Optimal timber management decisions in the face of future uncertainties

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Abstract

This study develops a global model of climate change impacts on optimal forest management. The model integrates a global dynamic vegetation model with a global dynamic forestry model and examines the impacts on forests of future income, population, and climate change across the Shared Socio-economic Pathways (SSPs) presented by the Intergovernmental Panel on Climate Change. Special attention is devoted to decisions over how much to invest in forest management, a decision that can only be reversed by harvesting and replanting. To address this, a min-max-regret analysis is conducted whereby the modelers calculate a robust path of management investments in commercial forests that factors in key uncertainties. The results suggest that while climate change can have important consequences for forests, economic growth has the strongest impact on forested ecosystems in the future. Total forest area increases in some scenarios and decreases in others, although large areas of natural forests are converted to agricultural uses and commercial forests. The area of forests decreases in the north, and increases in the south. Similarly, investments in forests increase in the south and decrease in the north. The impacts of climate change occur sufficiently far in the future that foresters can continue making decisions without considering climate change through the middle of the century, but over the second half of the century will need to start adjusting management to account for climate change.

Introduction

Climate change is expected to have far-reaching impacts on the world's forests. The IPCC (2014) suggests changes along three dimensions in response to rising CO2 concentrations and changing temperature and precipitation: shifts in forest growth rates, shifts in where species can grow, and changes in disturbance regime. For example, ecosystem models have shown potentially large scale movements in forested ecosystems over the next century, and large growth responses (e.g., Kim et al., 2017).

A number of economic models have integrated ecosystem impacts and examined how the ecological changes could influence timber production and management. One of the first studies, Joyce et al. (1995) found that forest growth would likely increase with climate change, leading to increased timber production and lower prices. That study did not consider the effects of changes in forest disturbance and the movement of ecosystems across the landscape as climate changes. Sohngen and Mendelsohn (1998) illustrated the importance of modeling the full dynamic adjustment pathway to measure welfare effects of climate change on forests. Guo and Costello (2013) also use a dynamic approach and show how adaptation strategies will rely heavily on the extensive margins, finding that much of the effort on adaptation will occur when forests are harvested and regenerated rather than through management or the timing of harvests. Sohngen et al. (2001), Perez Garcia et al. (2001) and Tian et al. (2016) use global models to account for the price effects of large-scale shifts in ecosystem productivity.

None of the existing models of climate change impacts in forestry have explicitly factored in the impact of uncertainty on forest management decisions. Uncertainty is important for a number of reasons. First, we do not know the future path of carbon emissions, and thus do not know the climate forcing factors that will affect ecosystems. Second, we do not know exactly how ecosystems will respond to changes in climate. Forest dieback, for instance, is currently an important source of uncertainty for forest managers. It could increase or decrease with climate change, depending on relative changes in temperature versus precipitation and other factors, making future decisions about when to harvest trees and what to replant substantially more complex. Third, timber prices are uncertain. Nearly all studies in forestry that have considered uncertain timber prices, however, have treated prices as a function of some exogenous process, typically unrelated to climate change. With climate change, however, prices must be determined endogenously with climate change impacts and uncertainty unfolding in multiple regions.

To address these issues, we develop a global dynamic forward looking model of land use with detailed representation of forests, building on work documented in Sohngen et al. (1999, 2001) and Tian et al. (2016), and apply a Min-Max Regret (MMR) criterion (Lempert et al. 2006, Cai and Sanstad 2016) which allows us to find optimal intensity of investments in forest management in the 21st century in the face of future uncertainties. . The MMR approach allows us to determine a set of intertemporal forest management decisions that minimizes the potential adverse welfare consequences of assuming one future but experiencing another. Regrets are the welfare consequences of making decisions consistent with one scenario while in fact the world follows a different pathIn this paper we focus on just one element of the set of management decisions in forestry – biome specific intensity of investments in forest management over time.

Within our global timber model, the management decisions that affect adaptation include choosing the optimal age class of harvesting trees, the intensity of investments in forest management at replanting time (which are fixed for the life of the tree), the type of trees to grow in a given area, the area of forests to manage for timber production, the area of forests to leave in a natural state, and the overall area of forest cover. In the model, the global land endowment is split into biomes, and competition for land among agriculture and forests (both managed and unmanaged) differs across biomes. Representation of forests is based on the deterministic analysis and data in Tian et al. (2016). Climate impacts are derived from the MC2 model (Kim et al., 2017). Scenarios from the MC2 model have been linked to temperature and atmospheric carbon dioxide concentrations in the Shared Socioeconomic Pathways (SSPs) database (IIASA 2015). Thus, we examine impacts across the five SSPs, characterized by SSP specific global population, income, change in global surface temperature and carbon dioxide concentrations, and then use the MMR approach to determine biome specific paths of intensity of investments in forest management that minimize the maximum regret across these scenarios.

The results illustrate that investments in forest management should continue to increase in most regions of the world over the next 25-40 years. They are expected to increase most rapidly for the fastest growing forest types, for example Southern Pine in the US and other non-indigenous species in other regions of the world, with investments in forestry management in these types growing at roughly 3% per year. Investments in management in slower growing species also increase, but less rapidly at 1.6% per year. Beyond 2050, our model projects that investments in forest management slow down and decline in the US, while they continue to grow in other regions. One reason for the slow-down in the US is the large increase in forest fire activity that occurs in this region, making investments in the US substantially more risky in the longer run.

Methods

We start with the per capita utility of consumption of wood, Q_t, and all other products, Y_t,[1]

(1) $U(Q_t, Y_t)$

In the context of a forestry model, $\Pi_t Q_t$ is the total volume of wood harvested from amongst the age classes of trees in various forest types that are harvested:

(2) $\Pi_t Q_t = \sum_{i=1}^{I} \sum_{a=1}^{A} H_{a,t}^{i} V_{a,t}^{i}$

where $H_{a,t}^{i}$ are the hectares harvested and $V_{a,t}^{i}$ is the volume per hectare, and subscript *a* and *i* denote age class of trees and types of forests harvested (biomes). Π_t denotes global population.

The volume of timber per hectare, $V_{a,t}^{i}$, is the product of a logistic function, $G_{a,t}^{i}$, which adjusts as forests age according to

(3) $G_{a,t}^{i} = \exp(\alpha^{i} - \frac{\beta^{i}}{a})$

and a timber management intensity function, $f^{i}(Z_{a,t}^{i})$, which is controlled by management inputs. $V_{a,t}^{i}$ is thus:

(4) $V_{a,t}^{i} = f^{i}(Z_{a,t}^{i}) G_{a,t}^{i}$

The intensity function, f(Z), has the following properties:

[1] In the model, the consumption bundle include wood products, crop-based food, livestock-based food, energy that includes bioenergy, and other goods and services. The representation of the consumption bundle adopted in this paper is a simplification for easier exposition.

(5) $\quad {}^{df}\!/_{dZ} \geq 0 \quad and \quad {}^{d^2f}\!/_{dZ^2} \leq 0$

The intensity decision (optimal Z) is made at the time the forest is planted, as this dictates the way the forest will grow. Higher intensity of planting will increase yields in the future at harvest time, but the benefits of increasing Z are diminishing. With climate change, the volume per hectare will shift due to changing temperature and precipitation levels. The shift in timber biomass growth per period is given as γ_t, which adjusts the growth of trees. The cumulative effect of biomass growth, combined with the impacts of climate change, is the timber yield, given as the volume per hectare $V_{a,t}^{c,i}$:

(6) $\quad V_{a,t}^{c,i} = V_{a-1,t-1}^{c,i} + (1+\gamma_t^i)(V_{a,t}^i - V_{a-1,t-1}^i)$

Over time, the stock of trees evolves as

(7) $\quad X_{a+1,t+1}^i = X_{a,t}^i - H_{a,t}^i - \delta_t^i X_{a,t}^i$

$X_{1,t}^i = N_t^i$

where *N* represents the replanted hectares.

In the equation of motion above, the parameter δ_t represents dieback from forest fires and other disturbances that affect trees.

and the stock of management evolves as

(8) $\quad Z_{a+1,t+1}^i = Z_{a,t}^i$

$Z_{1,t}^i = m_t^i$

The deterministic forestry problem involves maximizing global welfare for each SSP scenario *k*: $\sum_{t=1}^{\infty} \rho^t \, \Pi_t \mathrm{U}(\mathrm{Q}_t, \mathrm{Y}_t)$, subject to equations (7) and (8), as well as resource availability and other constraints, to find paths of resource allocation variables *X*, H^i_a N^i, m^i, as well as land conversions from natural state to commercial use and among commercial uses Δ. Given uncertainty over the path of population, income, carbon concentrations and global surface temperature change, the deterministic problem taken alone is unlikely to yield a satisfactory outcome. For instance, we assume the effect of climate change on shifts in forest growth is largely controlled by carbon concentrations, so we can express γ_t as a function of carbon concentrations, P_t, such that $\gamma = \gamma(P_t)$. Dieback in contrast is a function of temperature, τ_t, so that $\delta = \delta(\tau_t)$. Similar to dieback, the change in biome size is modeled as a function of temperature. Carbon concentrations and temperatures, of course, are a function of population, income and technology choices. For consistent representation of the future in terms of population, income and climate in the model, we use SSPs developed to cover the broad range of economic and climate futures (O'Neill et al. 2014, IIASA 2015). These scenarios are presented in Figure 1 and demonstrate that development of population, income, and climate change is very uncertain in the 21st century. Absent multi-variable probability distributions, and also probability of each scenario, we employ MMR approach to determine optimal response to future uncertainties. First, we compute:

(9) $\quad W(m, H, N, \Delta, X; k) \triangleq \sum_{t=0}^{\infty} \rho^t \, \Pi_{t,k} U(Q_{t,k}, \mathrm{Y}_{t,k})$

where *W* is global welfare associated with policy path *m*, *H*, *N*, Δ, *X*, and SSP scenario *k*. We then solve:

(10) $\quad F(k) \triangleq \max_{m,H,N,\Delta,X} W(m,H,N,\Delta,X;k).$

That is, for each SSP we solve the model to find intensity of investments in forest management, as well as other decision variables, that maximize global welfare. Then, the regret function is defined:

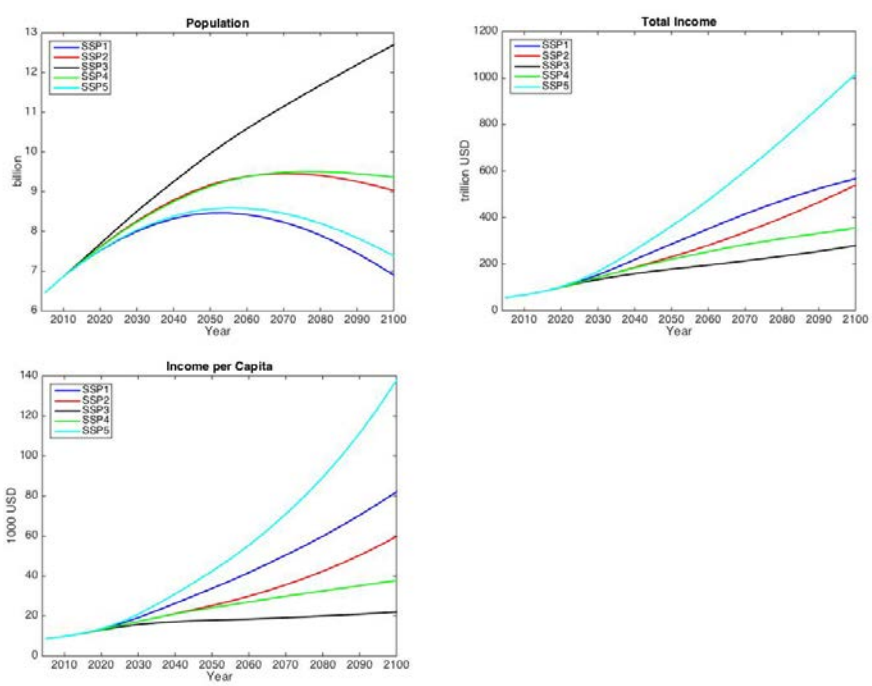
(11) $\quad R(m;k) \triangleq F(k) - \max_{H,N,\Delta,X} W(m,H,N,\Delta,X;k)$

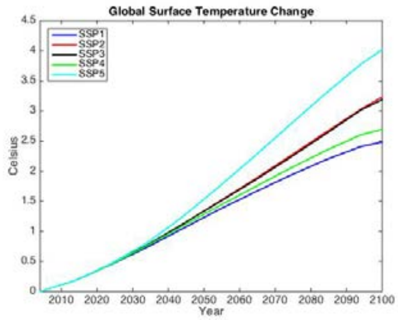
for a given matrix of forest management intensities m and scenario k. That is, for the k-th realized SSP scenario, the regret is difference between (a) wealth attained when we can choose both optimal m and other decision variables and (b) wealth attained when m is given. The optimization problem which minimizes the maximum regret R associated with several possible outcomes k is then formulated as:

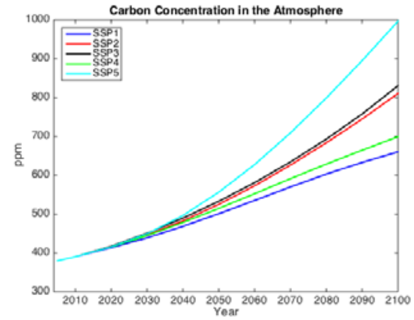
(12) $\quad \min_{m} \max_{k} R(m;k)$

For this problem, we consider the five SSP scenarios presented by the IPCC. These scenarios imply different growth rates for population, income, energy consumption, emissions, and climate forcing. We map the forcing to changes in forest yields, dieback, and potential changes in biome areas using results from the MC2 dynamic global vegetation model.

Figure 1. SSP scenarios of population (in billions), income (in trill USD), their associated per capita income (in 1000 USD per capita), CO2 concentration, and changes in global surface temperature (in Celsius) relative to the beginning of the 21st century. Source: https://tntcat.iiasa.ac.at/SspDb







Analysis

The underlying forestry data are obtained from the Global Timber Model described in Sohngen et al. (1999). The data have been updated and recently utilized to assess climate change impacts on over 250 forest types around the world in Tian et al. (2016). For the purposes of this study, we aggregate these forest types into 4 forest types within the United States and 4 forest types for the rest of the world. The forest types in the US are: southern pine, southern hardwoods, northern hardwoods, and western pine. The forest types in the rest of the world represent key forest types that are important for timber production in temperate, boreal and tropical regions.

Forests in this model are further allocated into commercial and natural regions. Commercial forests are those where active timber production occurs and natural forests are those that are too expensive to harvest due to accessibility constraints, climate and growth conditions, or other factors. We incorporate a set of access cost functions into the model, so that natural forests can become commercial forest over time if timber prices are rising, or they can shift into agricultural uses.

All timber that is harvested is aggregated and consumed by a single global demand function. This means that timber is deemed homogeneous in quality, and freely traded across regions. This assumption abstracts from the more complicated trade relationships that currently exist, but our focus in this paper is on adaptation to long term changes in forest productivity due to climate change, not short-term market fluctuations that may arise from changes in trade policies. Over the long run, we believe that the current geography of timber trade will adjust to reflect changing comparative advantage.

The data on climate change impacts are obtained from the MC2 dynamic global vegetation model (DGVM) of Kim et al. (2017), which in turn employs emission scenarios documented in Paltsev et al. (2015). The MC2 model provides data on the impacts of climate change on forested ecosystems. Specifically, we use the MC2 model to obtain estimates of the parameters γ and δ. The parameter γ accounts for perturbations in annual forest growth due to climate change and carbon fertilization. To model changes in forest growth, we utilize changes in net primary productivity (NPP) of forested ecosystems to adjust changes in forest growth. NPP is the net carbon flux remaining from photosynthesis after accounting for plant respiration, or in other words, the maintenance and growth of the existing plant.

At the ecosystem level, where our model actually accounts for the growth effects of climate change, additional processes could affect the net amount of plant growth each year. For instance, forest fires and other mortality processes reduce carbon annually. Thus, applying NPP across forested ecosystems to measure climate change impacts, as suggested above, could overestimate those impacts. To account for this, we model dieback directly, through δ above. The term δ in our model is measured as the amount of vegetation carbon burned by forest fires in the MC2 model.

The MC2 model was recently run under several representative carbon concentration pathways that cover a range of potential future concentration pathways up to warming potential of 9.0 watts per m^2 2110 (see Kim et al., 2017). For the purposes of this economic analysis, we express γ as a function of CO2 concentration. Thus, starting with CO2 concentrations in the climate model used to perturb MC2, we link CO2 concentrations to the predicted NPP changes from the MC2 model for the forest types of interest. We then calibrate a function to the resulting data points. Similarly, we link δ, dieback, and biome area to the temperature change in the climate model.

Figure 2A: relationship between CO2 concentration and θ

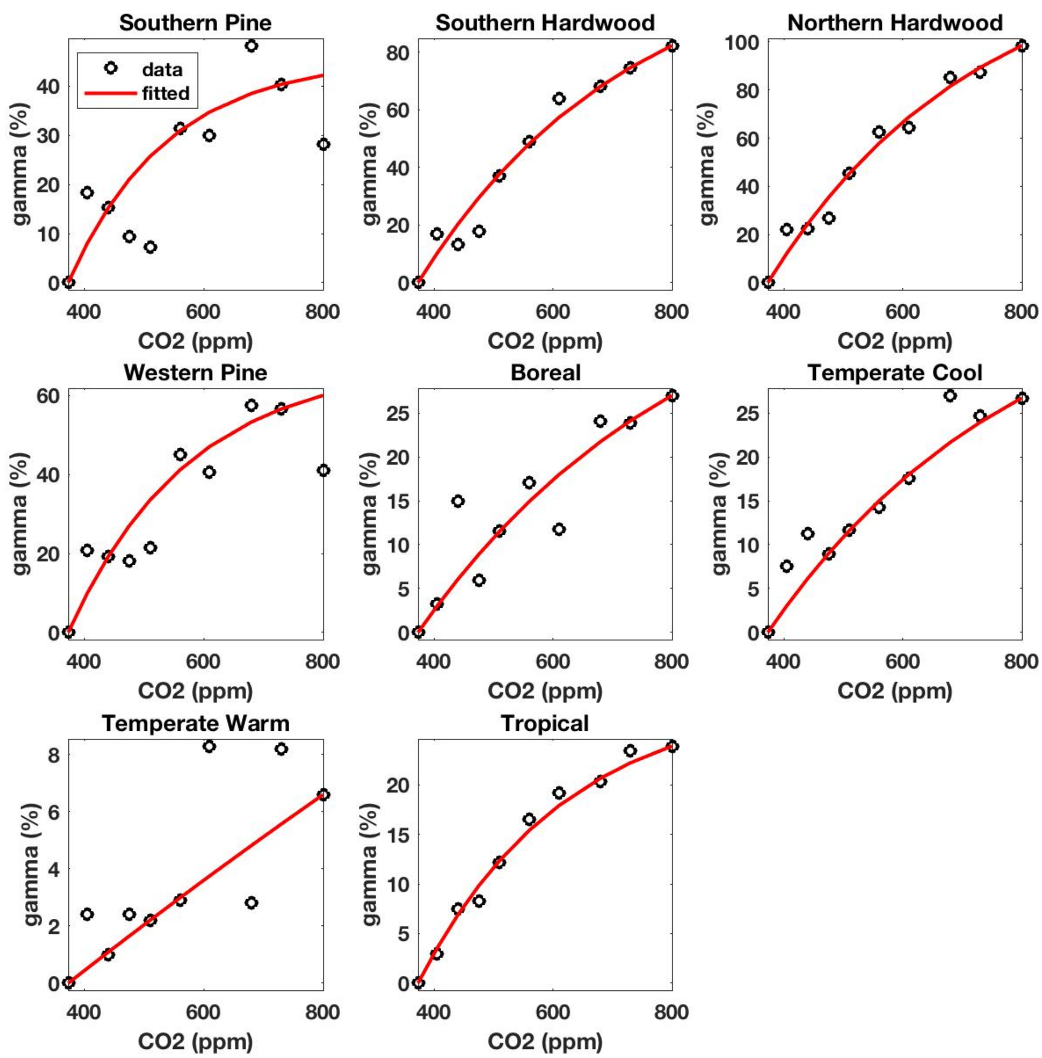


Figure 2B: relationship between temperature and δ.

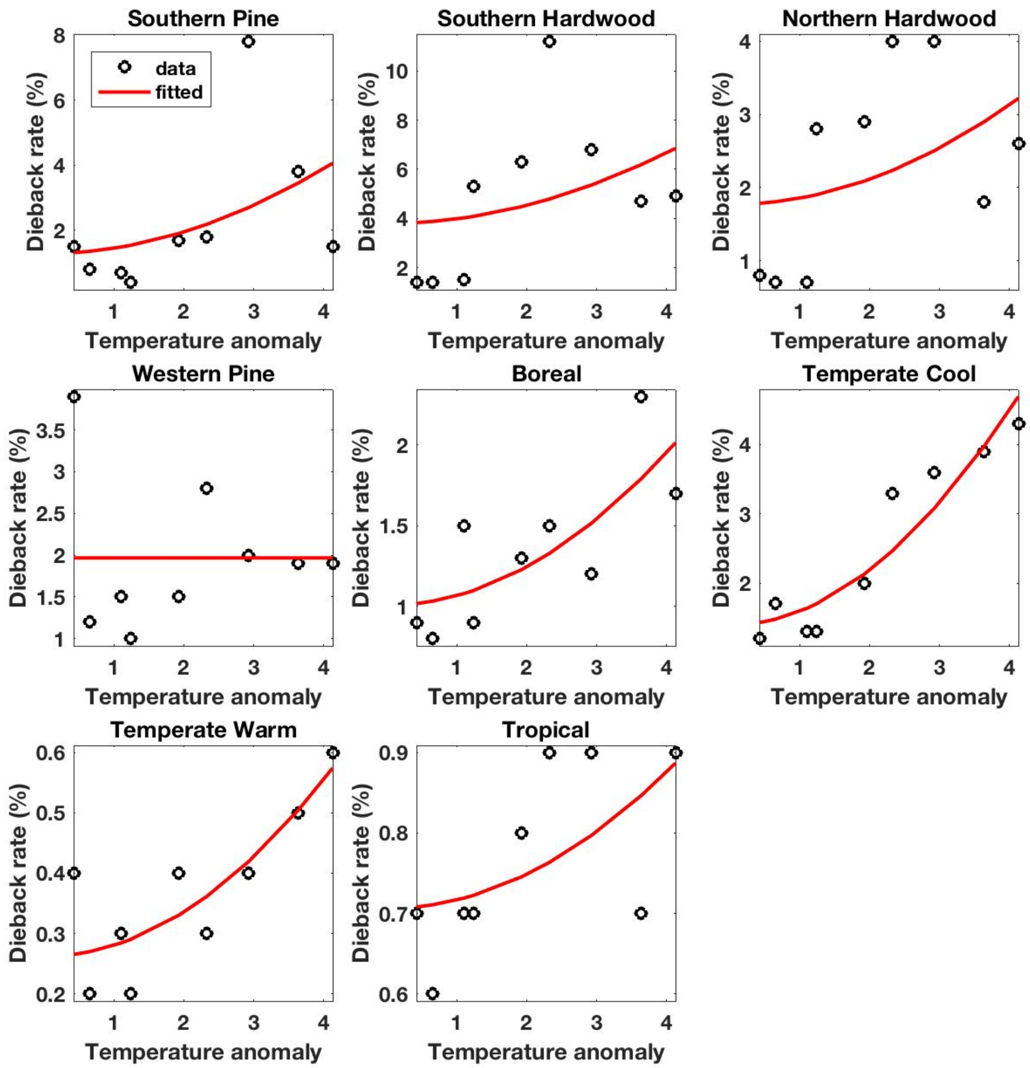
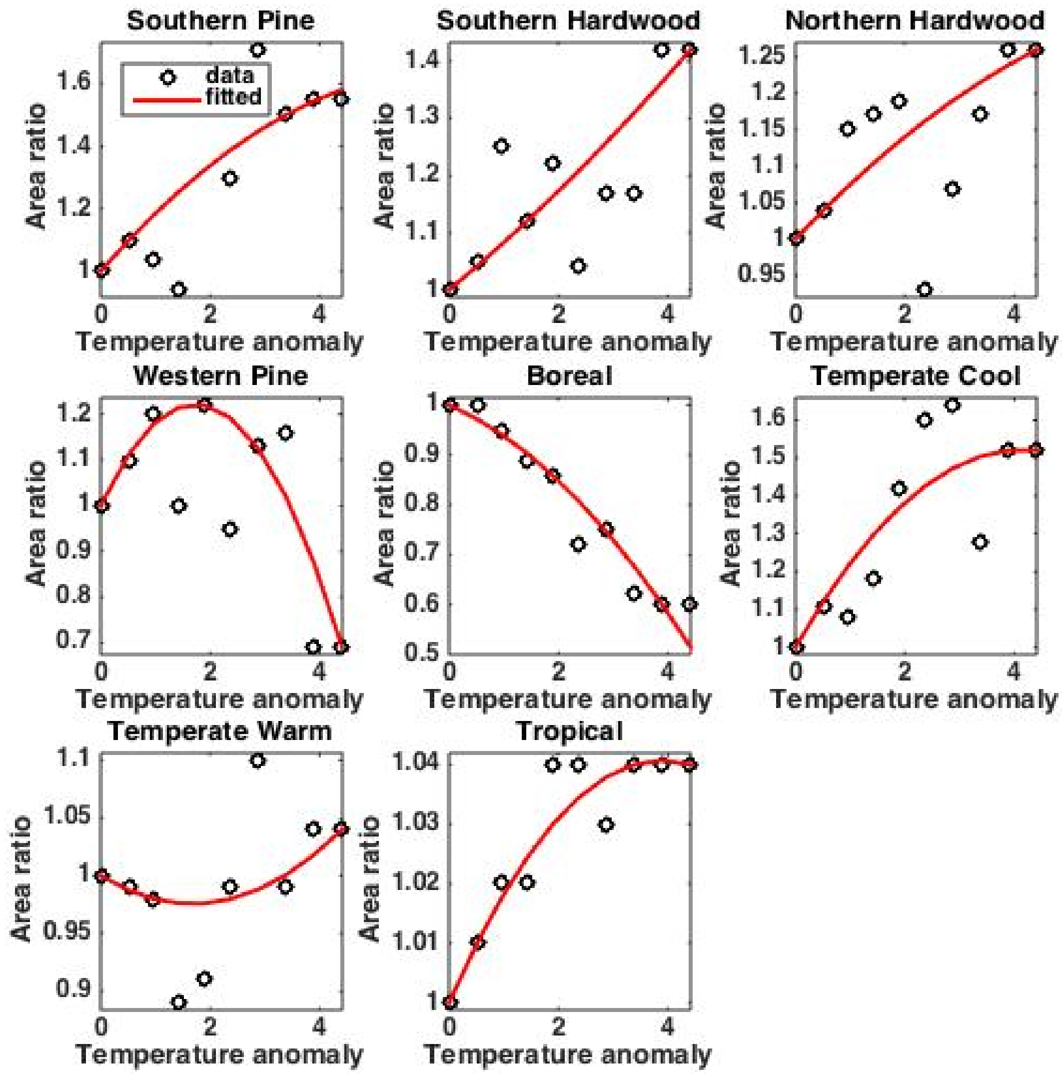


Figure 2C. Relationship between change in global surface temperature and biome area ratio



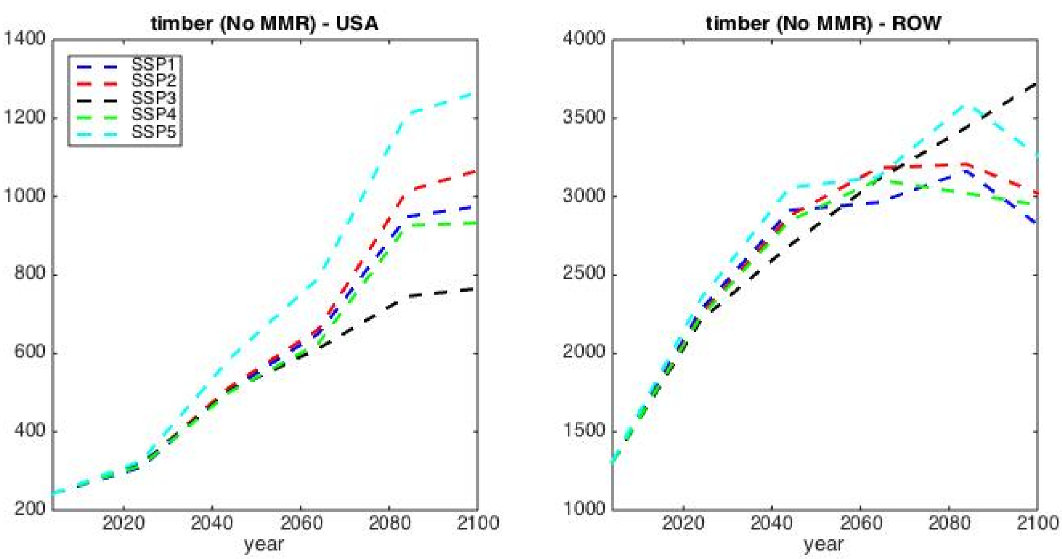
The functions that relate γ to CO2 concentration, δ to temperature and biome area to temperature differ for the 8 ecosystem types included in the model (Figures 2). In general, higher CO2 concentrations lead to increased NPP, or forest growth, in each region, but the increases attenuate at higher levels of CO2, and the relationship varies by forest type. In contrast, forest dieback appears to strengthen in most regions as temperature increases. These results suggest that while climate change may increase overall productivity of forests over a range of CO2 and temperature change, the effects at increasingly large CO2 changes may turn negative.

To model climate change in our analysis, we utilize the Shared Socio-economic Pathways (SSP) of the Intergovernmental Panel on Climate Change (Nakicenovic et al., 2013) to synthesize economic drivers, carbon concentrations and temperature and precipitation changes. We then project future changes in each variable and use those as drivers in the optimization model of global forestry. In the deterministic case, these results provide information on the potential impacts of climate change without uncertainty. Given that there is large uncertainty over which set of economic and climate drivers will prevail, we then conduct the uncertainty analysis to determine which set of actions in the model will minimize the maximum regret.

Results

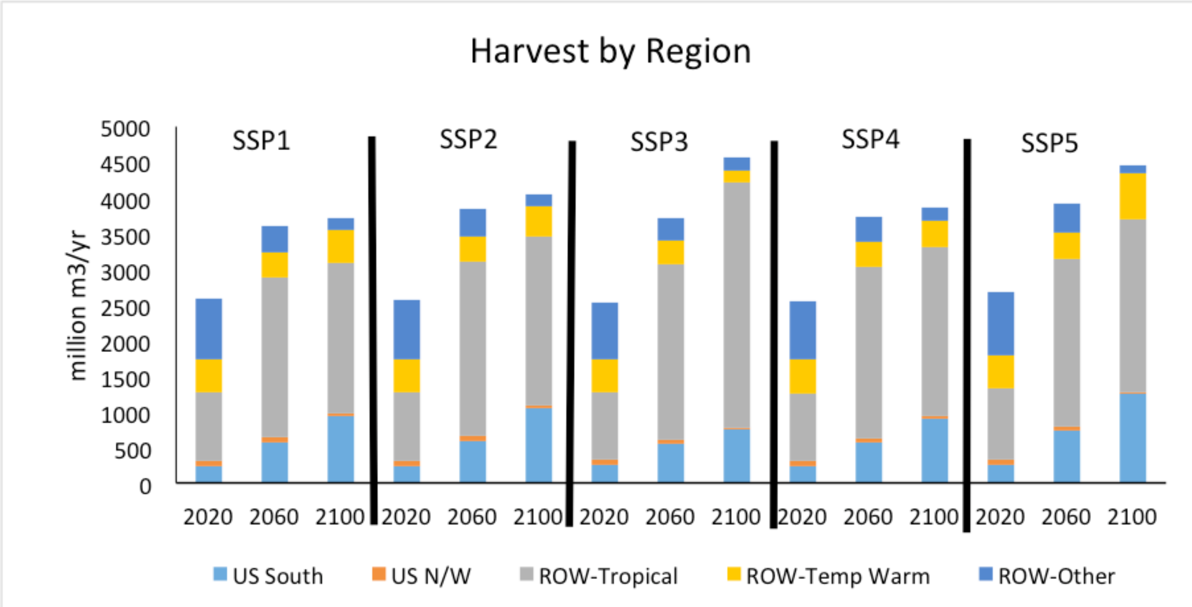
We begin by looking at results from the five deterministic models, each taking a different SSP as 'truth'. These suggest that timber outputs increase in all of the SSPs (Figure 3). Outputs double or more than double in the US and globally over the next century. It is reassuring that given the large potential increases in income and population shown in the SSPs, timber production can expand. Within the US, SSP3 yields the lowest increase in outputs in the US, and SSP5 the greatest. SSP3 has great population growth, but constrained income per capita, which limits consumption growth for timber. SSP5 in contrast has relatively high income per capita, and thus relatively large increases in consumption over time.

Figure 3: US and rest of world timber output (m3/yr) across the SSPs, without MMR.



Within the US, increased harvests are driven by gains of southern pines and hardwoods (Figure 4). Recent trends have already shifted US production towards southern pines and hardwoods, and the climate scenarios reinforce those trends. Globally, similar trends emerge, with tropical forest type generally gaining production over time and production from boreal and cool temperate types declining. In recent decades, there have been strong shifts towards increased production in tropical regions, and these results suggest that climate change will reinforce those trends. By the end of the century, between 60 and 80% of timber harvested will come from tropical regions in the rest of the world.

Figure 4: Harvest by region and across the SSPs



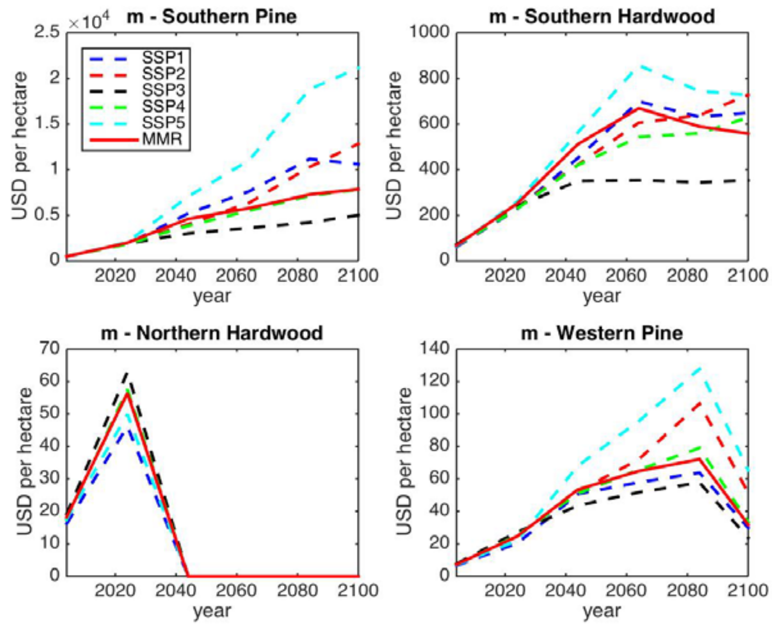
To achieve these large increases in timber harvests globally, significant investments in forestry are made. The largest investments are made in US Southern Pine forests, with investments rising the most under SSP5 (Figure 5). In the US in general, investments are highest under SSP5. Our results suggest that foresters disinvest from Northern forests over time. A similar pattern is observed in the rest of the world, where large investments are made in tropical and temperate warm forests, while investments increase initially in boreal and temperate cool forests, but ultimately decline.

The investment results have important implications for land areas (Figure 6). In the US, we project that forest area increases in the South and declines in the North. As temperatures continue to increase, northern forests become increasingly susceptible to dieback. Thus, given their long time horizons, landowners begin to reduce investments in northern forests and instead focus on southern types. In contrast, forest investments increase in the South. The results are similar for the rest of the world, with a reduction in forest uses and an increase in agricultural uses of land in northern regions, and an increase in forest area and reduction in agricultural areas in the southern, tropical regions. The rationale is similar, although the differential in dieback between northern and southern regions in the ROW is larger.

A large share of forestland in our model is initially set-aside for economic reasons, either because it is too remote and costly to be harvested, or because society has determined it should be reserved from other uses for environmental reasons (Table 1). We call this land natural forestland in our model, and it amounts initially to 244 million ha in the US, or 83%, and 2.3 million ha globally (74%). Over time, the increases in economic growth in all of the scenarios have consequences for these natural lands, reducing them by 11% (in the US) in SSP3 to 32% in the US or 48% in the ROW in SSP5 with its strong economic growth.

Figure 5: Timberland investments in $/ha by forest type.

Panel 5A: management intensity in US biomes



Panel 5B: management intensity in Rest of World biomes

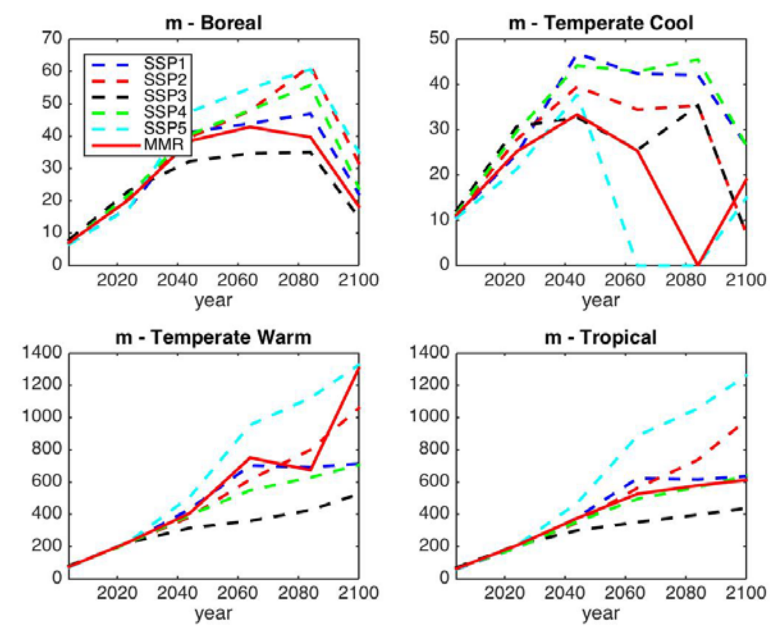
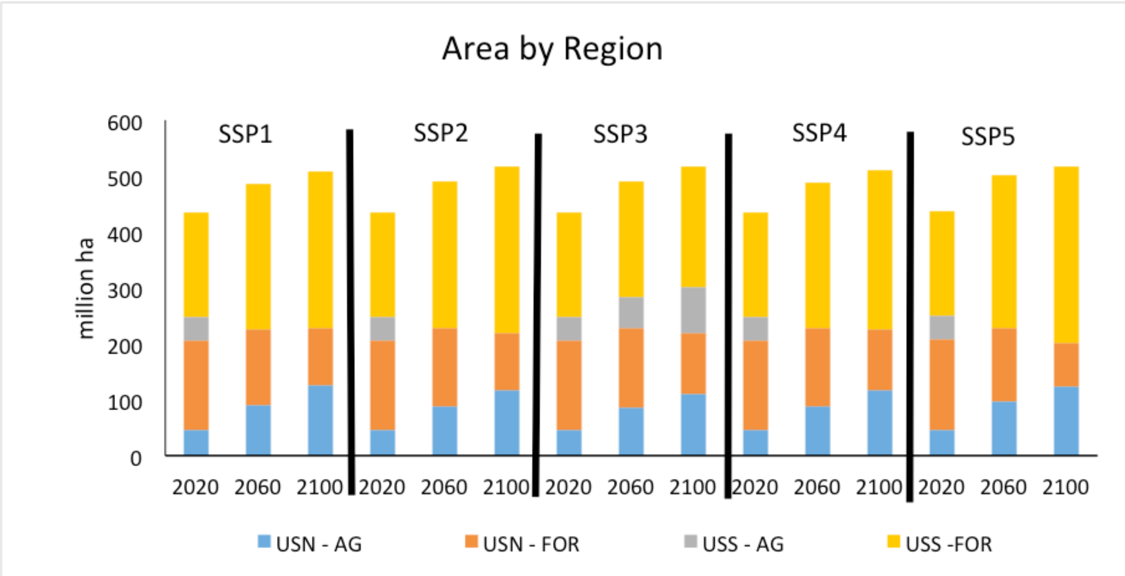


Figure 76: Proportions of forest and agricultural land in northern and southern parts of the US and rest of world.

Panel 6A: US Land area



Panel 6B: Rest of World Land Areas

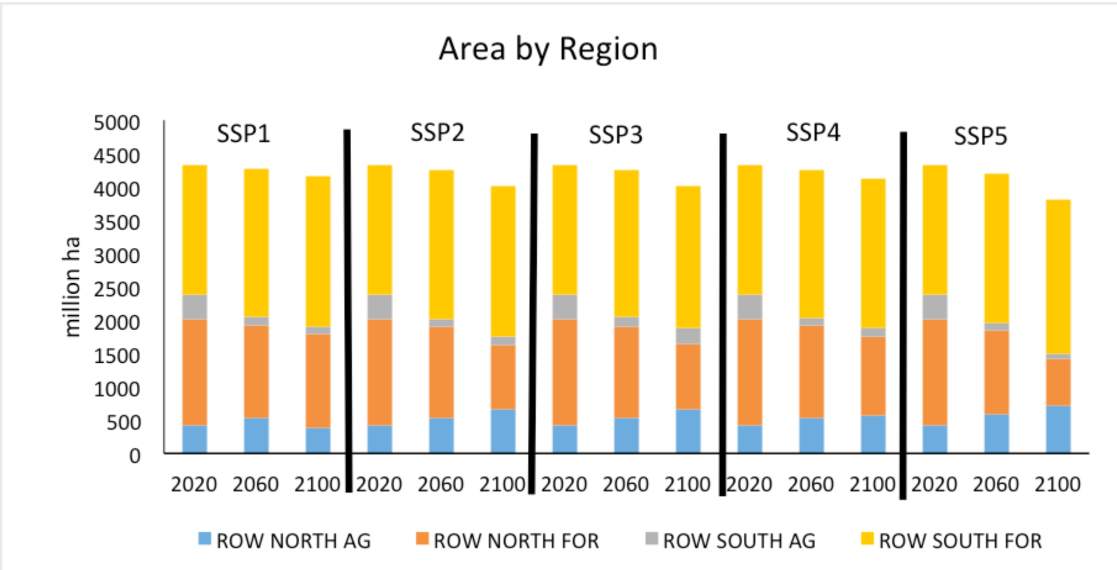


Table 1: Forestland areas in commercial and natural type forests aggregated for the US and ROW regions.

	Commercial			Natural		
	2000	2100	Change (%)	2000	2100	Change (%)
			Million hectares			
US						
SSP1	48.6	191.4	142.8 (294%)	244.5	190.8	-53.7 (-22%)
SSP2	48.6	202.9	154.3 (317%)	244.5	197.2	-47.3 (-19%)
SSP3	48.6	109.3	60.6 (125%)	244.5	217.0	-27.5 (-11%)
SSP4	48.6	188.9	140.2 (288%)	244.5	205.2	-39.2 (-16%)
SSP5	48.6	226.9	178.3 (367%)	244.5	165.2	-79.3 (-32%)
ROW						
SSP1	829.4	1642.6	813.2 (98%)	2316.0	1642.6	-673.5 (-29%)
SSP2	829.4	1496.2	666.8 (80%)	2316.0	1496.2	-819.9 (-35%)
SSP3	829.4	1605.9	776.5 (94%)	2316.0	1605.9	-710.2 (-31%)
SSP4	829.4	1660.5	831.2 (100%)	2316.0	1660.5	-655.5 (-28%)
SSP5	829.4	1201.5	372.1 (45%)	2316.0	1201.5	-1114.6 (-48%)

In addition to assessing outputs over a range of SSP economic and climate drivers, we have conducted a robustness analysis using Min-Max Regret (MMR) routines. The MMR routines focus on determining a robust set of management inputs to use given uncertainty about which future will evolve. These results for management intensity are shown in the solid red lines of Figure 5 above. Under the given scenarios, the results suggest that management decisions need not change much in the near term to account for climate change. In the US, the robust management level starts to deviate mid-century. Interestingly, the robust decision suggests hedging towards lower levels of management in Southern softwoods and higher levels of management in hardwoods.

Discussion

The big driver on timber prices is the rate of economic growth. Higher growth under SSP5 encourages strong increases in demand for timber and subsequently large increases in prices over time, while lower growth under SSP3 leads to lower overall increases in prices. Timber production in the US and globally is relatively similar across the scenarios through 2060, but starts to deviate after that. In the US, timber production rises to its highest level under the stronger growth scenario and higher prices in SSP5, and it is lowest under SSP3. In the rest of the world, however, output increases the most under SSP3, which is somewhat surprising given that this scenario has fairly low economic growth. This is driven by strong increases in output in tropical forest types under SSP3, which is one of the more benign climate scenarios.

Timberland investments in the northern US are low to begin with, but are projected to decline to 0 by the middle of the century. This is primarily due to the effects of increasing dieback in the northern US. Similar impacts occur in temperate cool forests in the ROW region, although the reductions occur later. Investments in warmer regions build over the century and continue climbing throughout, both in the US and globally. These results mirror those in Sohngen et al. (2001) which suggested that investments in faster growing species would be prioritized if dieback becomes more prominent during climate change.

When considering the robust management strategy, the results suggest that there are not large risks associated with using inputs that mirror the average across the scenarios for the next couple of decades. By the middle of the century, the results suggest that landowners should become more cautious, in particular in northern species. Although dieback has important consequences for forests, it turns out that the near term consequences of dieback are not large enough to drive large changes in investment strategies. Over time, as warming becomes more pronounced, and dieback increases, there are stronger incentives to reduce management inputs.

Conclusion

This paper develops a dynamic global model of forestry that integrates the results of the MC2 dynamic global vegetation model (Kim et al., 2017) with a dynamic optimization model. The model is used to illustrate how economic and climatic drivers potentially influence timber outputs, timber prices, forest areas, and forest stocks. We then apply the Min-Max-Regret technique to determine robust management decisions in light of uncertainty about which future scenario will evolve.

The results suggest that economic drivers dominate the results over prices and harvests. That is, the large variation in outputs and timber prices across the SSP's derives mainly from the difference assumptions in the SSPs about population and income growth. For example, under SSP5, with high income per capita and high levels of carbon in the atmosphere, prices are at their highest levels and in SSP3, with lower income per capita, prices and quantities are lowest.

Although the economic drivers have the most important implications for forests, it is reassuring that even with very strong climate change in SSP5, society can expand timber production to meet demand. Overall forest area does not change significantly over the century, reversing the trends of the last century which saw over 700 million ha of forestland converted to agricultural uses. This particularly true in the US and ROW south, where forest area expands over the century. This increase in forest area is driven in part by increasing productivity driven by climate change and the value of the resulting forest investments, but also by the movement of agricultural uses northward.

There is a cost to large scale demand increases, namely the loss of natural forestland. Although total forestland remains fairly stable over the century, natural forests are heavily converted to other uses, including agriculture and commercial forest. The largest changes of course occur in the largest demand scenario (SSP5), with 79 million ha of natural forest (or 32%) in the US lost by 2100, and 1115 million ha in the ROW.

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