenarios projected an expansion of carbon pools (Fig. 7b). Total AGC stocks increased by an average (across all RCPs) of 94 Mt. C (0.2%/yr) in SSP1 by 2100, while in SSP2, the increase was 21 Mt. C (0.1%/yr). The largest reductions in AGC were found in the SSP3 groups, with a loss of 74 Mt. C (0.2%/yr) between 2020 and 2100. SSP4/SSP5 experienced a cumulative loss of 43 and 37 Mt. C (0.1%/yr) by 2100. Looking strictly at the effect of climate change, we estimate that RCPs on their own would contribute to a 0.1–16 Mt. C loss in AGC stocks between now and the end of the century if all socioeconomic effects are held constant.

### 3.3. Carbon and timber supply elasticities

This study found that socioeconomic factors, more than climate change, played a major role in the estimated changes in timber supply and carbon stocks in Maine's forests. Results also indicated that both timber supply and carbon stocks have inelastic responses to socioeconomic factors (i.e., timber price/demand, population, income), as all key elasticity estimates are  $<1$ , indicating that a 1% increase in the 'input' factor of interest leads to a  $<1\%$  change in output (Fig. 8). The results showed negative elasticity for per capita income and population density, averaging  $-0.2$  and  $-0.02$ , respectively, across all harvest and forest stock estimates. This result indicates that when all else held equal, an increase in income or population would cause a decrease in both fiber and carbon stocks, primarily because these factors have a strong influence on converting forestland to development (see Zhao et al., 2022a).

Timber price elasticity was positive and varied over time, with higher effects observed in the early part of the century (2020–2060). Sawlog prices generally had the highest elasticity value with the response of different forest products and carbon stocks. In addition, the supply of sawlogs was slightly more sensitive to price changes than the supply of pulplogs. The findings also indicated that large changes in biomass prices result in very little change in sawlog and pulplog supply. However, with respect to biomass supply, the median elasticities of sawlog price (0.58), pulplog price ( $-0.01$ ), and biomass price (0.23) reveal that a high sawlog price could indirectly increase the supply of

low-diameter timber.

For AGC, the elasticity ranged from  $-0.22$  for income to  $0.05$  for sawlog prices. Nearly all total aboveground carbon stock elasticities were negative, except for the early-period sawlog price elasticity. These responses indicated that in most cases, forest carbon stocks would decrease with high economic growth, except for the case where a 1% increase in sawlog prices could produce a modest (0.05%) increase in total carbon stocks. Similarly, the elasticity estimates for HWP carbon were very inelastic, ranging from  $-0.06$  for income to  $+0.05$  for sawlog prices, indicating that changes in key model inputs have minimal to no impact on total HWP carbon. These results underline that forest carbon stocks and the carbon stored in harvested wood products are relatively insensitive to changes in these socioeconomic factors, strategies aimed at mitigating climate change through increased forest carbon storage might not be significantly affected by shifts in income or product prices.

### 3.4. CO<sub>2</sub> fertilization sensitivity analysis

The LANDIS-II model simulations show that rising atmospheric CO<sub>2</sub> concentrations, also known as the CO<sub>2</sub> fertilization effect, can stimulate greater biomass growth in forests than if concentrations were held constant. The estimates indicate that increasing CO<sub>2</sub> will result in more biomass growth than if concentrations were held constant. The exact magnitude of this effect varies, with higher biomass growth observed for RCP 8.5 scenario, little difference in biomass growth for RCP 2.6. The sensitivity analysis (Table 3) examined a range of scenarios (RCP 4.5, RCP 8.5, SSP1, and SSP3) under both increasing CO<sub>2</sub> fertilization and constant CO<sub>2</sub> fertilization assumptions. The findings highlight that incorporating CO<sub>2</sub> fertilization assumptions in climate change projections might have limited effects on biomass growth and carbon storage. The CO<sub>2</sub> fertilization effect can be complex and is not guaranteed to persist in the long term, as indicated by the modest influence on forest biomass at 2100, even under RCP 8.5. Intriguingly, the analysis reveals an initial surge in total harvest under the CO<sub>2</sub> fertilization assumption, particularly noticeable in 2040 data. This could be due to a variety of factors such as changes in forest composition, growth rates, and the maturity of trees that are ideal for harvest.

## 4. Discussion

Using an integrated modeling framework that included forest

dynamics, harvest, and land use changes for Maine, USA, we estimated that continued forest succession and growth contribute to a substantial increase in carbon stock in the Baseline scenario, which could potentially increase by 2.40 times the annual level from 2100 to 2020 if there are no human activities (e.g., harvests). Climate change has a relatively small but positive impact on forest carbon dynamics, with 2100 AGC increasing by 2.44–2.64 times the 2020 estimate under various climate scenarios. However, the introduction of harvesting activities to the model substantially mitigated this increase, resulting in only a 16% increase in AGC between 2020 and 2100 relative to the baseline scenario. For comparison, Wu et al. (2020) also indicated that changes in forest AGB are mostly driven by succession and harvest, while Albani et al. (2006) estimated that biomass from the eastern United States will keep growing at least through 2100. These findings are similar to other forest growth and disturbance modeling studies for the region, including Daigneault et al. (2021), Duvaneck and Thompson (2019). The study showed that forest succession contributed to the largest increase in Maine's AGB and AGC, reflecting that the relative lower average live aboveground biomass and forest carbon density in Maine's present landscape compared to landscapes dominated by late-successional forests. This aligns with Thompson et al. (2011)'s points that sustained forest recovery will continue to be the main mechanism affecting forest carbon dynamics, considering the legacy of agricultural abandonment and policies restricting clear-cutting.

Moreover, climate change (temperature and precipitation) had a net positive impact on our forest biomass accumulation estimates, which is consistent with other studies conducted at various scales (Campbell et al., 2009; Favero et al., 2018; Thompson et al., 2011). In our simulations, climate change brought the addition of 5%–24% more AGB/AGC by 2100 in RCP2.6–RCP8.5 scenarios, with higher increases occurring under the more serious climate change scenario. These findings are in line with the estimates of a 10–15% increase in regional forest biomass from climate change reported in Thompson et al. (2011), Duvaneck and Thompson (2019), and Daigneault et al. (2021).

The simulated biomass might accrue faster or slower than actual rates, without accounting for impacts of emerging natural disturbances in our simulations. However, our projected patterns of forest biomass change in the northeast US under different climate change pathways are likely reasonable (Thompson et al., 2011; Duvaneck and Thompson, 2019; Simons-Legaard et al., 2013). In addition, while our study included a broad range of alternative socioeconomic and climate futures, the probability that each of the RCP-SSP combinations will vary (Riahi et al., 2017). A strong sustainability SSP1 pathway will more likely lead to a future climate in the RCP 2.6 to 4.5  $\text{W m}^{-2}$  range, while a fossil fueled SSP5 pathway is likely to fall within RCP 4.5 to 8.5  $\text{W m}^{-2}$  (Rogelj et al., 2018). For example, multi integrated assessment model analyses have resulted in infeasible solutions for some of the SSP and RCP extremes (e.g., SSP5–RCP1.9) due to the incompatibility between the economic growth, technological change, and fossil fuel use assumptions (Riahi et al., 2017; Rogelj et al., 2018). In response, decision makers should take caution when interpreting individually modeled scenarios.

While the study estimated only minor impacts of climate change on the relative composition of the 13 species modeled, some studies have found that climate change might shift tree species distributions in the Northeast (Iverson et al., 2004; Janowiak et al., 2018; Simons-Legaard et al., 2013), particularly of keystone species like spruce-fir in Maine (Andrews et al., 2022). In addition, our LANDIS-II model simulations estimated that continued recovery dynamics will favor fast-growing (e.g., eastern white pine and red maple) and shade-tolerant species (e.g., red spruce, white spruce, eastern hemlock, northern white cedar). Previous studies also found that balsam fir and white birch were projected to decline in responding to increasing temperatures (Ashraf et al., 2015), while red spruce could growth could increase (Kosiba et al., 2018). However, future carbon dynamics could be potential altered by disturbances like spruce budworm outbreaks (Chen et al., 2019) or hemlock

wolly adelgid expansions (Dunckel et al., 2017), which were not included in our simulations.

Forest harvests were highest in the high climate change and socio-economic development scenarios (RCP8.5 x SSP1/SSP5), with an estimated 15–29% increase in harvest volume by 2100 compared to 2020. Low socioeconomic development scenarios (RCPs x SSP3/SSP4) resulted in 8–29% harvest reductions by 2100, but the low-diameter harvest was projected to be the highest in RCPs x SSP3. Results were fairly consistent with other forest SSP studies that estimate fiber supplies to be higher in SSP5 and SSP1 and lower in SSP3 (Daigneault and Favero, 2021; Favero et al., 2020; Hu et al., 2018; Daigneault et al., 2022).

Forest C pools were only estimated to increase by the end of the century in RCPs x SSP1/SSP2, with 81–102 Mt. C (17–22%) accumulated in SSP1 groups and 13–29 Mt. C (3–6%) in SSP2 groups. Conversely, other SSP groups lost about 36–80 Mt. C (8–17%) between 2020 and 2100. The study's findings highlight that socioeconomic factors (SSPs) have a greater impact on timber harvest and carbon stocks than climate change (RCPs), a conclusion in line with other studies showing that the impact of SSP on changes in land use and commodity production is much greater than that of the RCP-only scenario (Ausseil et al., 2019; Favero et al., 2017; Popp et al., 2017; Tian et al., 2016).

Sensitivity analysis indicated that sawlog and pulplog prices were key factors driving changes for the SSPs. We also found positive sawlog price elasticities and negative income per capita and population density elasticities of supply and carbon stocks. Because the urban share of land increases as a function of increasing population and personal income (Hardie et al., 2000), economic and population growth could drive more conversion of forested land to urban lands (Chen et al., 2020; Wade et al., 2022; Zhao et al., 2022a), which has generally been relatively low in parts of New England when compared to other portions of the eastern USA (Puhlick et al., 2017). These negative responses indicated that forest carbon stocks could decrease with high economic growth, while pulplog and sawlog prices may increase, which again is consistent with other recent forest sector analyses (Daigneault et al., 2022; Nepal et al., 2019).

We take an in-depth look at the complex effects of both climate and socioeconomic change on Maine's forests at a relatively fine scale, but note some limitations to our approach. First, our econometric modeling is only as robust as the data available dependent on projections from other studies or expert-based assumptions to assign quantitative inputs to our qualitative narratives. However, this is an issue to some degree in every SSP-based forest sector study regardless of whether it employs econometric (e.g., Hu et al., 2018; Johnston and Radeloff, 2019) or dynamic optimization (e.g., Lauri et al., 2019; Daigneault and Favero, 2021) modeling. Second, we use a deterministic model and thus are not able to account for adaptive behavior from possible stochastic shocks to the socioeconomic (business cycle) or ecological (biological thresholds) system. However, stochastic forestry models are typically restricted to conducting stand-level analysis with exogenous price and cost assumptions to solve (e.g., Amacher et al., 2005; Susaeta and Carney, 2023), although recent efforts have been made to better incorporate natural hazards and risk into regional forest sector analyses (Chudy et al., 2016; Riviere et al., 2022). Third, we assume that Maine's forest sector is a price-taker and hence must follow our exogenously specified price trajectories. This is a reasonable approach given the relatively small contribution of Maine's forests to the global timber market and that we model a wide range set of price changes across our full suite of scenarios. However, other regional studies have endogenously modeled the effect of climate change on the forest sector and found that timber prices are typically lower under the long run due to increased growth (e.g., Favero et al., 2018; Henderson et al., 2020). Fourth, our data do not differentiate across private landowner types (e.g., corporate, non-industrial, etc.), so we are unable to assess the potential impact this might have on Maine's timber supply and forest carbon stocks. While we do use county-level fixed effects to account for this to some degree, results could vary with better ownership data. Other model and data limitations

that could be explored in future research include expanding the options for climate adaptation beyond changing the harvest timing and intensity, improving our representation of management costs, and adding more non-timber and amenity values that landowners take into consideration.

Forest landscape modeling enabled us to perform an assessment of climate change impacts on forestland, while the SSPs framework enabled us to capture the influence of social and economic developments and environmental policy on forestland and the forest products industry. This regional framework could give insights into the implications of climate and socioeconomic factors for Maine's forest sector and could isolate (or integrate) the effects of climate change from (or into) socioeconomic conditions. Our study integrated a harvest choice model with socioeconomic and climate change pathways to estimate the future of Maine's forest sector under a range of plausible futures. While the comprehensive approach to our study includes more than twenty scenarios and robust sensitivity analysis, there is still uncertainty associated with model parameterization and the socioeconomic assumptions. As a result, it is not intended to be an accurate prediction of the future but rather a tool to help evaluate what Maine's forest sector could look like under a range of conditions. In terms of climate change, this analysis represents plausible scenarios based on the continuation of recent trends or emission assumptions. As highlighted above, the study did not account for fires, windstorms, pests, disease, or nutrient limitations on forest growth. Previous research has indicated that the effects of factors like wildfires, pests, and diseases might counteract the tree growth promoted by climate change (Loehman et al., 2018). Disturbances such as hurricanes and insect outbreaks could delay or even decrease biomass accrual rates, while CO<sub>2</sub> fertilization could accelerate biomass growth (Ausseil et al., 2019; Ollinger et al., 2008). These factors should be considered in future research to provide a more comprehensive understanding of the potential impacts of climate change on Maine's forests.

Our core analysis did not account for the potential effects of increasing carbon fertilization due uncertainties of how northeast US forests may respond to increasing GHG concentrations, including nutrient and water availability, ozone pollution, and tree species, age, and size. Instead, we conducted a sensitivity analysis to evaluate the impact of including the CO<sub>2</sub> fertilization assumption in our climate change projections (Ollinger et al., 2008; Jones et al., 2014; Janowiak et al., 2018). We found that inclusion of increasing CO<sub>2</sub> fertilization in climate projections might have somewhat limited positive impacts on biomass growth, compared to scenarios with constant CO<sub>2</sub> concentrations. Although we observed an initial surge in total harvest under RCP 8.5, the effects of CO<sub>2</sub> fertilization beyond 600 ppm were not typically considered in previous studies (Janowiak et al., 2018). The literature appears to be inconclusive as to whether elevated GHG concentrations will cause forests to grow faster and store more carbon (Korner et al., 2005; Hickler et al., 2008; Jones et al., 2014; Dai et al., 2016). This intricate relationship between CO<sub>2</sub> fertilization, biomass growth, and forest management could be explored in more depth in future analyses.

We used a uniform landscape to represent the forest landscape in LANDIS-II, as this approach is effective and efficient in capturing total biomass change across the entire landscape. However, one major limitation is that it doesn't account for spatial variation in factors such as soil, topography, and hydrography, which are known to influence AGB. Despite these noted limitations, we believe that our approach for modeling the complex forest growth and harvest dynamics across a diverse set of local climate and socioeconomic drivers can be leveraged to inform state and regional forest policies under a wide range of alternative futures.

## 5. Conclusions

This paper provides an integrated modeling framework and overview of potential impacts of climate change and socio-economic changes

on forest biomass and timber harvests in Maine, USA. A detailed modeling approach integrated the climate change effects, as modeled by LANDIS-II, with the socioeconomic effects encapsulated in SSPs into an econometric-based land allocation and harvest choice model that incorporated nearly 9000 stand-level observations to project impacts from 2020 to 2100.

Shared socioeconomic pathways were downscaled to the regional level and narratives were provided to explore the consequences of socioeconomic elements on the future forest sector. Quantitative assumptions were combined with a stand-level harvest choice and land use change model developed in Zhao et al. (2022a). Four emission scenarios (RCP2.6-RCP8.5) were combined with two climate models to yield a range of warming scenarios through 2100. The LANDIS-II model was run with these scenarios to simulate climate change impacts on AGB. These outcomes were used to normalize and calibrate forest yield curves that were linked with the stand-level harvest choice model. We then combined the SSPs framework with harvest choice models to explore the physical impacts of climate change as well as socioeconomic drivers on Maine's forest sector.

Our results revealed that continued forest successional dynamics contribute to the largest increase in Maine's AGB/AGC followed by harvesting, with harvesting practices coming next, and climate change having the least impact. In the absence of human activities, the potential aboveground carbon stock by 2100 could be as high as 2.40 times the level of forest C in 2020. Climate change may slightly elevate this figure, leading to AGC in 2100 being 2.44–2.64 times the 2020 levels. However, harvesting activities have significant influence over forest C dynamics, such that AGC in 2100 only reaches 1.16 times the amount of forest C since 2020.

Socioeconomic factors (SSPs) had larger effects on timber harvest and carbon stocks than climate change (RCPs). Under medium or high socioeconomic development pathways (SSP1/SSP2/SSP5), we projected 9–29% higher harvest volumes by 2100, while unfavorable socioeconomic development scenarios (RCPs x SSP3/SSP4) were estimated to result in 8–29% harvest reductions by 2100. Forest C pools were only estimated to increase through 2100 in RCPs x SSP1/SSP2, with 17–22% more C accumulated in RCPs x SSP1 and up to 6% in RCPs x SSP2.

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

During the preparation of this work the author(s) used QuillBot in order to paraphrase. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## CRediT authorship contribution statement

**Jianheng Zhao:** Formal analysis, Software, Methodology, Data curation, Writing – original draft. **Adam Daigneault:** Conceptualization, Methodology, Supervision, Writing – review & editing, Funding acquisition. **Aaron Weiskittel:** Data curation, Writing – review & editing, Funding acquisition. **Xinyuan Wei:** Software, Methodology.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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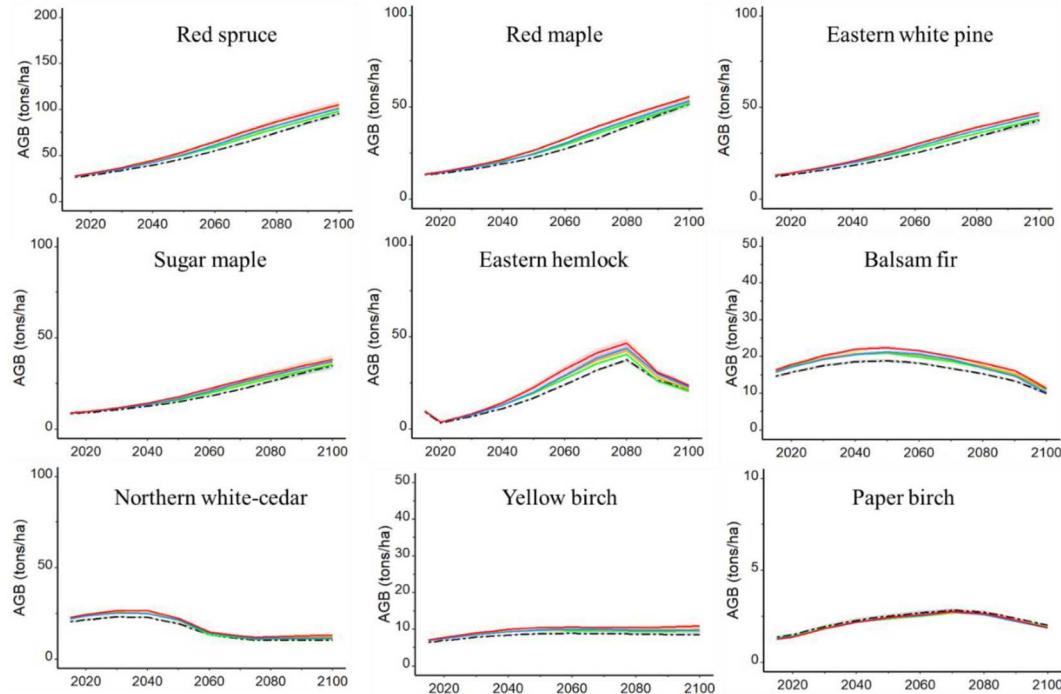
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## Appendix A. Appendices

**Table A1**  
Summary of key Maine harvest choice model variables.

| Variable  | Description   | Units               | Source |
|---|---|---------------------|--------|
| <i>Harvest<sub>saw, pulp, low-diameter</sub></i>        | Harvest choices and intensity by fiber grade: none, partial, or full harvest  | —                   | 1      |
| <i>Revenue<sub>ForestType</sub></i>                     | Revenue earned from harvest by forest species type: commercial hardwoods, hemlock, spruce-fir, eastern white pine, other softwood, other hardwood | \$ ha <sup>-1</sup> | 1,2    |
| <i>Total Biomass</i>                                    | Total aboveground biomass of all species and fiber grades   | t ha <sup>-1</sup>  | 1      |
| <i>Biomass Growth<sub>saw, pulp, low-diameter</sub></i> | Net biomass growth over five-year period by fiber grade   | t ha <sup>-1</sup>  | 1      |
| <i>PriceSaw<sub>County</sub></i>                        | Mean 5-year county-level price of sawlogs   | \$ t <sup>-1</sup>  | 2      |
| <i>PricePulp<sub>County</sub></i>                       | Mean 5-year county-level price of pulplogs  | \$ t <sup>-1</sup>  | 2      |
| <i>LDBio<sub>County</sub></i>                           | Mean 5-year county-level price of low-diameter biomass  | \$ t <sup>-1</sup>  | 2      |
| <i>Mill<sub>saw, pulp</sub></i>                         | Number of saw and pulp mills within 50 km radius buffer   | #                   | 3      |
| <i>LandValue</i>  | Average ad valorem value of forestland by municipality  | \$ ha <sup>-1</sup> | 4      |
| <i>HighwayDist</i>                                      | Distance to nearest national highway  | km                  | 5      |
| <i>Conservation<sub>non, private, public</sub></i>      | Conserved land designation: Non, private, public  | —                   | 6      |

**Sources:** 1. USDA Forest Service. (2020). Forest Inventory and Analysis National Program (link). 2. Maine Forest Service. (2018). 2017 Stumpage Price Report (link); 3. University of Maine. (2020). Maine Mill Database (link); 4. Maine Revenue Service. (2018). 2017 Municipal Valuation Return Statistical Summary (link); 5. U.S. Geological Survey (2017). National Transportation Dataset. January 1, 2017 version (link); 6. Maine Office of Geographic Information Systems (2019). Maine Conserved Lands. Augusta ME, Maine GIS Data Catalog (link).



**Fig. A.1.** Trends in total aboveground biomass (AGB; t ha<sup>-1</sup>) for key Maine forest species simulated under Baseline, RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5 climate scenarios.

## Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolecon.2023.107979>.

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