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Forest carbon under increasing product demand and land use change in the US Southeast

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ABSTRACT

Increased demands for timber products remove carbon from forests, however previous literature has suggested that higher resulting prices could spur forestland expansion, ameliorating the forest carbon impacts. We examine the impacts on forest carbon from harvest increases with an empirical forest sector model, coupled with an econometric model of endogenous land use change that differentiates the impacts of population, income, and pine plantation rents among forest management types and non-forest land uses. We explore the sensitivity of forest area and carbon to a suite of scenarios by varying timber product demands combined with a sensitivity analysis on pine plantation responses to pine plantation rents. The econometric results show that pine plantation rents lead to increases in pine plantation area and that all non-urban land uses are negatively related to both per capita income and population. Scenario projections show that (1) higher pulpwood demands driven by wood pellets lead to lower forest carbon outcomes; (2) higher sawtimber demands exacerbate the known cycles in sawtimber prices and result in corresponding cycles in forest area and carbon. All scenarios show increases in forest carbon over time, though some scenarios increase faster than others. Within the study period, the highest forest carbon level is achieved by the high sawtimber demand and low pulpwood demand scenario. Long term growth cycles over the course of the projection period, however, lead to alternating forest carbon outcomes, indicating that conclusions about forest carbon depend on the projection length.

1. Introduction

Land-use change is an important component of environmental-economic models and in greenhouse gas accounting generally (Houghton and Nassikas, 2017; Hurtt et al., 2011; Riahi et al., 2017). Historical cumulative emissions from land-use change globally are positive (Evans, 2021), while forests remain important carbon sinks in national accounts (United States Environmental Protection Agency, 2021). Therefore, understanding how forests interact with socioeconomic factors can improve knowledge about the mitigation potential of forests.

Simulations using forest sector models at both the global and regional scale have demonstrated that increases in forest product demand leads to an increase in forest land area by way of increasing product prices or land rents (Austin et al., 2020; Daigneault and Favero, 2021; Henderson et al., 2020b). On the other hand, modeling shows that productivity increases, whether from carbon fertilization or intensive management, can lower prices in the long term (Henderson et al., 2020b; Sohngen et al., 2001), which feeds back into a reduced incentive to plant forests.

The dynamics of forest area expansion or retraction are important in numerous forest policy contexts. For example, the wood pellets industry in the US Southeast[1] emerged over the last decade, spurred by European renewable energy policy and more recently by contracts between pellet manufacturers in the U.S. and buyers in the Pacific Rim (Abt et al., 2014; Merritt, 2020; Voegele, 2019; Voegele, 2018). As an emerging southern forest product demand driven by climate or renewable energy policy, pellets have generated controversy regarding their carbon neutrality and impact on forest ecosystem services in the popular and scientific press (Cornwall, 2017; Crowley and Robinson, 2022; European Academies Science Advisory Council, 2019). These questions have been important in the US Southeast and to European consumers and policymakers

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[1] Defined here as including the states Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas (east), and Virginia.

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(Commission, E, et al., 2016; Galik and Abt, 2016). The argument in favor of wood pellets has been that the price increase due to increased demand for wood pulp could spur forest area expansion (Abt et al., 2014; Alig et al., 2010; Duden et al., 2017; Hanssen et al., 2017; Sedjo and Tian, 2012). But a question remains – where does the forest area expansion come from? If planted forests replace marginal agricultural land, one may assume net carbon benefits, whereas replacement of mature oak forests may imply a more nuanced or negative forest carbon outcome.

In this paper, we develop an empirical land-use model that differentiates among forest types, agricultural and urban land uses. This differentiation will allow the estimated land use model to determine which land uses respond positively to increases in pine plantation rent. The model will also test the impacts of per capita income and population, variables usually associated with expansion of development, on land uses.

Based on the estimated model, we then examine the market, carbon and land use effects of increased forest product demand and pine plantation rent sensitivity in the US Southeast. The projection results will evaluate forest area and forest carbon outcomes under a set of twelve scenarios combining low and high pulpwood[2] and sawtimber demand and variations on the sensitivity to pine plantation rents.

2. Methods

In this study, as in Abt et al. (2012), we use a partial-equilibrium timber market model to examine impacts on regional forest product markets (price, harvest) and forests (forest types, age class distribution, and carbon). In contrast to the prior work, in which the land use model was based on Wear (2011) and accounted for three land-uses – urban, agriculture and forest – we bolster our conclusions by using an empirical land use change model which differentiates forest area changes by forest type.

2.1. Sub-regional timber supply model

To capture nuances of timber supply and the forest product supply chain in the US Southeast, we use the Sub-Regional Timber Supply model, a recursive dynamic partial equilibrium model (Henderson et al., 2020a; Abt et al., 2009). The Sub-Regional Timber Supply model (SRTS) has been used previously to answer questions about the sustainability of wood pellets in the US Southeast under a variety of assumptions and scenarios (Abt et al., 2014; Commission, E, et al., 2016; Duden et al., 2017; Galik et al., 2016; Galik and Abt, 2016).

Data on the forest structure and dynamics are derived from Forest Inventory and Analysis (FIA) data, using the SRTSv35c version of compiled FIA data (Southern Forest Resource Assessment Consortium, 2021). These data include the growing stock volume, growth rates, distribution of tree diameters, forest area, and baseline volume of removals summarized by 5-yr age class[3] and by private ownership type (corporate, non-corporate), forest type, and region (FIA survey units). The definition of forests used in the input data is timberland under private ownership (omitting public lands and forest incapable of producing 20 cubic feet of wood volume per acre per year). We run the model annually for the entire US Southeast for the years 2018 through 2070.

2.2. Product interrelationships

Pulpwood and sawtimber are co-produced at final harvest. The model accounts for this relationship with a parameter (cull factor) representing the proportion of volume that is merchandised as pulpwood. We assume factors of 0.15 and 0.3 for softwood and hardwood, respectively. The best empirical sources for these factors are from harvest utilization studies, and our assumptions are in line with Wall et al. (2018) and Bentley and Johnson (2009).[4] Overstocking above the empirical volume distribution permits pulpwood volume to be acquired via simulated thinning (Abt et al., 2009). Finally, we model the proportion of volume wasted at sawmills from new sawtimber demand, which can be used by pulpwood consumers, assuming 25% is used in this way, which agrees with rates reported in Krigstin et al., 2012. Demand for pulpwood being met with sawmill residue results in lower demand for pulpwood from forests.

2.3. Carbon estimation methodology

In this section, we describe (1) how carbon values are calculated from the SRTS output data, and (2) how initial carbon values break down by pool, illustrating that changes to forest carbon from harvest are not equal to the removal of growing stock carbon. Thus, reporting only growing stock would not sufficiently measure total forest carbon.

Carbon is calculated for each carbon pool of forest carbon in both catchment areas by forest type, ownership, and age class (Foley, 2009; Smith et al., 2006) (Table 1). The forest carbon pools used include live tree, standing dead, understory, dead and down wood, and forest floor. We do not include soil organic carbon, which can be a large pool, in our calculations.[5] Foley (2009) explains that changes in soil carbon over a rotation are small on continuously managed timberland.

Once SRTS calculates the growing stock volume and area for each of

Table 1
Forest ecosystem carbon pools used in this analysis (Smith et al., 2006).

Carbon pool	Definition
Live tree	Live trees with diameter at breast height (d.b.h.) of at least 2.5 cm (1 in.), including carbon mass of coarse roots (>0.2 to 0.5 cm, published distinctions between fine and coarse roots are not always clear), stems, branches, and foliage.
Standing dead trees	Standing dead trees with d.b.h. of at least 2.5 cm, including carbon mass of coarse roots, stems, and branches.
Understory vegetation	Live vegetation that includes the roots, stems, branches, and foliage of seedlings (trees <2.5 cm d.b.h.), shrubs, and bushes.
Down and dead wood	Woody material that includes logging residue and other coarse dead wood on the ground and larger than 7.5 cm in diameter, and stumps and coarse roots of stumps.
Forest floor	Organic material on the floor of the forest that includes fi ne woody debris up to 7.5 cm in diameter, tree litter, humus, and fi ne roots in the organic forest floor layer above mineral soil.

[2] We use the term "pulpwood" to mean small roundwood which can be used as an input for paper, wood pellets, or other chipped products.

[3] Volumes and acres in five-year age classes are uniformly distributed across one-year age classes in the model.

[4] The ratio of softwood pulpwood products to total removed products, excluding firewood and poles, was approximately 14% in Wall et al. (2018) and 17% in Bentley and Johnson (2009). The ratio of hardwood pulpwood products to total removed products ranged from 22% (Wall et al., 2018) to 42% (Bentley and Johnson, 2009).

[5] From Foley (2009): "However, the mineral soil carbon pool has not been included in this analysis for two reasons. First, it has been shown that the changes in soil carbon over the length of a timber management rotation on historically forested lands are relatively small (Richter et al., 1999; Schlesinger and Lichter, 2001). For this analysis, it is assumed that all management decisions are being made on historically timber-productive lands. Thus, from a soil carbon standpoint the effects of extending the rotation age of a forest on these lands are likely minimal. Additionally, it has been shown that there can be wide variability in soil carbon content even within a certain forest-type, based on sub-regional climate factors and individual site history (Amichev and Galbraith, 2004). Thus, as the intent of this analysis is to model changes in forest carbon at the forest-type level, it would be improper to assume any one soil carbon condition to be representative of the ecosystem as a whole."

the buckets, we use the equations developed in Foley (2009) to generate the carbon values for each pool for each forest type, ownership, and age class. We present only total forest carbon results in this paper.

2.4. Land use change model

To understand land use change dynamics among developed, agriculture, and five different forest types,[6] we constructed an annual data set for the years 2005 to 2015. We estimate area in each land use by year and region using the temporally indifferent estimator in the rFIA R package (Stanke et al., 2020). Estimates were grouped according to management types used in SRTS (Supplementary Materials, Table 1S). Area estimates can be made at various spatial scales, such as by county, FIA-standardized multi-county regions called survey units, or at the state level.

We specify a parsimonious model. Models with a large number of variables could potentially produce a superior fit over historical data but would come with the disadvantage of requiring forecasts of a large number of variables in model projections. The explanatory variables widely supported by the literature to induce land use change are population density, income per capita, and land rents (Mauldin et al., 1999; Ahn et al., 2002; Mihiar and Lewis, 2021; Fisher, 2020; Korhonen et al., 2021). Mihiar and Lewis (Mihiar and Lewis, 2023; Mihiar and Lewis, 2021) calculate pine forestland rents using county-level von Bertalanffy volume functions, prices from Timber Mart-South (Timber Mart-South, 2015) and assuming a single rotation. We use pine plantation rent data developed by Kaya (2021), which uses the same volume functions as Mihiar and Lewis (Mihiar and Lewis, 2023; Mihiar and Lewis, 2021) but employs price data from Forest2Market (Forest2Market, 2015) and assumes infinite rotations. To complete our model, we also generate fixed effects for state[7] and physiographic region.[8] The cross-section of state, survey unit, physiographic region and county is provided in the Appendix of Henderson et al. (2020a). The hypothesized relationships are that population density and income per capita would be positively related to increases in development, thus reducing the share of agriculture and forest types. We anticipate a positive relationship between pine plantation rent and pine plantation share of land (Table 2). The specification of the model, similar to Mauldin et al. (1999) and Nagubadi and Zhang (2005), is:

$$ln\left(\frac{y_k(t,u)}{y_1(t,u)}\right) = \beta_k X_{ut} + \alpha_{ut} + \epsilon_{ut} \quad (1)$$

Here y is the observed share of land-use k at time t for area unit u. In our case, the denominator y_1 in the left-hand side for each equation ($k > 1$) is developed use. A standalone equation is therefore not defined for developed use, but instead the share of developed use is implicit. On the right-hand side, X is a vector of explanatory variables, α is the normal regression error, and ϵ is measurement error which is induced from the fact that within the system the errors are potentially correlated, since overestimation of one land-use can lead to underestimation of another.

Based on tests of county level and survey unit level models, we selected the survey unit model due to superior model fit. Our county level version of the model achieved an overall fit similar to Nagubadi and Zhang (2005), which demonstrated a conventional R-squared of 0.35 to 0.36. Our choice to model based on the survey unit scale is more consistent with FIA sampling procedures, which are designed to produce better estimates at the survey unit or state level (Burrill et al., 2018).

2.5. Calibrating and integrating the land use change model

Here we describe how estimated models are calibrated and integrated within a projection framework. We calibrate the base period by indexing the projections of explanatory variables and adjusting the intercept term to precisely match observed data. This ensures that historical and projection data line up without jump discontinuities. To demonstrate this in concrete terms, consider the kth land-use which has the following functional form:

$$ln\left(\frac{y_k}{y_1}\right) = \widehat{\beta}_{0k} + \widehat{\beta}_{1k} lnR + \widehat{\beta}_{2k} ln(P) + \widehat{\beta}_{3k}(I) + fixedEffects \quad (2)$$

We can rewrite the preceding at the survey unit level, eliminating *fixedEffects* and adding a survey unit index u:

$$ln\left(\frac{y_k}{y_{1u}}\right) = \widehat{\beta}_{0ku} + \widehat{\beta}_{1k} lnR + \widehat{\beta}_{2k} ln(P) + \widehat{\beta}_{3k}(I) \quad (3)$$

From the properties of logarithms, we can rewrite each right-hand side variable with a fixed baseline component and a dynamic index component. For example, in the case of population this means:

$$\widehat{\beta}_{1k} ln(P) = \widehat{\beta}_{1k} ln(P_{base} {}^* P_{index}) = \widehat{\beta}_{1k} ln(P_{base}) + \widehat{\beta}_{1k} ln(P_{index}) \quad (4)$$

So we sum the intercept term with fixed base components to create a new intercept term γ, and rewrite the log-relative share equation as:

$$ln\left(\frac{y_k}{y_{1u}}\right) = \gamma_{0ku} + \widehat{\beta}_{1k} ln(R_{index}) + \widehat{\beta}_{2k} ln(P_{index}) + \widehat{\beta}_{3k}(I_{index})\Big) \quad (5)$$

By exponentiation on both sides we obtain:

$$\frac{y_k}{y_{1u}} = e^{\gamma_{0ku}} \cdot R_{index}^{\widehat{\beta}_{1k}} \cdot P_{index}^{\widehat{\beta}_{2k}} \cdot I_{index}^{\widehat{\beta}_{3k}} \quad (6)$$

Because in the base year all indexes equal 1, and because our purpose is to calibrate the model to the base year, we can substitute the first term $e^{\gamma_{0ku}}$ with the observed relative share π. We also shorten variable names here:

$$\frac{y_{ku}}{y_{1u}} = \pi_{ku} \cdot R_{index}^{\widehat{\beta}_{1k}} \cdot P_{index}^{\widehat{\beta}_{2k}} \cdot I_{index}^{\widehat{\beta}_{3k}} \quad (7)$$

Recall that y_{1u} is the developed use share. Multiplying the above equation by that factor, we can see it is necessary to calculate the developed share before calculating other land shares. Using the fact that the sum of all shares equals 1, we can derive the following:

Table 2
Variables and data sources.

Variable	Expected Impact	Source
Pine plantation rent	increase pine plantation	Kaya (2021)
Population	increased urban	Bureau of Economic Analysis (BEA) (2015)
Income per capita	increased urban	Bureau of Economic Analysis (BEA) (2015)
State	fixed effect	Henderson et al. (2020a)
Physiographic region	fixed effect	Henderson et al. (2020a)

[6] pine plantation, natural pine, mixed pine and hardwood, upland hardwood, bottomland hardwood. All public forestland and forest not considered timberland is excluded. Bodies of water, beach, rangeland, and other land-uses are excluded (assumed fixed) because some survey units have no area in some categories.

[7] State (Abbreviation, state FIPS code): Alabama (AL, 1), Arkansas (AR, 5), Florida (FL, 12), Georgia (GA, 13), Louisiana (LA, 22), Mississippi (MS, 28), North Carolina (NC, 37), Oklahoma (OK, 40), South Carolina (SC, 45), Tennessee (TN, 47), Texas (TX, 48), Virginia (VA, 51). Tennessee represents the null model.

[8] Physiographic region (code): Coastal Plain (1), Delta (2), Mountain (3), Piedmont (4). Coastal Plain represents the null model.

$$y_{1u} = \frac{1}{1 + \sum_{k=2\ldots n} \pi_{ku} \cdot R_{index}^{\hat{\beta}_{1k}} \cdot P_{index}^{\hat{\beta}_{2k}} \cdot I_{index}^{\hat{\beta}_{3k}}} \tag{8}$$

After calculating developed share in this manner, we can then calculate other land shares using the preceding equation. Land shares are updated on an annual basis by updating the exogenous variables and updating the pine plantation rents which are calculated endogenously. The calculation of rent within the SRTS model uses annual prices generated regionwide to calculate the land expectation value of 25-year pine plantations with thinnings at age 17, using a discount rate of 4%. Projections for population and income are tied to Shared Socioeconomic Pathways (SSPs), derived from county level estimates by Wear and Prestemon (2019) and aggregated to the survey unit areas used in SRTS. In all model runs we use population and income trajectories associated with SSP 2, which is a "middle of the road" trajectory for climate adaptation in which countries generally follow prior trends of social and economic development (Riahi et al., 2017).

2.6. Demand scenarios and sensitivity analysis

To understand how the combined forest sector model and land use module interact, we develop a set of scenarios. The scenarios are not intended to be realistic forecasts but are instead designed to evaluate a range of impacts on model results relative to a defined baseline. Demand scenarios represent aggregate demand for pulpwood and sawtimber and were created based on announcements for new wood pellet mills and sawmills, respectively. Initial levels of demand are specified at the survey unit level, and subsequent demand increases are met where the marginal cost of supply is minimized. Our low demand scenario assumes that 100% of announced capacity comes to fruition by 2030, whereas our high demand scenario doubles announced capacity by 2030. After 2030, for both the low and high demand scenarios, we increase demand for both pulpwood and sawtimber at the US population growth rate, which assumes constant per capita consumption. In these demand trajectories beyond 2030, we are agnostic about the end use of pulpwood, whether it be for wood pellets or other pulp uses. The demand trajectories only increase and do not consider random shocks or disturbances.

As a sensitivity analysis, we run three scenarios that vary the pine plantation rent elasticity in the land use model. The base scenario uses the estimated value (β), and the '$+\sigma$' and '$-\sigma$' scenarios represent a pine plantation rent elasticity increased and decreased by one standard deviation, respectively. The labeling convention of scenarios is comprised of the demand scenario for pulpwood (low (L) or high (H)), followed by the demand scenario for sawtimber (low (L) or high (H)), and finally the pine plantation rent elasticity case (β, $+\sigma$, $-\sigma$). The list of scenarios is presented in Table 3. The schematic in Supplementary Materials (Fig. S1) illustrates how the scenarios and other data sources are integrated into the overall model.

Table 3
Scenario labels and assumptions.

Scenario label	Pulpwood demand	Sawtimber demand	Pine rent elasticity
$LL\beta$	low	low	as estimated
$LL+\sigma$	low	low	plus one SD
$LL-\sigma$	low	low	minus one SD
$LH\beta$	low	high	as estimated
$LH+\sigma$	low	high	plus one SD
$LH-\sigma$	low	high	minus one SD
$HL\beta$	high	low	as estimated
$HL+\sigma$	high	low	plus one SD
$HL-\sigma$	high	low	minus one SD
$HH\beta$	high	high	as estimated
$HH+\sigma$	high	high	plus one SD
$HH-\sigma$	high	high	minus one SD

3. Results

In Table 4, we provide parameter estimates for socioeconomic variables by model and land-use. Because the explanatory variables were log-transformed, the parameter estimates can be interpreted directly as elasticities as in Eq. (2). Assuming a negligible change in y_{1u} in the short term, we see that a negative sign for $\hat{\beta}_{ik}$ indicates an inverse non-linear relationship with its respective variable, and a positive sign indicates a direct non-linear relationship. Conversely, because the share of developed use (y_{1u}) is in the denominator of each equation's left-hand side, developed use has the opposite relationship. For example, while agriculture shows a negative relationship with population (−0.141, Table 3), developed use would have a positive relationship.

Tests for multicollinearity give variance inflation factors (VIF) of ranging from 2.2 to 3.2 for the log-transformed explanatory variables, indicating moderate correlation of the variables. The model is estimated by seemingly unrelated regression using the *systemfit* package in R (Henningsen and Hamann, 2007). The overall fit of the model, measured by McElroy's R-squared is 0.78.

The land use model estimation showed that (a) pine plantation rents lead to increases in pine plantation area and decreases in both other forest area and agricultural area; and (b) that all non-urban land uses are negatively affected by both per capita income and population. Thus (c) developed land area increases with increases in population but decreases with increases in pine plantation rents.

3.1. Market model projections

Table 4
Selected parameter estimates for the estimated model (n = 492 for each equation).

Equation	Variable	Elasticity	Std. Error	t-value	Pr(>|t|)
agriculture	ln(rent)	−0.093	0.073	−1.276	0.203
$\left(R^2_{adj} = 0.710\right)$	ln(population)	−0.141	0.031	−4.476	<2e-16
	ln(per capita income)	−1.044	0.188	−5.563	<2e-16
pine plantation	ln(rent)	0.560	0.130	4.294	<2e-16
$\left(R^2_{adj} = 0.786\right)$	ln(population)	−0.668	0.056	−11.928	<2e-16
	ln(per capita income)	−0.204	0.334	−0.612	0.541
natural pine	ln(rent)	−0.098	0.086	−1.143	0.254
$\left(R^2_{adj} = 0.808\right)$	ln(population)	−0.294	0.037	−7.985	<2e-16
	ln(per capita income)	−0.882	0.220	−4.007	<2e-16
mixed pine & hardwood	ln(rent)	−0.041	0.069	−0.599	0.55
$\left(R^2_{adj} = 0.819\right)$	ln(population)	−0.255	0.030	−8.577	<2e-16
	ln(per capita income)	−1.025	0.177	−5.785	<2e-16
upland hardwood	ln(rent)	−0.019	0.061	−0.305	0.76
$\left(R^2_{adj} = 0.828\right)$	ln(population)	−0.279	0.026	−10.703	<2e-16
	ln(per capita income)	−1.058	0.155	−6.803	<2e-16

For the projection phase of the study, the necessary metrics to answer our study questions and provide necessary context include: (1) a presentation of market results over time for pine products,[9] including growing stock volumes, removals, and prices by product, (2) forest area by forest type, (3) forest carbon by forest type and in total. For each set of results we provide a figure that shows the absolute values of metrics or values indexed to the base year, and we provide a figure showing values indexed the baseline throughout time.

3.2. Pine market outcomes

Results for pine product market outcomes, which drive pine rents, include growing stock, removals, and prices. The results are presented as an index to the base year (Fig. 1.a) and as an index to the low pulpwood and low sawtimber demand scenario with the empirical pine rent elasticity (*LLβ*) (Fig. 1b). The scale of indexed changes in prices are larger than those in growing stock and removals due to inelastic supply (Fig. 1b). In general, deviations in results due to the pine plantation rent elasticity show up only after the first decade for pine pulpwood and after two decades for pine sawtimber. A higher pine rent elasticity (+sigma) is associated with a brief and small price decline in the short term, but a larger price increase in the long term.

For growing stock, we observe that the cases with higher demand deplete growing stock in the first decade, but subsequently begin trending to levels higher than the low demand baseline. In the longer term, we observe cyclic behavior as the high demand scenarios move back toward the baseline (Fig. 1.b, left column). As designed, removals in the high demand cases show increases relative to the their low counterparts (Fig. 1.b, middle column). The difference in short term pulpwood removals predominantly results from higher sawtimber removals, which co-produces pulpwood, reducing the need to harvest a portion of pulpwood from pulpwood growing stock. This dynamic is observed in between the cases *LL* and *LH* and between *HL* and *HH*, as well as in the diverge in prices for these respective scenarios.

3.3. Forest area

Additional context for the market outcomes can be derived from the land use change dynamics, which are driven by endogenous pine rents and exogenous population and income trends. Fig. 2 demonstrates that increasing pine prices leads to an expansion of forest area in pine plantations alongside declines in other forest types. Total forest area declines over the study period (Fig. 2.a). Pine plantation area increases with respect to the *LLβ* scenario are constrained within an indexed value of 1.25 within the study period (Fig. 2.b). After expanding, the high sawtimber demand scenarios oscillate downward after 2030 (Fig. 2.b), when the projected demand switches to per capita consumption levels. The highest proportional losses occur in natural pine, followed by mixed pine and hardwood, and upland hardwood. However, not all increases in pine plantation come at the expense of other forest types. The right column in Fig. 2.b shows a relative increase in total forest area due to scenarios that increase demand over the baseline. In absolute quantities, total forest area declines over the study horizon, with the largest drop coming from upland hardwood (Fig. 2.a).

In terms of pine rent elasticity scenarios, the high sensitivity ($+\sigma$) case shows an initially faster increase in pine plantation acres, but the high sensitivity results in faster losses as pine sawtimber prices decline. Conversely, low pine rent sensitivity ($-\sigma$) leads to slower adaptation to pine rents, which leads to a longer build-up and longer retention of pine plantation area.

[9] While hardwood markets are included in the model simulation, they are omitted from the results since they do not impact pine plantation rents and thus play no role in the land use change model. Furthermore, bottomland hardwoods are held constant throughout the study period and are excluded from the land use change model.

3.4. Forest carbon

On the metric of forest carbon by forest type, we observe a delayed relationship of forest carbon with forest area for pine plantations, consistent with the time it takes to grow volume on forest area expansions (Fig. 3). In absolute terms, total forest carbon increases for all forest types, but turns toward a decline or flattens for natural pine, mixed pine and hardwood, and upland hardwood (Fig. 3.a). Maximum declines relative to the *LLβ* baseline in forest carbon for non-plantation forest types range from 5% to 12% (Fig. 3.b). The largest relative decline occurs in natural pine forests under high demands for both sawtimber and pulpwood (*HH*). Compared to the baseline, the scenario with low pulp demand and high sawtimber demand achieves the highest total forest carbon over the study period and peaks at an approximate 2.75% gain. However, by 2070 this gain in forest carbon diminishes, and the scenarios that produced carbon gains converge toward or below the baseline – the *LHβ* scenario obtains a 0.03% gain above *LLβ*, whereas *HHβ* obtains a $-$ 0.03% loss. This decline in carbon for the high sawtimber scenarios is an echo of the price decline during the period 2040 to 2060, which reduced pine plantation area and hence, the carbon on pine plantations at the end of the study period. It should also be noted that absolute forest carbon increases by about 2 billion Mg for all forest types across the study period (Fig. 3a).

4. Discussion and conclusion

The results confirm some important features that have entered the debate on the impact of wood pellets, a driver of new pulpwood demand, on forest carbon. For one, the cutoff date for measurement impacts the assessment of forest carbon consequences. By 2030, the ranking of total forest carbon by scenario is, from highest to lowest: LL, HL, LH, HH. In 2050, the ranking from highest to lowest is: LH, HH, HL, LL. Alternatively, if our study period was extended beyond 2070, we may have observed additional cycles of carbon relative to the baseline and a potential resurgence of carbon gains for the high sawtimber scenarios. Second, the results show that higher pulpwood (wood pellet) consumption, in the absence of higher sawtimber consumption results in a forest carbon deficit compared our baseline scenario (see Fig. 3, HL scenario, All Forest column). Higher demand for sawtimber (*LH* and *HH*) provides more residue production, offsetting pulpwood demand from forests and increasing pine rents, which expands plantation area.

Our results can be compared and contrasted to Sedjo and Tian (2012) and Abt et al. (2012). Sedjo and Tian (2012) employed a simulation and perfect foresight analysis that used a simulated, regulated forest age structure rather than the empirical representation used in this analysis. The thrust of the conclusion in Sedjo and Tian (2012) is that forward-looking agents would adapt to higher expected prices by intensifying forest management and that the simple notion that increased harvests would deplete forest carbon stocks misses this dynamic. While our model uses myopic expectations, the land use model is driven by pine plantation rents, which were derived from Faustmann (forward-looking) calculations. Therefore, price increases in our model have a similar effect to that shown in Sedjo and Tian (2012), a switch to more intensive forest management systems. In our case, intensification is captured by the growth in the share of pine plantations area, since pine plantations have higher productivity. However, our analysis captures a more nuanced perspective on forest carbon consequences of management intensification. We do not definitively conclude that total forest carbon will increase under higher wood pellet demand. In the least case, high pellet demand in combination with lower sawtimber demand can decrease total forest carbon stocks relative to low demand for both (Fig. 2.b). For relative carbon gains to occur, high pellet demand needs to come along with high sawtimber demand, because sawtimber carries more weight in pine plantation rents. Unlike Sedjo and Tian (2012), we show that additional forest carbon due to higher product demand is not immediate or permanent.

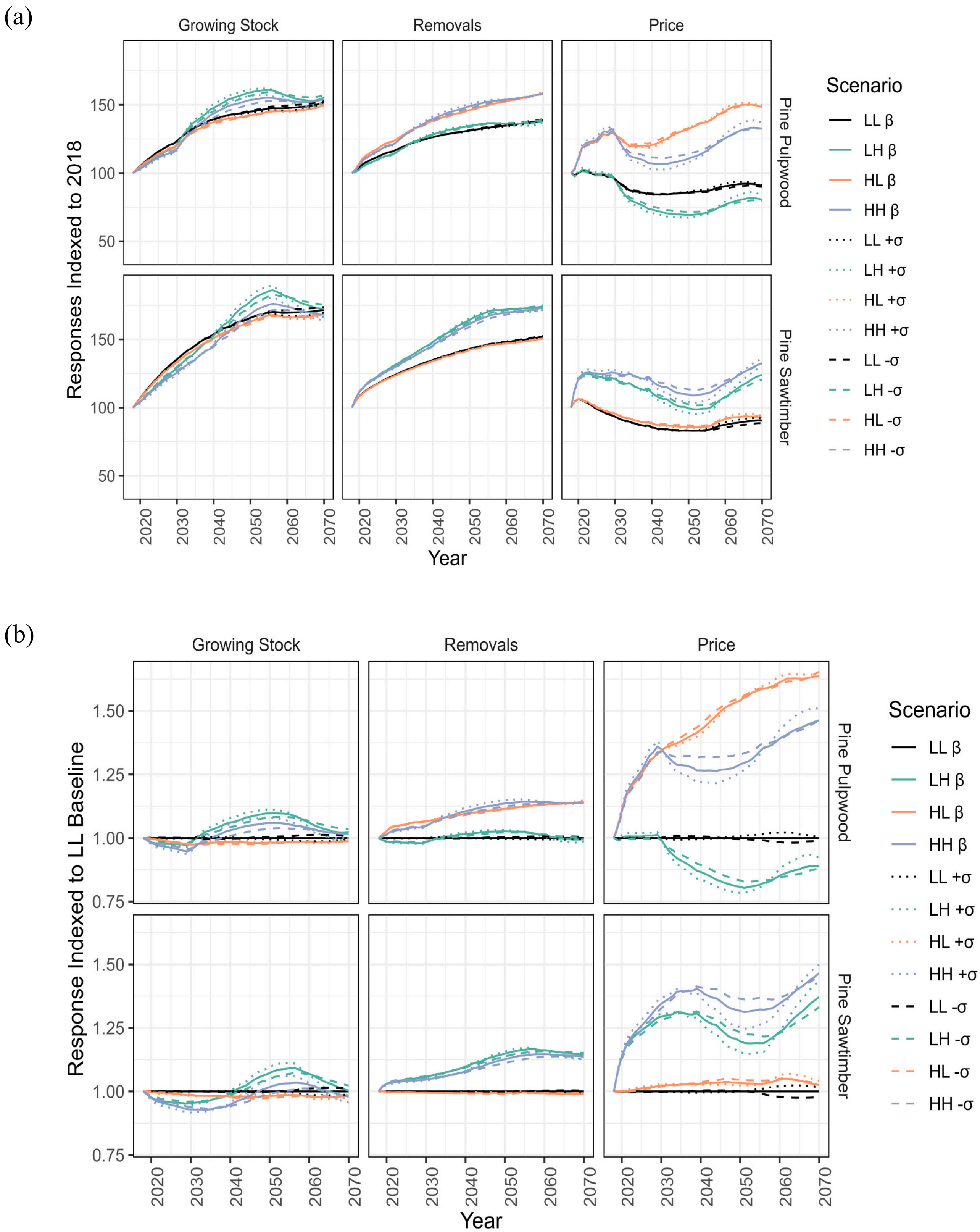

Fig. 1. Market outcomes for pine products (a) indexed to 2018 and (b) relative to the LL baseline.

Abt et al. (2012) employed a land use model for three Southern US states based on Hardie et al. (2000), which indicated a positive relationship between timberland area and pine sawtimber prices and a negative relationship between timberland area and harvesting costs. In contrast to Hardie et al. (2000), our land use model differentiated among forest types. Whereas Abt et al. (2012) assumed gains in pine plantations while leaving other forest type areas constant, our model indicated that increases in pine plantation area comes with some replacement of natural forests, though not one for one. Our econometric results are generally consistent with Hardie et al. (2000), since harvesting costs are

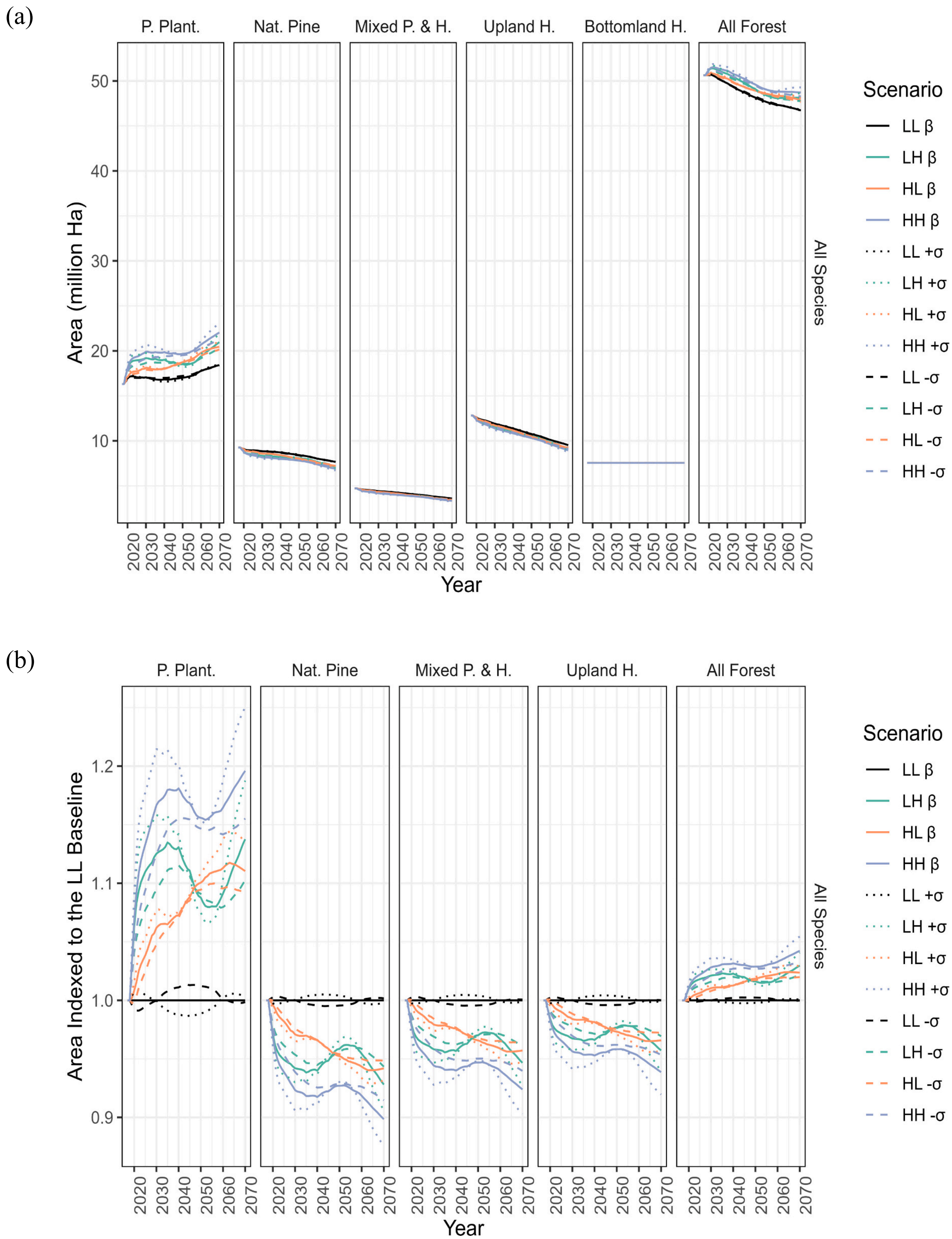

Fig. 2. Area by forest type and for all forest (a) in absolute terms and (b) relative to the LL baseline.

higher in natural stands compared to pine plantations, and pine plantations have the most to gain from pine sawtimber prices.

To varying degrees, our land use results could be compared to other land use modeling related to forestry. The land use model being structured as a share model makes it more closely related to Hardie et al. (2000) and Nagubadi and Zhang (2005). The share model approach allows for the identification of elasticities, making it well-suited for scenario analysis in a forest sector model context. However, a limitation of this approach is that the model does not track direct conversions between uses. Alternative land use models have been specified, typically on a probabilistic basis, to account for transitions from one land use to another (Puhlick et al. (2017); Mihiar and Lewis (2021)). Puhlick et al. (2017) employed a plot level model based on FIA data and generally identified single digit probabilities of forest conversion to other uses

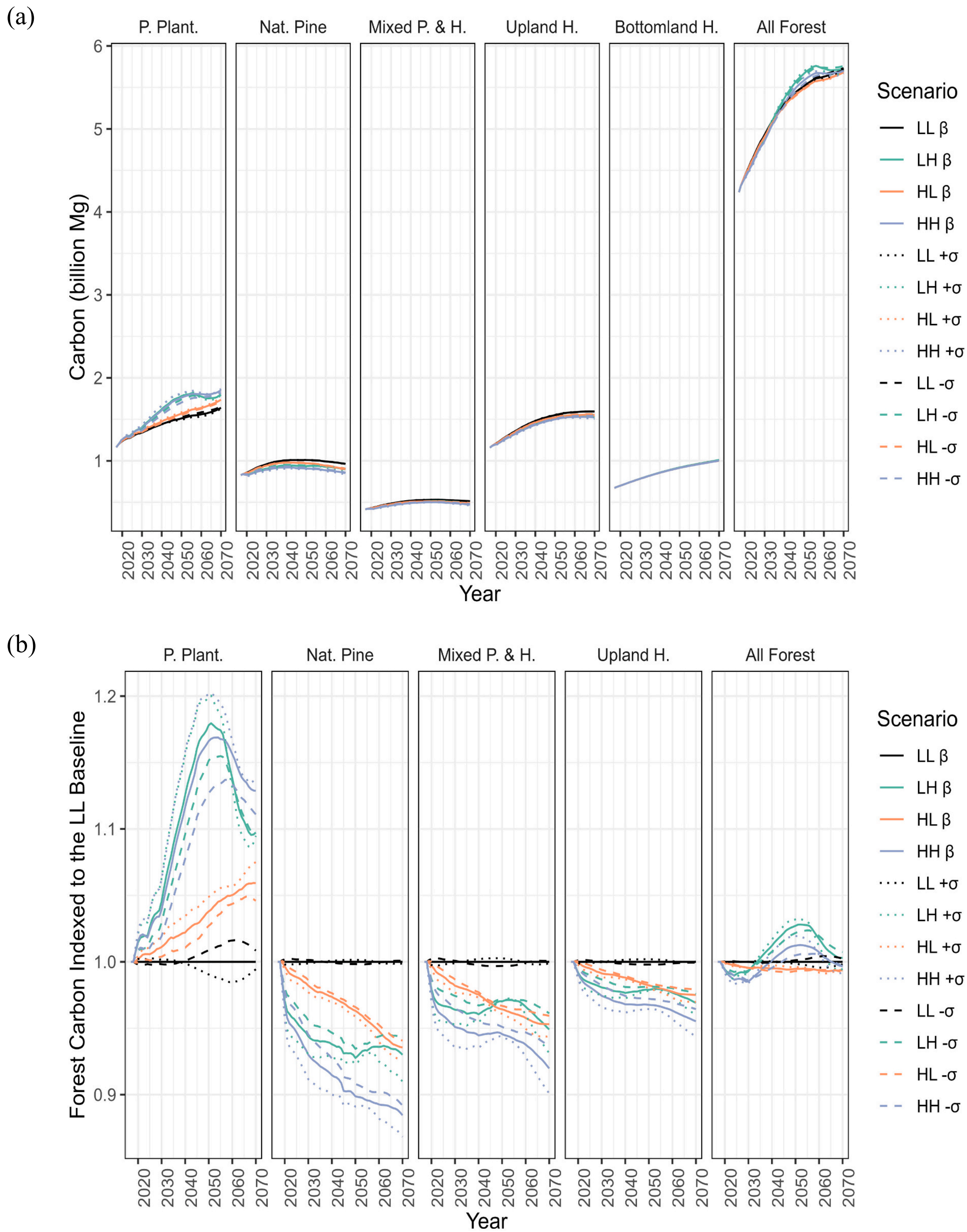

Fig. 3. Total forest carbon by forest type and for all forest (a) in absolute terms and (b) relative to the LL baseline.

with variations among regions. Mihiar and Lewis (2021) developed transition probabilities from forest to pasture, agriculture, developed, and other uses, and vice versa using National Resources Inventory data and timberland rents.

Global change models and global forest sector models also have embedded land use change dynamics (Buongiorno (2015); Riahi et al. (2017); Korhonen et al. (2021); Guo et al. (2023)), but at the global scale, data becomes a limitation on replicating our land use model by forest type. Buongiorno (2015) uses an environmental Kuznets curve (EKC) specification based on country gross domestic product to modify forest area over time. Riahi et al. (2017) and the global change literature generally tend to model forest as a land use with no forest type sub-components. Korhonen et al. (2021) improved on this limitation in global forest sector models by developing a model for planted forest area, distinguishing it from other forests. Guo et al. (2023) evaluated forest markets in the US South, linked to a global forest sector model using an environmental Kuznets curve (EKC) land use change model. The EKC approach can be contrasted with our approach and that of Hardie et al. (2000) and Mihiar and Lewis (2021) in that it typically does not include timberland rents in the model specification. The EKC approach may also lack a mechanism to ensure that total land allocated to all land uses is conserved.

The present study is constrained to address how demand and land use change interact to change the mix of forest types in the US South, the area of forests and total forest carbon. Future research could extend this to better examine impacts on biodiversity. While we do not measure it within our study framework, it is possible that trading natural forests for pine plantations would modify biodiversity (Hua et al., 2022). However, while the increase in pine plantations at the expense of natural forests persists over the study period, the downward trend natural forests is established by variables associated with development (Fig. 2.a). Within the study period, pine plantation expansion increases total forest area relative to the baseline, so given the negative pine rent elasticity for agriculture, some of the expansion comes from agricultural land. This dynamic is historically plausible, sense marginal agricultural land has transitioned to forest repeatedly in the US Southeast (Lubowski et al., 2006).

The results demonstrated that the particular value of the pine rent elasticity is perhaps less important than the levels of wood product demand. The primary function of the pine rent elasticity is as a parameter for the speed of adjustment to prices. This did impact the results, but shifts in demand impacted the feedback mechanisms of the system in more substantial ways. More removals reduced growing stock, shifting the supply curve to the left, increasing the prices that determine pine rents.

One of our key conclusions is that total forest carbon can increase with higher forest product demand, particularly as a result of sawtimber demand. We also conclude that high sawtimber demand combined with low pulpwood demand confers the highest total forest carbon benefit overall, with the important caveat that total carbon follows the cyclical nature of growing stock and trends back toward the baseline at the end of our study period. High pulpwood demand alone results in a net forest carbon loss compared to the alternative scenarios, yet in absolute terms all scenarios show forest carbon gains over time (Fig. 3.a).

In our analysis, we observed pine plantation replacing natural forest commensurate with higher demand scenarios. However, it is important to note that our results showed that increases in non-forest land uses, represented by the downward trend in total forest (Fig. 2.a), is the primary driver of forest disappearance, the most extreme form of forest degradation. Our results could also be extended beyond forest carbon through the inclusion of carbon flows in wood products. While carbon in wood products decays over time, accounting for wood product carbon would partially compensate for the early drop observed in forest carbon in high demand model runs.

On the question of wood pellet sustainability, we can conclude from the study results that there is no scenario in which wood pellets are carbon neutral relative to alternative scenarios if the increased demand for pulpwood is not supported by increased sawtimber demand. Our results also demonstrate that the carbon consequences of wood pellets cannot be separated from the stumpage products that are co-produced or the time horizon of the analysis. Under a scenario of high sawtimber and high pulpwood (wood pellet) demand, it is possible to achieve higher forest carbon than a scenario of low demand for both.

CRediT authorship contribution statement

Jesse D. Henderson: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Visualization. **Robert C. Abt:** Conceptualization, Methodology, Software, Validation, Writing – review & editing. **Karen L. Abt:** Conceptualization, Investigation, Validation, Writing – review & editing.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.forpol.2024.103296.

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