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Abstract

It is argued that the forest can provide low-cost options to reduce the atmospheric CO_2 concentration. However, many dimensions of the future dynamics of the forest, and its interactions with climate change are still not well understood. This paper provides new insights into how these types of uncertainties affect the optimal climate policy. We model uncertainty over several key forest parameters by using the novel state-contingent approach. Our main results show that the importance of including optimal forest controls in climate policy increases when the dynamics of the forest are uncertain. Ignoring uncertainties concerning the forest will lead to biased estimates of the social costs of carbon and be misleading when evaluating climate policies. Conversely, recognizing forest uncertainties and its potential to mitigate climate change will lead to a robust policy where the cost of uncertainty to a large extent can be avoided.

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1 Introduction

This paper provides an integrated assessment model that incorporates uncertainty over key parameters that affect forest carbon sequestration. Unlike most integrated assessment models, that treat forest carbon sequestration as deterministic, we incorporate uncertainty by using the state-contingent approach. This method yields insights into how uncertainty affects the benefits of using the forest in combating climate change.

Forests play an important role in the global climate cycle and have received attention over the last decades as a carbon abatement strategy. Several studies suggest that the forest carbon sequestration could be a low-cost option to slow down climate change, and an increasing number of integrated assessment models include different forest actions as abatement strategies. However, forest carbon sequestration may be a less certain way to reduce emissions than energy abatement, both in the long and in the short run. Various uncertainties are linked to forest sequestration, for example, uncertainty about the future growth rate of the forest, climate feedbacks, forest carrying capacity, carbon leakages, technological potentials of bioenergy, and cost of land. Assumptions about such variables are essential to the conclusion when evaluating the forest resource as a climate tool. Recognition of these uncertainties in integrated assessment models has been lacking, and we aim to contribute to the literature by reducing this gap.

In this paper, we address some uncertainties directly linked to forest carbon sequestration. Many aspects remain uncertain about the economics of climate change, and attention has been given to this recently in integrated assessment model literature (e.g., Ackerman et al. (2010); Cai et al. (2012); Golub et al. (2014)). There are multiple ways of conceptualizing uncertainty, and how we choose to model it will determine the robustness of the recommended policy. We use the state-contingent approach to incorporate uncertainty into an integrated assessment model with forest biomass. The main advantage of this approach is that it allows us to work with models that are too complex for stochastic dynamic programming (De Bruin et al., 2016), without having to rely on the commonly used Monte Carlo approach. Monte Carlo has been shown to derive unreliable optimal policies under uncertainty (Crost and Traeger, 2013).

The results of this paper indicate that forest uncertainty matters. Specifically, we find that the importance of including forest controls in climate policy increases when we model the uncertainty related to forests. These results imply that an optimal forest response allows us to reduce the costs associated with uncertainty.

This paper is outlined as follows. Section 2 describes our integrated assessment model. Section 3 explains our approach to include uncertainty and the unknown parameters. Section 4 presents the results. Section 5 concludes.

2 The Model

This paper is based on the FOR-DICE model by Eriksson (2015). The FOR-DICE model is an extension of the DICE-2007 model by Nordhaus (2008). The main feature of the FOR-DICE is the incorporation of the global forest biomass as three types of stocks, namely tropical forest, temperate forest, and boreal forest. In addition to the control variables of the original DICE-2007 model, investment and abatement, the optimization problem in the FOR-DICE model also includes bioenergy harvest and avoided deforestation. In this paper, we further extend the controls of the FOR-DICE model by including afforestation.

We asses in this paper whether the optimal choice of these control variables change when we account for key uncertainties regarding forest carbon sequestration. Uncertainty is implemented by using the state-contingent approach described in Section 3. This section briefly describes some of the main features of the model. Appendix A contains the equations of the model. Appendix B provides tables summarizing all parameters and variables.

Dynamics of the Forest

The dynamics of the forest biomass follows a logistic growth function formulation. In this non-linear formulation, the growth of forest biomass increases until the size of the stock is half of its carrying capacity. Beyond this midpoint, the growth of biomass decreases as the stock further approaches its carrying capacity. Besides the natural growth of the forest, the stock is also affected by harvest and changes in the forest area. Harvest consists of removals for goods and services, and removals for energy. While harvest decreases the size of the stock, it increases the growth rate of the forest biomass. Change in forest area comes from deforestation, afforestation, or climate change. These changes affect the biomass carry capacity of the land. Afforestation, or increase in forest area due to climate change, increases the growth potential of the forest biomass through an increased carrying capacity. Deforestation, or decrease in forest area due to climate change, reduces the growth potential through a decreased carrying capacity and decreased forest biomass. Accordingly, avoided deforestation will have a larger short-run benefit than afforestation.

Deforestation

Deforestation is mainly caused by the conversion of forest to agricultural land in the tropics. The tropical forest in the FOR-DICE model is subject to baseline deforestation, which can be reduced through the deforestation control variable. The path of the uncontrolled tropical deforestation is derived from the exogenous emissions from land in the DICE-2007 model. The cost of reducing this deforestation is derived from estimates by Kindermann et al. (2008). The cost can be seen as a rental payment to land owners necessary in each period to prevent the conversion of forest land. This rental payment will reoccur each future period because once forest land is conserved, it cannot be converted in future time periods. The avoiding deforestation policy covers all potential participants, and forest conversion prevented in one location cannot be reallocated to another location, this is known as leakages.

Afforestation

Another control of forest land is afforestation. Afforestation, in contrast to deforestation, involves increasing the forest area by converting non-forest land into forest land.[1] We extend the FOR-DICE model to include the possibility of afforestation in the tropical and temperate zone. These areas are established to have the largest carbon sequestration potential from afforestation (Sohngen and Mendelsohn, 2003). Afforestation, like avoided deforestation, displays increasing marginal cost curves due to the opportunity cost of land. However, in addition to the opportunity cost of land, afforestation efforts usually also require a plantation cost (Nabuurs and Masera, 2007).[2] Because of this cost, it is likely that afforestation is more expensive than avoided deforestation (van Kooten et al., 2004). Given the difficulty in modeling the opportunity cost of land there is a broad range of afforestation cost estimates (Richards and Stokes, 2004). We use the total agricultural production value per hectares from the Global Agro-Ecological Zones (GAEZ v3.0) geospatial dataset (Fischer et al., 2012) to estimate the value of land. Land areas unsuitable for afforestation are excluded. We compute cost curves from the raster data with Arc

[1] We also include reforestation in the concept of afforestation.

[2] We use a plantation cost of 800$/ha for the tropical and temperate zone. This cost equals the one used by Benítez et al. (2007) for tree plantation in Brazil.

GIS and perform symbolic regression to derive the afforestation cost equations.[3] Appendix C contains detailed information regarding the cost estimates.

Effects of Climate Change on the Forests

While the forest affects global warming through release and sequestration of carbon, the forest is also affected by the climate. Another extension of the FOR-DICE model is that climate change also impacts the forest. An increasing temperature affects the forest in two ways. First, by changing the growth rate of the existing forest biomass. Second, by changing the geographical distribution of the forest.

We model the first effect of climate change through the intrinsic growth rate of the forest biomass. While the relationship between the change in the growth rate and the temperature is negative in all forest zones under high warming scenarios, moderate warming scenarios have a positive effect on the boreal forest growth. Warmer temperatures are generally estimated to increase the boreal forest productivity, but the growth effect is counteracted by increases in insect outbreaks, storms, droughts and wildfires triggered by climate change (IPCC, 2014). Trees in boreal forests are in many cases growing below their temperature optimum and will, therefore, respond to an increase in temperature with a higher growth rate (Way and Oren, 2010). It is, however, likely that the boreal forests will be negatively affected by very high temperatures due to a rapid increase in forest dieback and disturbances (Scholze et al., 2006). Therefore, for the boreal forest, we model the net effect of climate change to be positive under moderate warming scenarios but negative under high temperatures. Conversely, trees in the tropics are already operating within their optimal temperature and will therefore not benefit from higher temperatures (Way and Oren, 2010). The growth rate of tropical forest in the hottest regions is expected to decrease due to temperatures reaching levels above the tolerance of the forest and a reduction in rainfall (IPCC, 2014). The negative relationship between the change in the temperature and the growth rate for the tropical forest is modeled to be small at low warming scenarios but highly nonlinear. Until recently, the temperate forest has shown increases in their growth rate in many regions, partly as a result of higher CO_2 concentration and longer growth periods. However, the forest is starting to show more signs of climate stress (IPCC, 2014). We model the relationship between the change in the temperature and the growth rate for the temperate forest to be nonlinear with

[3]This type of regression analysis simultaneously searches for the parameters and the functional form that best fits a given dataset, while minimizing the complexity of the expression. We use the mathematical software Eureqa to perform the symbolic regressions.

small effects at low and moderate warming scenarios.

As previously mentioned, climate change will also affect the geographical distribution of the forest. We model this effect of climate change through the carrying capacity and the size of the forest biomass. The carrying capacity increases in the case of an expansion of the forest area and decreases in the case of a reduction in forest cover. A reduction of forest land also leads to a direct loss of forest biomass. Distribution of forest biomass is generally restricted by either water availability or temperature (Kirschbaum et al., 1995). The boreal forest is predicted to exhibit a northward expansion into the tundra and to undergo a composition change towards more temperate forest species. The tropical forests are expected to undergo replacement by savannas due to forest dieback caused by higher temperatures and increased water stress (IPCC, 2014). Temperate forest area is expected to change the least compared to other forest zones (Kirschbaum et al., 1995). We model increased temperatures to increase boreal forest area and decrease the tropical forest area while the temperate forest area is assumed to be unchanged in the deterministic scenario. The relationship is nonlinear for all forest zones as Scholze et al. (2006) conclude that the risk of biome shifts depends strongly on the degree of warming. They show that risks are already apparent at temperatures below 2°C, and increase greatly for temperatures between 2 - 3°C, and even more for temperatures higher than 3°C. The effects of climate change will cover substantially larger areas if temperatures are higher than 3°C than for temperatures less than 2°C (Scholze et al., 2006).

Harvest

The total harvest is the sum of the industrial roundwood removals and woodfuel removals.[4] While harvest to produce energy is a control variable in all forest zones, the industrial roundwood harvest grows linearly with labor to maintain the simplicity of the model.[5] This simplification implies that the competition for biomass for energy and carbon storage will increase over time, with harvest to wood products being predominant.

[4]The definition of wood removals follows the definition by FAO. Industrial roundwood removals represent harvest for all goods and services except energy. Woodfuel removals represent all wood removed for industrial, commercial and domestic energy production purposes.

[5]According to FAO (2010), the global industrial roundwood harvest has been quite stable during the last decade and is expected to increase moderately.

Energy

Energy in FOR-DICE is a perfect complement to the constant return to scale Cobb-Douglas production function of labor and physical capital. The energy-output ratio is exogenously declining over time due to an increase in energy efficiency. Energy can either be of non-carbon-based types or carbon-based types. The non-carbon-based energy technologies, such as solar or nuclear power, is represented by the carbon control rate. The carbon-based energy comes from a constant return to scale Cobb-Douglas production function of fossil carbon and bioenergy harvest. The energy elasticities of bioenergy harvest are defined by their share of the total global energy production in the initial period.[6]

Emissions and Sequestration

Total carbon emissions come from two sources, i.e., from fossil fuels and forest biomass. The forest releases carbon through loss of biomass from bioenergy harvest, from industrial roundwood harvest, and from loss of forest area through deforestation or climate change.[7] However, these emissions are partly, or fully, offset by the sequestration of carbon that occurs with forest growth. This growth, net of the loss of forest biomass through harvest and the change of forest land, amounts to either net sequestration or emissions. Net sequestration takes place if the growth of forest biomass is greater than the total loss of forest biomass, and vice versa. The total net emissions from fossil fuels and the forest enter the geophysical equations of the DICE-2007 model causing the temperature to change.[8] The change in temperature affects economic output through the polynomial damage function of the DICE-2007.

3 Uncertainty

Modeling uncertainty is important for optimal decision making. To model uncertainty, the integrated assessment literature has primarily relied on stochastic optimization, and on the Monte Carlo approach. In this paper we focus on a third method: the state-contingent approach.

[6] Data on the harvest for energy production in each forest zone comes from FAO (2010), and data on the energy production is mainly from IEA. For more information about the calibration of the energy function, see Eriksson (2015).

[7] Carbon in the industrial roundwood harvest is released within one decade. Hence, we do not take into consideration long-lived wood products that can store the carbon for a considerable amount of time. Most of the harvested biomass is, however, already being lost in the processing chain (Ingerson, 2009).

[8] The reader is referred to Nordhaus (2008) for the geophysical equations of the DICE-2007 model.

In this section, we begin by describing the method we use to model uncertainty. We then describe the sources of uncertainty on which this method is applied.

3.1 State-contingent uncertainty

In this paper, we use the state-contingent approach to model parameter uncertainty. Only a few papers have so far used this method in the integrated assessment literature. In a pioneering study, Pizer (1999) determines optimal climate change policy under uncertainty by using a dynamic contingent state approach in a DICE model setting. De Bruin et al. (2016) further builds on this approach by assessing the effects of uncertainty on adaptation and mitigation with multiple uncertain parameters, including several parameters with fat-tailed distributions.

The state-contingent approach is a form of non-recursive stochastic programming and introduces uncertainty as multiple states of the world.[9] The random parameters in each state are drawn from known or estimated distributions in advance, so uncertainty is partly resolved before optimization. In this model, we make our drawings from probability distributions of parameters affecting: the exogenous growth rate of the forest, the climate change effect on the forest growth, and the climate change effect on the forest cover. The sample points define the state space, which means that each state has a unique set of parameters and variables, populated by draws from assigned distributions. Hundreds of states are used to simultaneously determine the optimal policies for each scenario. This large number of states is necessary to explore the realistic policy consequences of uncertainty, otherwise important features of the uncertain parameter space may go unrecognized.

The optimal policy is found by maximizing the state probability weighted sum of utility in each state.[10] At optimization, it is not known which state will occur, hence, the policy maker has to take into account all potential futures. Given equal state probability weights, the objective function is written as:

$$\max_{I_t,\mu_t,\nu_t} \frac{1}{S}\sum_{s=1}^{S} W_s(.) \tag{1}$$

where $s = \{1, ...S\}$ is the state index and W_s is the welfare in one state, described by Equation 29

[9] In this paper, a state refers to a set of parameter realizations. This should not be confused with the term state variable sometimes used in the literature, which we instead refer to as stock variable.

[10] Because of the complexity of the problem, a solution can only be obtained numerically.

in Appendix A. The control variables are: investment I_t, carbon control rate μ_t, and a set of forest control variables ν_t (bioenergy harvest, avoided deforestation and afforestation). In this setting, the policy maker has to simultaneously evaluate the consequences of policies in all states. This includes accounting for the fact that a policy that raises the utility in one state might decrease the utility in another. This can be viewed in contrast to the Monte Carlo approach where the policy maker optimizes each state of the world separately and then averages the resulting paths. The Monte Carlo approach is often used in integrated assessment models to simulate uncertainty (e.g., Nordhaus (2008) and Ackerman et al. (2010)). This approach is, however, essentially an averaged sensitivity analysis where uncertainty is not part of the decision process. Crost and Traeger (2013) show that the results from the Monte Carlo approach can be misleading, not only in terms of magnitudes but also in the direction of the effects of uncertainty.

While stochastic dynamic programming (SDP) is the most comprehensive approach to model uncertainty, these models are inherently difficult to solve and suffer from the so-called curse of dimensionality. Each stock, control, and stochastic variable adds a dimension to the problem, making it hard or impossible to solve numerically for high dimensions. Most of the DICE implementations using SDP have proposed ways to reduce the dimensionality problem (e.g., Kelly and Kolstad (1999), Cai et al. (2012), and Crost and Traeger (2013)). The SDP framework has many advantages, including the ability to model shocks and the endogenous updating of probability distributions. Nonetheless, in a SDP framework it would be very difficult to model the forest with sufficient detail. All in all, while the state-contingent framework limits the complexity of the uncertainty that can be modeled, it does allows us to use a model that includes significantly more dimensions than the original DICE model.

3.2 Parameters subject to uncertainty

As explained above, uncertainty in this model is derived from unknown parameter values. In this section, we describe the subset of parameters for which we implement uncertainty.

Our prior is that parameters are independently and normally distributed around their deterministic value.[11] The value of the standard deviation is chosen so that for, at least, draws within two standard deviations, the forest outcome is within reasonable values. While these standard deviation values are conjectural, we investigate the sensitivity of the results to these assumptions

[11] While it might be reasonable to assume that there exist some correlation between the different uncertain parameter in nature, we do not attempt to model such a relationship in this paper.

in Appendix E. To conform with biological constraints, such as non-negative intrinsic growth rates, we further restrict our distributional choices by truncating the distributions when appropriate. These truncations guarantee that the results will be consistent with nature even in the case of low probability draws. Table 1 provides an overview of the uncertain parameters and their distributional assumptions.

Table 1: Uncertainty parameters

Parameter	Description	Distribution [mean, std dev, low limit, high limit]
$\widetilde{\psi}_{tro,t=1}$	Initial intrinsic growth rate	$TN[0.1989, 0.022, 0, 1]$
$\widetilde{\psi}_{tem,t=1}$	Initial intrinsic growth rate	$TN[0.3726, 0.022, 0, 1]$
$\widetilde{\psi}_{bor,t=1}$	Initial intrinsic growth rate	$TN[0.1128, 0.022, 0, 1]$
$\widetilde{\phi}_{1tro}$	Temperature-growth parameter	$TN[-0.04, 0.02, -10, 10]$
$\widetilde{\phi}_{1tem}$	Temperature-growth parameter	$TN[-0.03, 0.015, -10, 10]$
$\widetilde{\phi}_{1bor}$	Temperature-growth parameter	$TN[0.79, 0.027, 0, 10]$
$\widetilde{\kappa}_{1tro}$	Temperature-forest cover parameter	$TN[-20, 10, -\infty, 0]$
$\widetilde{\kappa}_{1tem}$	Temperature-forest cover parameter	$N[0, 2]$
$\widetilde{\kappa}_{1bor}$	Temperature-forest cover parameter	$TN[20, 10, -\infty, 0]$

3.2.1 Intrinsic growth rate of the forest

A key source of uncertainty in assessing global carbon sequestration is the dynamics of forest biomass. Recognizing this uncertainty is important because global carbon sequestration models may be sensitive to the assumptions made on the forest growth rate. The dynamics of the forest biomass in this model follows a logistic growth function formulation. Hence, the growth rate of the forests depends on the intrinsic growth rate and the size of the stock relative to its carrying capacity.[12] We take this direct forest growth uncertainty into account by assuming that the initial intrinsic growth rate, $\widetilde{\psi}_{n,t=1}$, for the boreal, temperate, and tropical forest are unknown with truncated normal distributions.

3.2.2 Climate effects on the forest

Boreal, tropical and temperate forests will undoubtedly be affected by a warmer climate, although the impact is ambiguous. Climate change is expected to affect forests through a large number of channels that could have many interactions, threshold effects, and nonlinearities. Accordingly,

[12]We use the intrinsic growth rates of the FOR-RICE model. These rates are calibrated with FAO data under the assumption that the initial carrying capacity is twice as large as the initial stock of growing biomass.

the net impact of atmospheric CO_2 concentrations and temperatures beyond observed levels are highly uncertain. Forests in our model are affected by climate change through two mechanisms: changes in the dynamics of the existing forest and changes of the geographical distribution of the forest. Here we implement uncertainty for both of these mechanisms. First by implementing uncertainty of the climate effect on the intrinsic growth rate. Second by implementing uncertainty of the climate effect on the change in forest area.

Climate effect on the intrinsic growth rate

The intrinsic growth rate of forest biomass is affected by climate change through a temperature-growth function. The function for each type of forest is derived to capture the key features of the relationship between these two variables as described in the literature. See the previous section for a discussion of the literature. Specifically, these functions represent a percentage change of the initial intrinsic growth rate caused by a warmer climate. The temperature-growth function for the tropical and temperate forest is written as:

$$TI_{n,t} = \widetilde{\phi}_{1n} \Delta T_t^2 \tag{2}$$

and for the boreal forest is written as:

$$TI_{bor,t} = \widetilde{\phi}_{1bor} \Delta T_t^2 + \phi_{2bor} \Delta T_t^3 + \phi_{3bor} \Delta T_t^4 + \phi_{4bor} \Delta T_t \tag{3}$$

ΔT_t is the increase in the global mean temperature from the first time period. ϕ_{2n}, ϕ_{3n}, and ϕ_{4n} are deterministic temperature-growth parameters. The temperature-growth parameter for each type of forest, $\widetilde{\phi}_{1n}$, are unknown with truncated normal distributions.

Figure 1 to Figure 3 shows the percentage effect on the intrinsic growth rate of the boreal, temperate, and tropical forest under different levels of temperature increase. The dashed lines show the effect of an uncertain parameter value one standard deviation higher, and lower, than the deterministic value. Figure 1 shows that the boreal forest productivity increases under moderate warming of the climate while higher temperatures lead to a negative effect on the forest growth. The initial positive growth effect will, at an unknown temperature increase, be dominated by the increase in insect outbreaks, storms, droughts and wildfires expected by climate change.

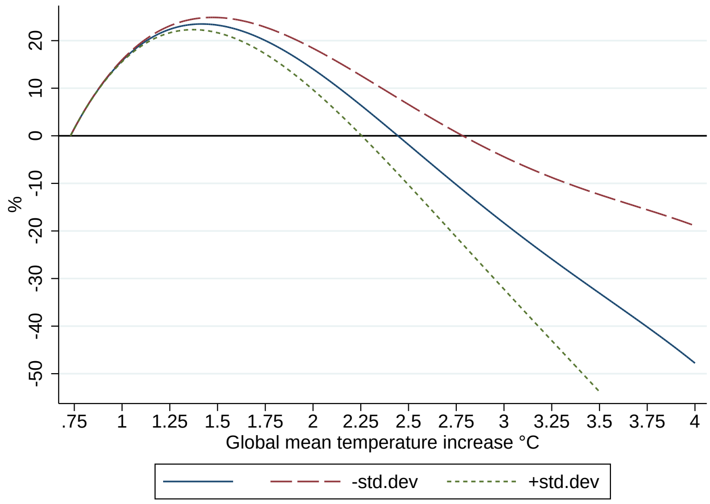

Figure 1: Climate change effect on the boreal intrinsic growth rate, %

The net growth effect on the temperate and tropical forest, on the other hand, is negative already at moderate warming scenarios, as shown in Figure 2 and Figure 3. The nonlinear growth effect is larger for the tropical forest, as the sensitivity of the tropical forest is expected to be more extensive.

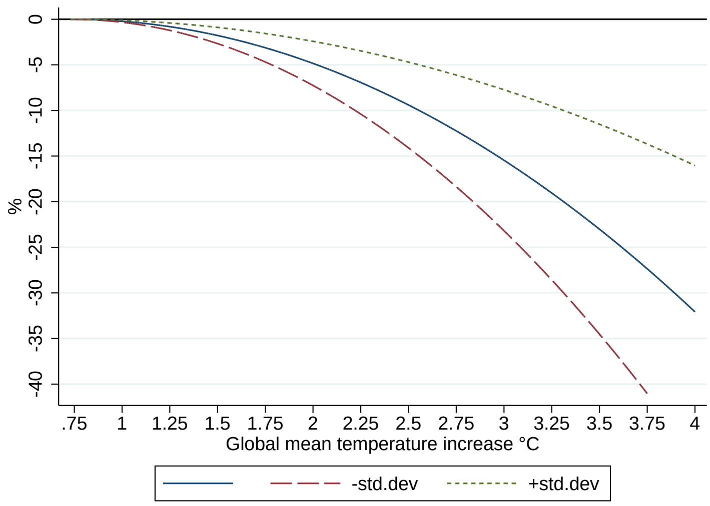

Figure 2: Climate change effect on the temperate intrinsic growth rate, %

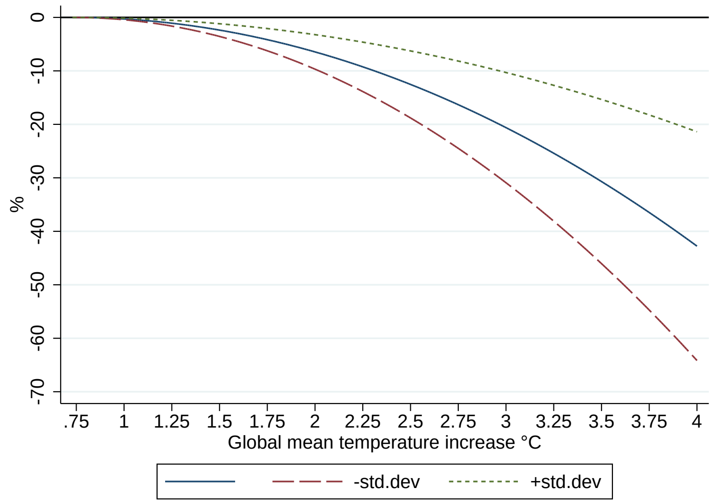

Figure 3: Climate change effect on the tropical intrinsic growth rate, %

Climate effect on the forest area

The size of the forest area is affected by climate change through a temperature-forest-area function. As in the previous case, this function is derived with the objective of capturing the key features of the relationship between these two variables as described in previous literature. The proposed non-linear function that describes the hectare change in forest area induced by climate change, is written as:

$$TF_{n,t} = \widetilde{\kappa}_{1n} \Delta T_t^2 \tag{4}$$

where $\widetilde{\kappa}_{1n}$ is an uncertain temperature-land parameter and ΔT_t is the increase in the global mean temperature. The uncertain temperature-forest-area parameter, $\widetilde{\kappa}_{1n}$, is normally distributed for all forest zones.

Figure 4 - 6 show, for the boreal, temperate and tropical forest, the hectare change in forest area under different levels of temperature increase. The dashed lines represent the effect on the forest land area with the uncertain parameter value one standard deviation higher, or lower, than the mean value. Figure 4 shows a positive nonlinear effect on the boreal forest area, Figure 5 shows a zero expected effect on the temperate forest area, and Figure 6 shows a negative nonlinear effect on the tropical forest area.

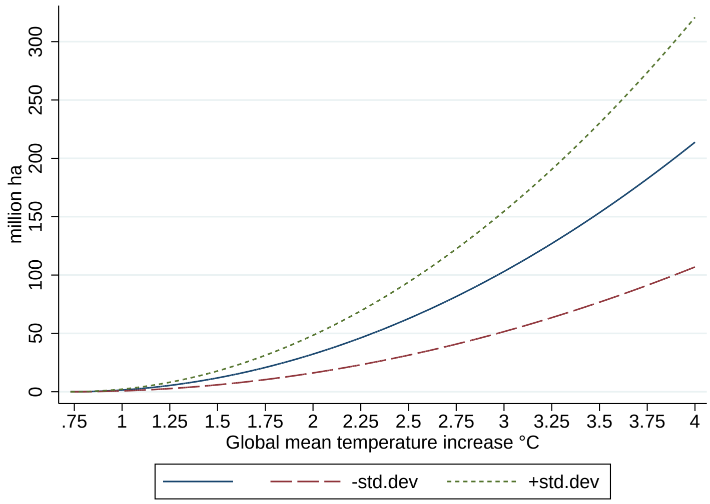

Figure 4: Climate change effect on the boreal forest cover, million ha

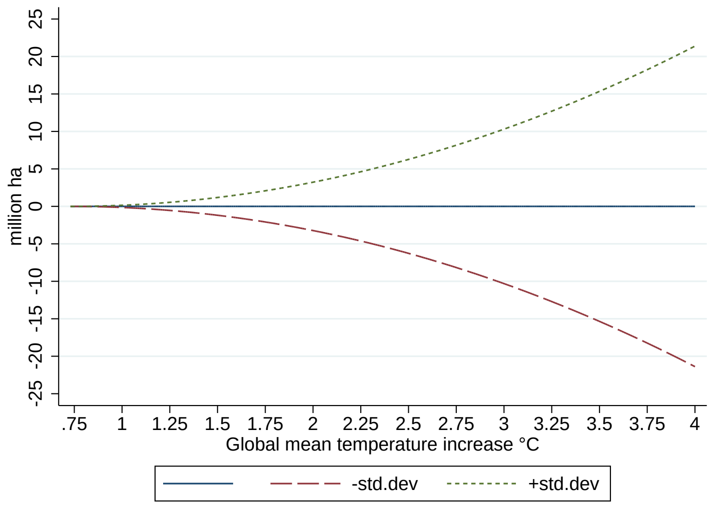

Figure 5: Climate change effect on the temperate forest cover, million ha

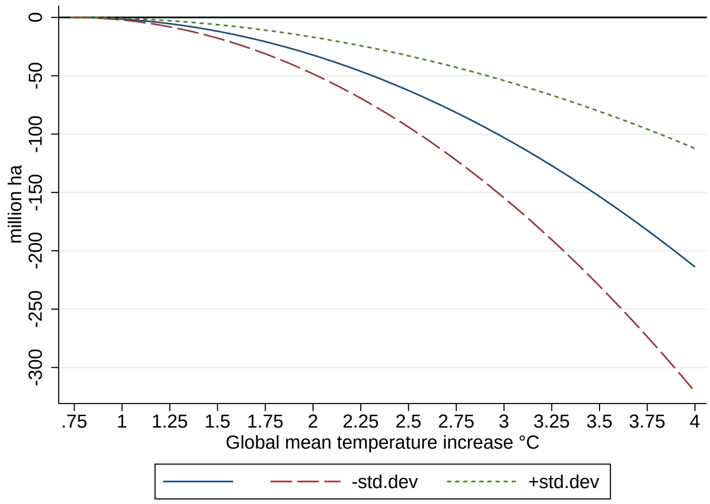

Figure 6: Climate change effect on the tropical forest cover, million ha

4 Results

In this section, we show how uncertainty impacts climate policy. The optimal policy is found by choosing the level of savings, the carbon control rate, and the forest controls, which maximizes the present value of the weighted sum of welfare in all states. The forest controls include: bioenergy harvest in all zones, afforestation in the tropical and the temperate zone, and deforestation in the tropical zone. To investigate the role of using the forest in climate policy we run four main scenarios: Optimal forest control (FC), No forest control (NFC), Optimal forest control with uncertainty (UncFC), and No forest control with uncertainty (UncNFC). Optimal forest control corresponds to choosing all control variables of the model. No forest control corresponds to choosing the level of savings and the carbon control rate. Uncertainty throughout the results section refers to uncertainty about forest parameters, as described in Section 3. Table 2 lists the main scenarios of the paper. In addition to the main scenarios, we also run a 2°C scenario in Appendix D where the global mean temperature increase is limited to 2°C. In Appendix E, we test the sensitivity of the result with respect to the standard deviation of the unknown parameters.

Table 2: Scenarios

	Scenarios
NFC	No forest control and no uncertainty
FC	Optimal forest control and no uncertainty
$UncNFC$	No forest control under forest uncertainty
$UncFC$	Optimal forest control under forest uncertainty

The figures in this section cover the 2015 to 2115 period. For the analysis, we define the period before 2045 as the short run; the period between 2045 and 2085 as the medium run; and the period after 2085 as the long run. While the control variables are constant across states, other variables can vary between states as a result of the random parameter draws. Accordingly, we calculate the distribution for some variables of the latter type and use the expected value for comparison in the analysis.

We begin by analyzing the effect of uncertainty on the forest controls. Figure 7 shows the optimal bioenergy harvest for the three types of forest. By comparing the FC and the UncFC curve, we can see that the effect of including uncertainty in the forest control scenarios differs across forest types. The temperate forest shows an uncertainty effect on the bioenergy harvest with both a lower initial level and a greater decline over time. The impact of uncertainty on the bioenergy harvest for the tropical and the boreal forest is, on the other hand, insignificant. The rebalancing of forest controls that occurs when uncertainty is introduced differs across forest types because of their different properties. The reason it is optimal to reduce bioenergy harvest in the temperate forest comes from the objective of reducing emissions. Note that the expected sequestration value of preserving the temperate forest is higher as the temperate forest biomass will have a higher expected growth rate.

If we instead compare the optimal bioenergy harvest curves to the NFC curves, we find that the NFC harvest is non-optimal in all forest zones, both with and without uncertainty. The NFC curve is higher than the optimal forest control for the tropical and boreal forest while lower for the temperate forest. This result derives from differences in the carbon content of biomass, the bioenergy efficiency, and the growth rate of the biomass in each forest zone. The NFC tropical bioenergy harvest is high due to extensive use of wood fuel in the tropical region. The efficiency of the bioenergy conversion is, however, low and the carbon released from bioenergy production is high. Hence, it is optimal to have a more moderate tropical bioenergy harvest. The reason for the lower optimal boreal bioenergy harvest comes from its low biomass growth rate. The temperate forest control is higher both with and without uncertainty due to the high efficiency of the energy conversion and a high forest growth rate.

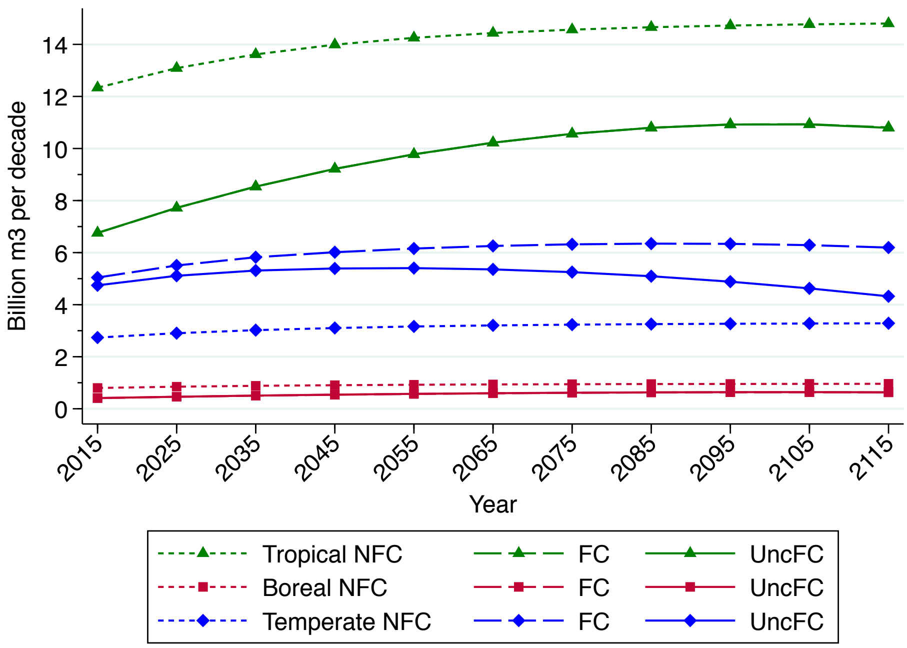

Figure 7: Harvest to bioenergy production, billion m^3 per decade

We next consider the afforestation controls. Figure 8 shows the cumulative hectare of tropical and temperate afforestation for the FC and the UncFC scenario. The figure does not contain the NFC scenario as the baseline afforestation is zero. While the tropical afforestation is slightly lower under uncertainty, the temperate afforestation is higher. The effect of uncertainty is, as in the case of bioenergy harvest, initially small but increasing over time for the temperate forest. The cumulative temperate afforestation is almost 30% higher under uncertainty by 2115. Given that we want to lower the expected value emissions under uncertainty, the temperate forest seems to be a more efficient tool than the tropical forest. The expected value of the growth rate of the temperate forest is higher while the difference in the marginal cost of land between the zones is small at this levels of afforestation.

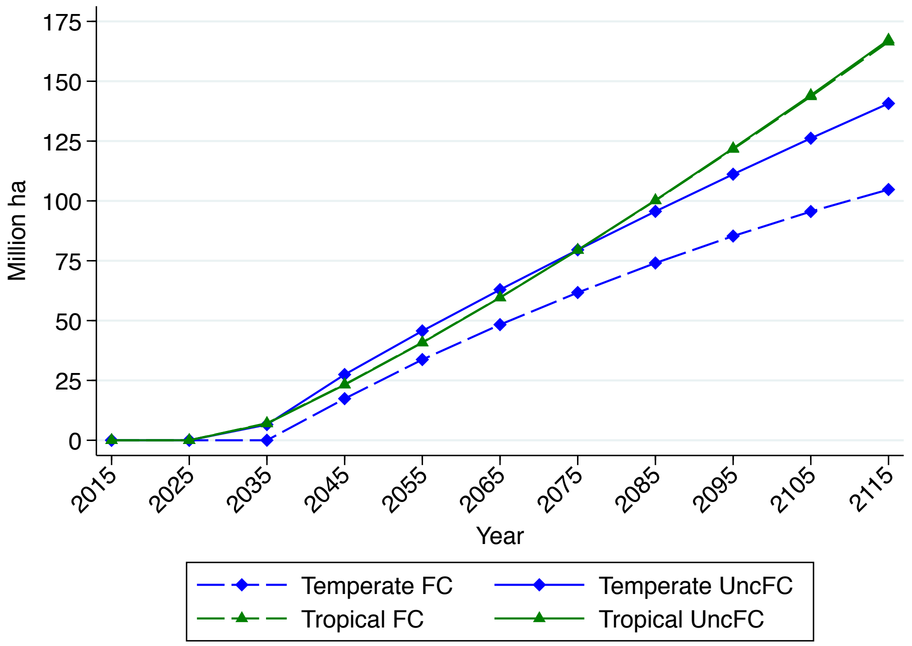

Figure 8: Tropical and temperate cumulative afforestation, million ha

In addition to the forest controls discussed above, the tropical forest also has avoided deforestation. The deforestation control rate represents the fraction of baseline deforestation that is avoided. While the level of baseline deforestation is exogenously decreasing over time, the optimal deforestation control rate increases until deforestation is fully avoided by the year 2115. In our results, uncertainty has a small impact on the avoided deforestation rate. Rebalancing avoided deforestation to decrease the cost of uncertainty seems to be inefficient. This occurs because increasing the level of avoided deforestation, even slightly, would increase the cost significantly as the marginal cost is highly non-linear.

On the whole, with and without uncertainty, optimal forest controls leads to a larger global stock of forest biomass. We can see in Figure 9 that both the stochastic and deterministic value of net sequestration is higher under forest control than under no forest control. The FC and the UncFC curve shows a positive net sequestration while the NFC and the UncNFC curve shows net emissions from forest starting in 2025. The result for the optimal net sequestration comes from afforestation, avoided deforestation, and the reduction of tropical bioenergy harvest. Note that, while afforestation only leads to higher sequestration, the effect of avoiding deforestation and of reducing the bioenergy harvest, leads to both higher sequestration and an immediate reductions in emissions.

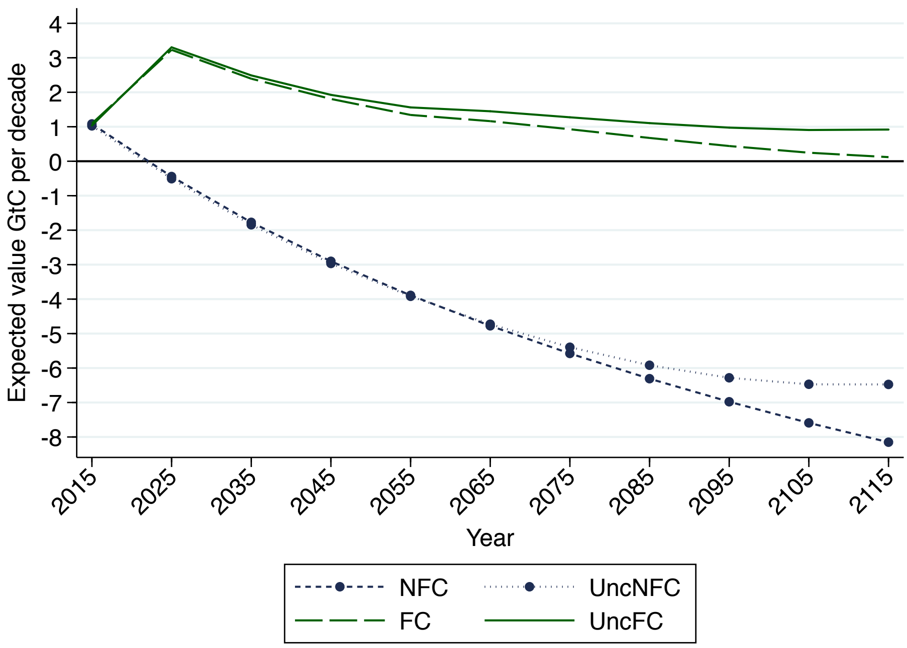

Figure 9: Expected value of carbon sequestration net of forest emissions, GtC per decade

The emissions from the forest without forest control are mainly driven by baseline deforestation and by bioenergy harvest in the tropical zone. The difference in sequestration between the uncertainty and the deterministic scenario under forest control is, however, driven by the difference in the temperate forest controls. The forest controls in the temperate forest seem to be efficient instruments to decrease the cost of uncertainty. The rebalancing of the forest controls that occurs to reduce the cost associated with uncertainty leads to a larger temperate forest stock. We can see in the figure above that the expected value of sequestration is higher for the UncFC scenario than for the FC scenario from the year 2055. For the case without forest controls, the UncNFC curve overlaps with the NFC curve until the year 2065 when the UncNFC curve surpasses the NFC curve. Because forest controls are exogenous in both these scenarios, the higher long-run sequestration value comes from the difference in the climate effect on the forest. The expected value of temperature is lower under uncertainty without forest control, which means a lower climate impact on the forest and a lower net sequestration.

Besides the forest controls, we can use non-carbon-based energy as a tool to reduce global emissions. The carbon control rate, shown in Figure 10, represents the share of non-carbon-based energy in the global economy. We can see that the forest controls do not affect the optimal carbon control rate if we do not have uncertainty. Furthermore, by looking at the FC and the UncFC curve, we can see that introducing uncertainty does not change the carbon control rate when we have forest controls. However, without the possibility to rebalance the forest controls under uncertainty, the carbon control is initially higher and increasing over time at a higher rate.

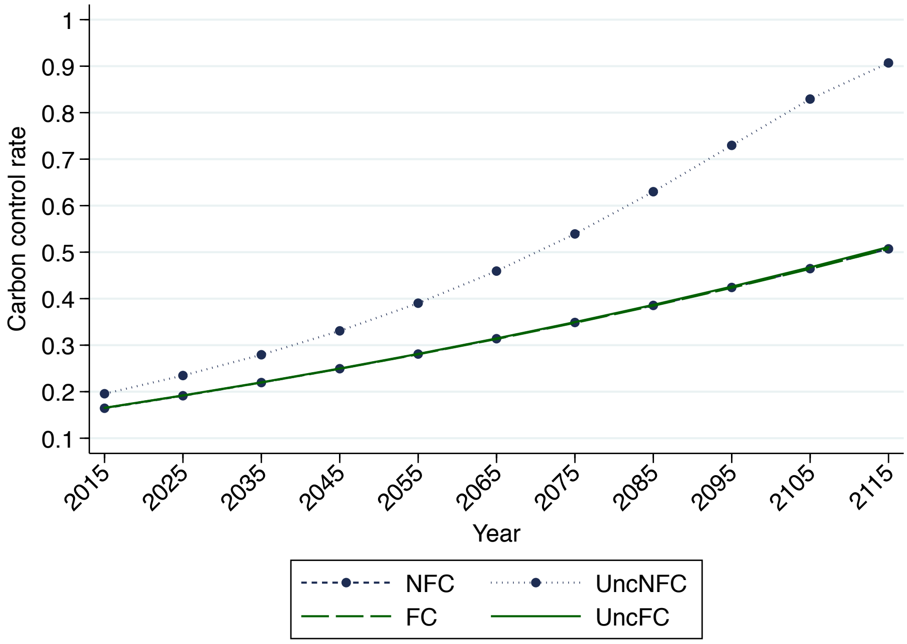

Figure 10: Carbon control rate, fraction of uncontrolled emissions

The carbon control rate together with the forest controls will limit the expected global mean temperature increase as shown in Figure 11. The NFC curve indicates that the temperature will be higher when uncertainty is not taken into account. We can also see that uncertainty does not affect the temperature if we have forest controls. However, including uncertainty without forest control leads to lower expected temperature in the medium to long run. This lower temperature is derived from the higher carbon control rate, shown in the previous figure. The cost associated with uncertainty cannot be reduced by the rebalancing of the forest controls in the UncNFC scenario, but is instead managed by a vast increase in the carbon control rate.

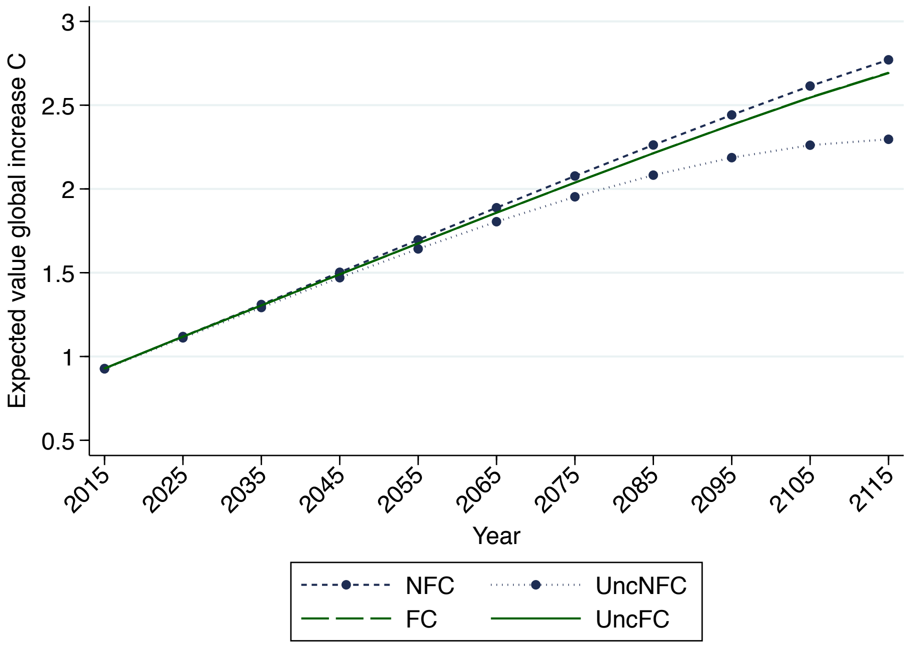

Figure 11: Expected value of global mean temperature increase °C

Differences in the figures shown in this section give us little information about the welfare consequences of forest uncertainty. To get an indication of the welfare gain from having the possibility to rebalance the forest controls we can turn to the objective value, the maximized sum of discounted utilities over all states and time. Table 3 shows that the objective value is the lowest when we have uncertainty and no possibility to rebalance the forest controls. However, we can also see that the cost of uncertainty can in large part be avoided under optimal forest controls. We can see that the benefit of using the forest carbon sequestration optimally increases under uncertainty.

Table 3: Objective value

Scenarios	NFC	FC	$UncNFC$	$UncFC$
Objective value	150 411	150 445	150 210	150 442

We can also see that uncertainty is costly without optimal forest controls by studying the carbon price. Table 4 shows the expected value of carbon price in the different scenarios. The carbon price balances the incremental cost of reducing carbon emissions with the incremental benefits of reducing damages. Without uncertainty, we only reach a slightly higher carbon price if we do not have forest controls. Under uncertainty, however, only using the carbon control rate to curb climate change proves to be costly. The carbon price by the year 2075 is more than twice as large for the UncNFC than for UncFC scenario.

Table 4: Expected value carbon prices, 2005 U.S. dollar per tC

	2015	2035	2055	2075
NFC	41.6	66.3	98.0	137.7
FC	41.4	66.0	97.6	137.5
$UncNFC$	57.0	102.9	179.2	309.0
$UncFC$	41.5	66.2	97.9	138.0

Appendix D explores the results of imposing a temperature limit of 2°C. This restriction implies lower emissions than in the main scenario and is attained by an increased carbon control rate and by changes in the forest controls. The changes in the forest controls include higher avoided deforestation, lower bioenergy harvest, and higher afforestation. By and large, the uncertainty effect on the controls is larger under the 2°C limit than in the main scenario.

The sensitivity of the results with respect to the level of uncertainty is investigated in Appendix E. Specifically, we explore how changes in the size of the standard deviations of the unknown parameters affect the results. The analysis focuses on the temperate forest controls as the forest controls for the tropical and boreal forest remain non-sensitive to uncertainties of these magnitudes. In the case of the temperate forest, we find, by and large, that lower standard deviations of the unknown parameters lead to less afforestation and more bioenergy harvest, and vice versa.

5 Conclusion

This paper studies the consequences of forest carbon sequestration uncertainties for optimal mitigation policy by constructing a state-contingent optimization model based on the integrated assessment model FOR-DICE by Eriksson (2015). This approach allows us to optimize over numerous possible states of the world to realistically assess a single course of action under uncertainty. The FOR-DICE is an extension of DICE 2007, with additional stock variables and multiple stochastic variables, giving a complexity that rules out any attempt to use stochastic dynamic programming. To our knowledge, the state-contingent method is the only way to solve a stochastic model like this and to find robust optimal policies. The importance of including uncertainty is attained by comparing the results from this optimal climate policy under uncertainty to the result derived from a more typical optimization with a single set of parameter values.

We find that ignoring uncertainties associated with forest carbon sequestration will give the wrong balance between different mitigation controls and a biased estimate of costs and hence the wrong carbon price. Accordingly, the results when evaluating climate policies will be misleading. The necessary rebalancing of the forest controls in our model mainly concerns the temperate forest, which seems to be an important tool to reduce the cost of uncertainty. More afforestation and less bioenergy harvest are optimal under uncertainty as the marginal benefit of temperate sequestration increases when forest parameters are uncertain. While uncertainty leads to a relatively small rebalancing of the controls initially, the controls with and without uncertainty increasingly diverge over time. Because of the aggregated nature of the model, these results can only be indicative to further research.

The forest is a cost-effective tool for mitigating climate change, regardless of whether uncertainty concerning the sequestration potential and climate feedbacks are taken into account. However, the importance of using the forest optimally in climate policy increases when we include forest sequestration uncertainties. Our results show that the welfare gain from using the forest optimally in climate policy is greater under uncertainty. Without the possibility to rebalance the forest controls under uncertainty, we will experience high costs from reducing emissions by vast increase non-carbon fuels. On the whole, including forest controls in the set of mitigation tools makes us more resilient to uncertainty.

References

Ackerman, F., Stanton, E. A., and Bueno, R. (2010). Fat tails, exponents, extreme uncertainty: Simulating catastrophe in dice. *Ecological Economics*, 69(8):1657–1665.

Benítez, P. C., McCallum, I., Obersteiner, M., and Yamagata, Y. (2007). Global potential for carbon sequestration: Geographical distribution, country risk and policy implications. *Ecological Economics*, 60(3):572–583.

Cai, Y., Judd, K. L., and Lontzek, T. S. (2012). Dsice: A dynamic stochastic integrated model of climate and economy. *Center for Robust Decision-Making on Climate Policy, Working Paper*, (12-06).

Crost, B. and Traeger, C. P. (2013). Optimal climate policy: uncertainty versus monte carlo. *Economics Letters*, 120(3):552–558.

De Bruin, K., Krishnamurthy, C. K., and Vesterberg, A. (2016). The effects of uncertainty on adaptation and mitigation policy setting: an iam application. Unpublished manuscript. CERE and Umeå University.

Eriksson, M. (2015). The role of the forest in an integrated assessment model of the climate and the economy. *Climate Change Economics*, 6(3).

FAO (2010). *Global Forest Resources Assessment 2010 Main Report*. FAO.

Fischer, G., Nachtergaele, F., Prieler, S., Teixeira, E., Tóth, G., van Velthuizen, H., Verelst, L., and Wiberg, D. (2012). Global agro-ecological zones (gaez v3. 0): Model documentation. *International Institute for Applied systems Analysis (IIASA), Laxenburg. Rome, Italy: Austria and the Food and Agriculture Organization of the United Nations (FAO).*

Golub, A., Narita, D., and Schmidt, M. G. (2014). Uncertainty in integrated assessment models of climate change: alternative analytical approaches. *Environmental Modeling & Assessment*, 19(2):99–109.

Ingerson, A. (2009). Wood products and carbon storage: Can increased production help solve the climate crisis. *Washington, DC: The Wilderness Society.*

IPCC (2014). Climate change 2014: Impacts, adaptation, and vulnerability. part b: Regional aspects. contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change.

Kelly, D. L. and Kolstad, C. D. (1999). Integrated assessment models for climate change control. *International yearbook of environmental and resource economics*, 2000:171–97.

Kindermann, G., Obersteiner, M., Sohngen, B., Sathaye, J., Andrasko, K., Rametsteiner, E., Schlamadinger, B., Wunder, S., and Beach, R. (2008). Global cost estimates of reducing carbon emissions through avoided deforestation. *Proceedings of the National Academy of Sciences*, 105(30):10302–10307.

Kirschbaum, M. U., Fischlin, A., Cannell, M., Cruz, R., Galinski, W., Cramer, W., et al. (1995). Climate change impacts on forests. *Climate change*, pages 95–129.

Nabuurs, J. and Masera, O. (2007). Chapter 9, forestry. ipcc fourth assessment report.

Nordhaus, W. D. (2008). *A question of balance: Weighing the options on global warming policies.* Yale University Press.

Pizer, W. A. (1999). The optimal choice of climate change policy in the presence of uncertainty. *Resource and Energy Economics*, 21(3-4):255–287.

Richards, K. R. and Stokes, C. (2004). A review of forest carbon sequestration cost studies: a dozen years of research. *Climatic change*, 63(1-2):1–48.

Scholze, M., Knorr, W., Arnell, N. W., and Prentice, I. C. (2006). A climate-change risk analysis for world ecosystems. *Proceedings of the National Academy of Sciences*, 103(35):13116–13120.

Sohngen, B. and Mendelsohn, R. (2003). An optimal control model of forest carbon sequestration. *American Journal of Agricultural Economics*, 85(2):448–457.

van Kooten, G. C., Eagle, A. J., Manley, J., and Smolak, T. (2004). How costly are carbon offsets? a meta-analysis of carbon forest sinks. *Environmental science & policy*, 7(4):239–251.

Way, D. A. and Oren, R. (2010). Differential responses to changes in growth temperature between trees from different functional groups and biomes: a review and synthesis of data. *Tree Physiology*, pages 669–688.

Appendix A: Equations of the model

This section presents most of the equations of the model. We refer the reader to Nordhaus (2008) for omitted equations. The forest zone is denoted by n, where $n = \{bor, tem, tro\}$ represents the boreal, the temperate and the tropical forest. For simplification, we omit the state index, s, in the notation. The tilde ($\sim$) marks unknown parameters for which we make distributional assumptions, as discussed in Section 3.1.

Dynamics of the forest

The dynamics of the forest biomass is written as:

$$F_{n,t+1} = F_{n,t} + \psi_{n,t} F_{n,t} \left[1 - \frac{F_{n,t}}{F_{n,t}^{MAX}} \right] - H_{n,t} - D_{n,t} - B_{n,t}, \tag{5}$$

where $F_{n,t}$ is the stock of forest biomass, $\psi_{n,t}$ is the intrinsic growth rate and $H_{n,t}$ is the total harvest. $D_{n,t}$ and $B_{n,t}$ are loss of forest biomass due to decrease of forest land. $D_{n,t}$ represents loss from deforestation and $B_{n,t}$ represents loss from climate change. The forest biomass carrying capacity is written as:

$$F_{n,t+1}^{MAX} = F_{n,t}^{MAX} - \frac{F_{n,t}^{MAX}}{F_{n,t}} D_{n,t} + A_{n,t} + G_{n,t}. \tag{6}$$

The fraction $\frac{F_{n,t}^{MAX}}{F_{n,t}}$ is a rescaling to convert biomass deforestation, $D_{n,t}$, into biomass carrying capacity. $A_{n,t}$ represents an increase in carrying capacity from afforestation. $G_{n,t}$ represents an increase, or decrease, of the carrying capacity from a climate induced change in forest area.

Deforestation

The baseline deforestation in the FOR-DICE model comes from converting the exogenous DICE-2007 model emissions from land, $\Gamma_{tro,t}$, to biomass deforestation using the tropical carbon intensity parameter, θ_{tro}. The total tropical biomass deforestation in any time period is given by:

$$D_{tro,t} = \frac{\Gamma_{tro,t}}{\theta_{tro}}(1 - RD_t), \tag{7}$$

where $\frac{\Gamma_{tro,t}}{\theta_{tro}}$ represents the baseline deforestation in terms of forest biomass, RD_t is the deforestation control rate and represents the reduction of deforestation as a fraction of the baseline deforestation. The net reduction of direct emissions from deforestation is then given by:

$$RE_t = \Gamma_{tro,t} RD_t. \tag{8}$$

The marginal cost of avoiding deforestation is written as:

$$MD_{tro,t} = o_1 RE_{tro,t}^{o_2} + \left[(o_3 + o_4 t)^{(o_5 RE_{tro,t})} - 1\right] \tag{9}$$

where $RE_{n,t}$ is the reduction of direct carbon emissions from deforestation. o_1, o_2, o_3, o_4, and o_5 are cost parameters. The marginal cost increases with the level of reduction of carbon emissions. This occurs because land with low opportunity cost is adopted first, while deforestation in later time periods requirers land with higher opportunity cost. The total cost of avoiding deforestation is written as:

$$CD_{t+1} = CD_t + \int_0^{RE_{t+1}} MD_{t+1}(x)dx, \tag{10}$$

which is the sum of the rental payment to previously hindered conversion and the marginal costs up to a chosen level of emissions reduction, RE_{t+1}.

Afforestation

We include the possibility of afforestation in the tropical and temperate zone. Afforestation increases the growth potential of the forest biomass through an increased carrying capacity. The increased carrying capacity from afforestation is written as:

$$A_{n,t} = \xi_n HA_{n,t}, \tag{11}$$

which is the hectares of land afforested, $HA_{n,t}$ times the biomass carrying capacity per hectare,

ξ_n. The afforestation plantation cost,

$$PA_{n,t} = \tau_n HA_{n,t}, \tag{12}$$

is the per hectare cost of planting forest, τ_n, times the amount of of land being afforested, $HA_{n,t}$. The marginal rental cost of land, $MA_{n,t}$, is derived from the agricultural production value of land. The rental cost of afforestation in each time period,

$$RA_{n,t} = \int_0^{HC_{n,t}} MA_{n,t}(x)dx, \tag{13}$$

is the integral of the marginal cost function up to the cumulative hectare afforested, $HC_{n,t} = \sum_0^t HA_{n,t}$. Together with the afforestation plantation cost we get the total cost of afforestation in each time period:

$$CA_{n,t} = RA_{n,t} + PA_{n,t}. \tag{14}$$

Appendix C contains a detailed description of the marginal cost of afforestation.

Effects of Climate Change on the Forests

The intrinsic growth rate is written as:

$$\psi_{n,t} = \widetilde{\psi}_{n,t=1}(1 + TI_{n,t}), \tag{15}$$

where $\widetilde{\psi}_{n,t=1}$ is the initial intrinsic growth rate and $TI_{n,t}$ is the percentage change induced by climate change. The net effect of climate change is negative for the temperate and the tropical forest for all levels of warming. The effect on the boreal forest, on the other hand, is positive under moderate warming scenarios but negative under high temperatures. The temperature-intrinsic growth rate function for the tropical and temperate forest is written as:

$$TI_{n,t} = \widetilde{\phi}_{1n}\Delta T_t^2 \tag{16}$$

and for the boreal forest is written as:

$$TI_{bor,t} = \widetilde{\phi}_{1bor}\Delta T_t^2 + \phi_{2bor}\Delta T_t^3 + \phi_{3bor}\Delta T_t^4 + \phi_{4bor}\Delta T_t \tag{17}$$

where ΔT_t is the increase in the global mean surface temperature from the first time period, $\widetilde{\phi}_{1n}$ is an uncertain temperature-growth parameter. ϕ_{2n} , ϕ_{3n}, and ϕ_{4n} are deterministic temperature-growth parameters.

The change in biomass carrying capacity induced by climate change is written as:

$$G_{n,t} = \xi_n TF_{n,t}. \tag{18}$$

$TF_{n,t}$ is the change in forest cover in hectares and ξ_n is the biomass carrying capacity per hectare. The carrying capacity increases in the case of an expansion of the forest area, and decreases in the case of a reduction in forest cover. A reduction of forest area also leads to a direct loss of forest biomass, written as:

$$B_{n,t} = \varepsilon_n TF_{n,t} \tag{19}$$

which is the average biomass per hectare, ε_n times the loss of forest area, $TF_{n,t}$. The change in forest area induced by climate change is written as:

$$TF_{tro,t} = \widetilde{\kappa}_{1n}\Delta T_t^2 \tag{20}$$

where $\widetilde{\kappa}_{1n}$ is an uncertain temperature-land parameter.

Harvest

Total harvest of each type of biomass:

$$H_{n,t} = HB_{n,t} + HS_{n,t}, \tag{21}$$

is the sum of harvest dedicated to bioenergy production, $HB_{n,t}$, and industrial roundwood harvest, $HS_{n,t}$. The total industrial roundwood harvest is:

$$HS_{t+1} = \sum_n \chi_n HS_t \left[\frac{L_{t+1}}{L_t}\right], \tag{22}$$

which is the sum of the various forest biomass harvests, $HS_{n,t}$, where χ_n is the share of total harvest for forest biomass type and $\frac{L_{t+1}}{L_t}$ is labor growth.

Energy

Energy in this model is a perfect complement to the constant return to scale Cobb-Douglas production function of labor and capital. Output is denoted by Y_t. Energy can either be of non-carbon-based types or carbon-based types. The non-carbon-based energy comes from the carbon control rate, and the carbon-based energy comes from fossil fuels and forest biomass. Energy in the FOR-DICE model comes from the emissions from production in the DICE-2007 model:

$$\Xi_t = Y_t \sigma_t (1 - \mu_t). \tag{23}$$

The carbon emissions-output, σ_t, is declining over time due to an increase in carbon efficiency. The carbon emissions from production can be reduced by the carbon control rate, μ_t, which represents non-carbon based technologies to produce energy. The DICE-2007 model carbon emissions from production is converted back to energy units Ξ_t using an energy emissions parameter. The energy from carbon-based sources is modeled as a constant return to scale Cobb-Douglas function:

$$\Xi_t = \zeta HB_{tro,t}^{\beta_{tro}} HB_{bor,t}^{\beta_{bor}} HB_{tem,t}^{\beta_{tem}} FO_t^{1-\beta_{tro}-\beta_{bor}-\beta_{tem}}, \tag{24}$$

where ζ is a scale parameter, $HB_{n,t}$ is biomass harvest intended for energy production, and FO_t is fossil fuel carbon. $(1 - \beta_{tro} - \beta_{bor} - \beta_{tem})$ is the elasticity of fossil fuel carbon and β_{tro}, β_{bor} and β_{tem} are the bioenergy elasticities for tropical, boreal, and temperate biomass harvest.[13]

[13] There is no extraction or harvest cost. Fossil fuel is subject to a resource constraint, of 6000 billion tons of carbon, producing Hotelling rents.

Emissions and Sequestration

The total carbon emissions,

$$E_t = FO_t - \sum_n EF_{n,t}, \tag{25}$$

is the fossil fuel carbon, FO_t, minus the sum of the net forest carbon sequestration in each forest zone, $EF_{n,t}$. The net forest carbon sequestration,

$$EF_{n,t} = (F_{n,t} - F_{n,t-1})\theta_n, \tag{26}$$

is the change in biomass multiplied by a forest carbon intensity parameter, θ_n. This change of forest biomass is the growth of the forest minus the loss of forest biomass. Loss of forest is caused by bioenergy harvest, by industrial roundwood harvest, and by the decrease of forest area through deforestation or climate change.

The total carbon emissions cause the temperature to change via the geophysical equations of the DICE-2007 (Nordhaus, 2008).

Output

The output, net of costs and climate damages is given by:

$$Q_t = \frac{(1-\Lambda_t)Y_t}{(1+\pi_1 T_t^{\widetilde{\pi_2}})} - CD_t - \sum_n CA_{n,t}, \tag{27}$$

where Λ_t is the abatement cost function as a fraction of world output, Y_t is a Cobb-Douglas production function of capital and labor. T_t is the global mean surface temperature, π_1 and π_2 are damage scalars. CD_t is the total capital cost of avoiding deforestation and $\sum_n CA_{n,t}$ is the total cost of afforestation. Consumption per capita in any period equals output net of abatement and damages minus investment divided by labor,

$$c_t = \frac{Q_t - I_t}{L_t}. \tag{28}$$

Optimization

The social welfare function of each states is the present value of current and future utility from consumption:

$$W_s = \sum_{t=1}^{T} L_t \left[\frac{c_t^{1-\alpha}}{1-\alpha} \right] (1+\rho)^{-t}, \tag{29}$$

where α is the constant elasticity of the marginal utility of per capita consumption, ρ is the pure rate of time preference, c_t is consumption per capita, and L_t is labor. Given equal state probability weights, the objective function is written as:

$$\underset{I_t, \mu_t, RD_{n,t}, HA_{n,t}, HB_{n,t}}{max} \frac{1}{S} \sum_{s=1}^{S} W_s. \tag{30}$$

Appendix B: Parameters and Variables of the Model

Table 5: Parameters

Parameter	Description			
ζ	Energy parameter	65.6297		
δ_σ	Decline of the decarbonization rate	0.003		
π_1	Damage parameter	0.0028388		
π_2	Damage exponent	2		
γ	Elasticity of production of capital	0.3		
α	Elasticity of marginal utility of consumption	2.0		
ρ	Pure rate of social time preference	0.015		
		Boreal	Temperate	Tropical
θ_n	Carbon intensity in forest biomass (tc/m^3)	0.406084	0.456057	0.637926
ξ_n	Carrying capacity (m^3/ha)	203	248	288
χ_n	Share of total industrial roundwood harvest	0.277	0.535	0.188
τ_n	Plantation cost ($/ha)	800	800	800
β_n	Energy elasticity of bioenergy harvest	0.0017	0.0223	0.0394
o_1	Cost parameter of avoided deforestation			14.46
o_2	Cost parameter of avoided deforestation			0.26
o_3	Cost parameter of avoided deforestation			1.022
o_4	Cost parameter of avoided deforestation			0.03
o_5	Cost parameter of avoided deforestation			20
λ_1	First decade emissions from deforestation (tc)			11.0
λ_2	Deforestation decrease parameter			0.1
$\widetilde{\psi}_{n,t=1}$	Initial intrinsic growth rate	0.1128	0.3726	0.1981
ε_n	Forest biomass (m^3/ha)	101	124	144
$\widetilde{\phi}_{1n}$	Temperature-forest growth parameter	-0.79	-0.04	-0.03
ϕ_{2n}	Temperature-forest growth parameter	0.24		
ϕ_{3n}	Temperature-forest growth parameter	-0.026		
ϕ_{4n}	Temperature-forest growth parameter	0.78		
$\widetilde{\kappa}_{1n}$	Temperature-forest cover parameter	20	0	-20

Table 6: Variables

Variable	Description
$A_{n,t}$	Forest biomass afforestation in carrying capacity (m^3)
$B_{n,t}$	Biomass reduction due to climate change (m^3)
c_t	Per capita consumption ($)
$CA_{n,t}$	Total cost of afforestation ($)
CD_t	Total cost of reduced emissions through deforestation ($)
$D_{n,t}$	Forest biomass deforestation (m^3)
E_t	Total emissions (tc)
$F_{n,t}$	Forest biomass (m^3)
$F_{n,t}^{MAX}$	Forest biomass carrying capacity (m^3)
FO_t	Fossil fuel carbon (tc)
$G_{n,t}$	Forest cover change due to climate change in carrying capacity (m^3)
$H_{n,t}$	Total forest biomass harvest (m^3)
$HA_{n,t}$	Land area afforested (ha)
$HB_{n,t}$	Forest biomass harvest for bioenergy (m^3)
$HC_{n,t}$	Cumulative land area afforested (ha)
$HS_{n,t}$	Forest biomass roundwood harvest (m^3)
I_t	Investment ($)
L_t	Labor
$MA_{n,t}$	Marginal cost of afforestation ($)
MD_t	Marginal cost of reduced emissions through deforestation ($)
$PA_{n,t}$	Plantation cost of afforestation ($)
Q_t	Output net of abatement and damages ($)
$RA_{n,t}$	Rental cost of afforestation ($)
$RD_{n,t}$	Deforestation control rate (fraction of uncontrolled deforestation)
RE_t	Reduced carbon emissions through deforestation control (tc)
T_t	Global mean surface temperature (°C increase from year1900)
$TF_{n,t}$	Temperature- forest cover function (%)
$TI_{n,t}$	Temperature-intrinsic growth rate function (%)
Y_t	Gross output ($)
Ξ_t	Carbon-based energy function
$\Gamma_{tro,t}$	Baseline carbon emissions from land (tc)
Λ_t	Abatement cost function (fraction of world output)
μ_t	Carbon control rate (fraction of uncontrolled emissions)
Π_t	Emissions from production (tc)
$\psi_{n,t}$	Intrinsic growth rate of forest biomass
σ_t	Emissions-output ratio (tc)
Ω_t	Climate damages (fraction of world output)

Appendix C: Cost of Afforestation

We use the Global Agro-Ecological Zones (GAEZ v3.0) (Fischer et al., 2012) 5 arc-minute resolution composites of year 2000 world crop production values in GK$ per ha. We extract the raster data with Arc GIS and convert the values to year 2005 U.S.$ using the Consumer Price Index from the U.S. Bureau of Labor Statistics. Cropland with more than 20% forest and ruminant livestock larger then 50 TLU per km^2 are excluded. We then compute, for the tropical and temperate zone, the marginal cost curves of land eligible for afforestation. Next, we derive the equations associated with these marginal cost curves using symbolic regression with the software Eureqa. Figure 12 shows the estimated marginal cost curves for afforestation.

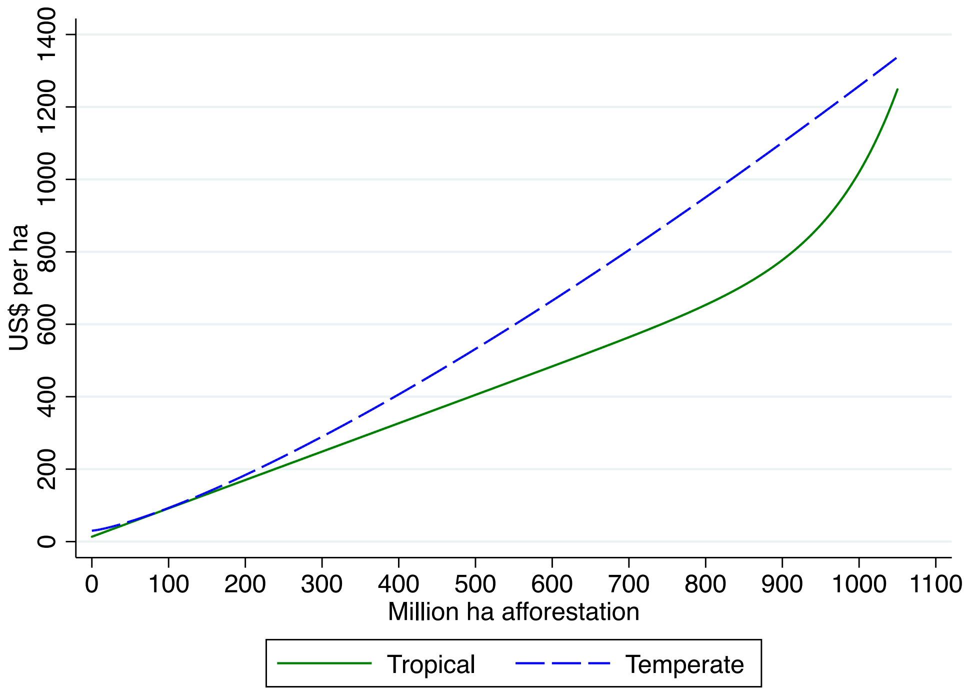

Figure 12: Cost of afforestation, US$ per ha

The marginal afforestation rental costs equations for the tropical and for temperate zone are written:

$$MA_{tro,t} = 13.5 + 0.783HC_{tro,t} + 3.08(10^{-36})HC_{tro,t}^{12.6} \tag{31}$$

$$MA_{tem,t} = 30.1 + 0.165HC_{tem,t}^{1.29} \tag{32}$$

where $HC_{n,t}$ is the cumulative hectares afforested.

Appendix D: A 2°C Temperature Limit

Meeting the goal of limiting global warming to 2°C implies lower emissions than our main scenarios suggest. The reduction in emissions comes both from increasing the carbon control rate and from changing the forest controls. We can see in Figure 13, both for the uncertain and the deterministic scenario, that a 2°C temperature limit leads to a steeper rise in the carbon control rate. As previously mentioned, without any temperature limit there are no differences in the carbon control rate between the uncertain and the deterministic scenario. However, when a temperature limit is imposed, uncertainty leads to a higher carbon control rate.

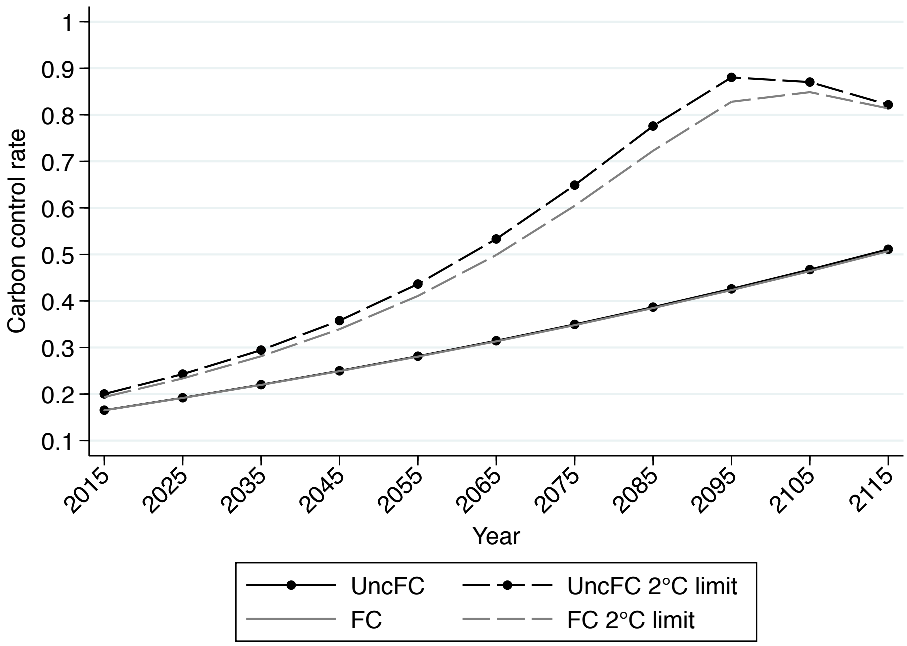

Figure 13: Carbon control rate as fraction of uncontrolled emissions

Similarly to the carbon control rate, the rate of avoiding deforestation increases when we impose a 2°C limit, as shown in Figure 14. In this case, we again find that imposing a temperature limit results in a higher avoided deforestation in the uncertain scenario compared to the deterministic scenario.

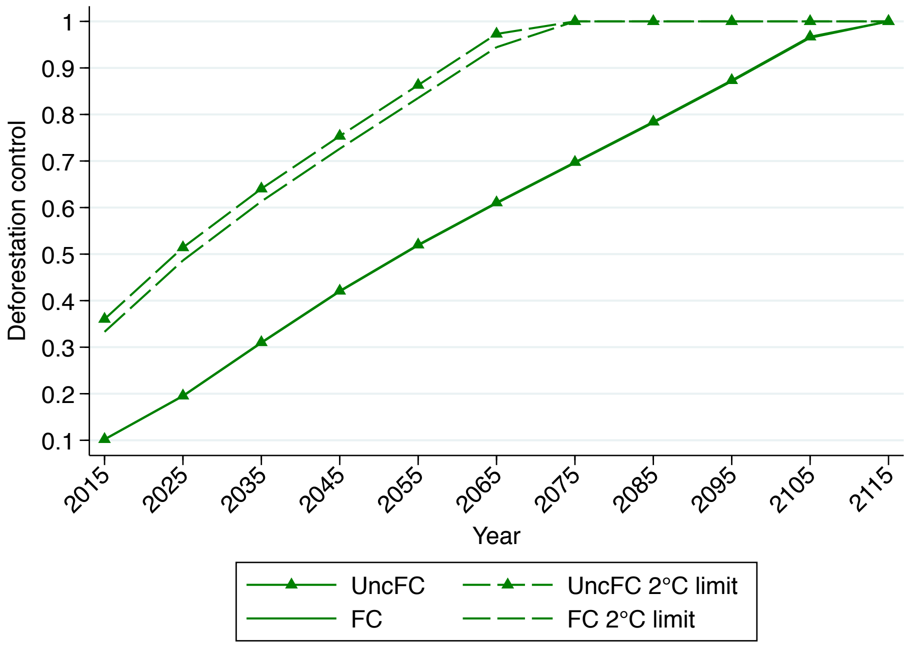

Figure 14: Avoided deforestation as fraction of baseline deforestation

All harvest to produce bioenergy are lower under the 2°C limit. The decrease is largest for the tropical forest, which has a high initial harvest, and smallest for the boreal forest, which has a low initial harvest. The temperature limit also leads to an uncertainty effect for all forests. Figure 15 and Figure 16 show the tropical and the temperate harvest, respectively. The uncertainty scenario under the 2°C limit displays the lowest harvest levels. As previously shown, only the temperate harvest has an uncertainty effect without any temperature limits.

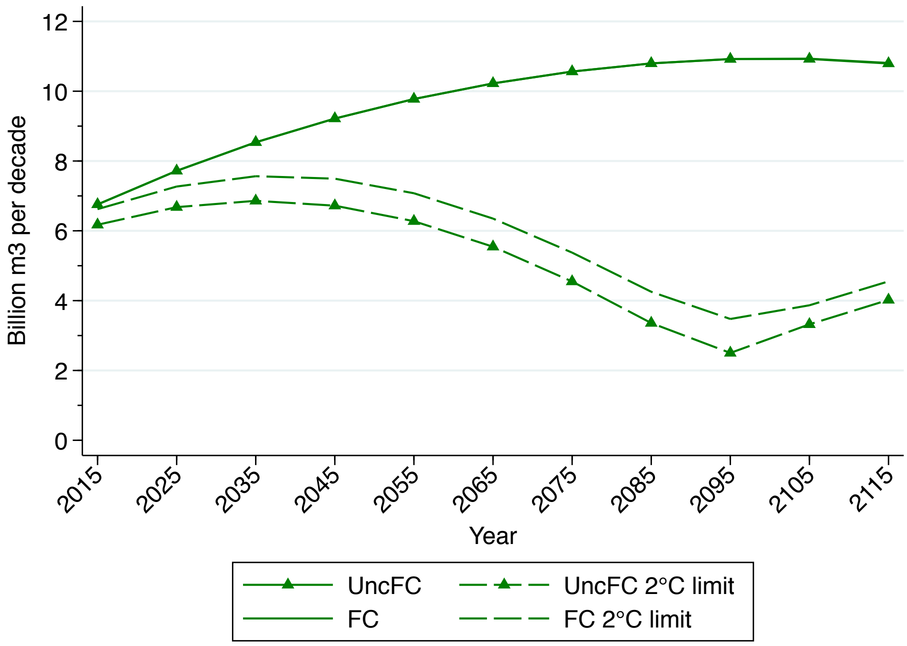

Figure 15: Tropical harvest to bioenergy production, billion m^3 per decade

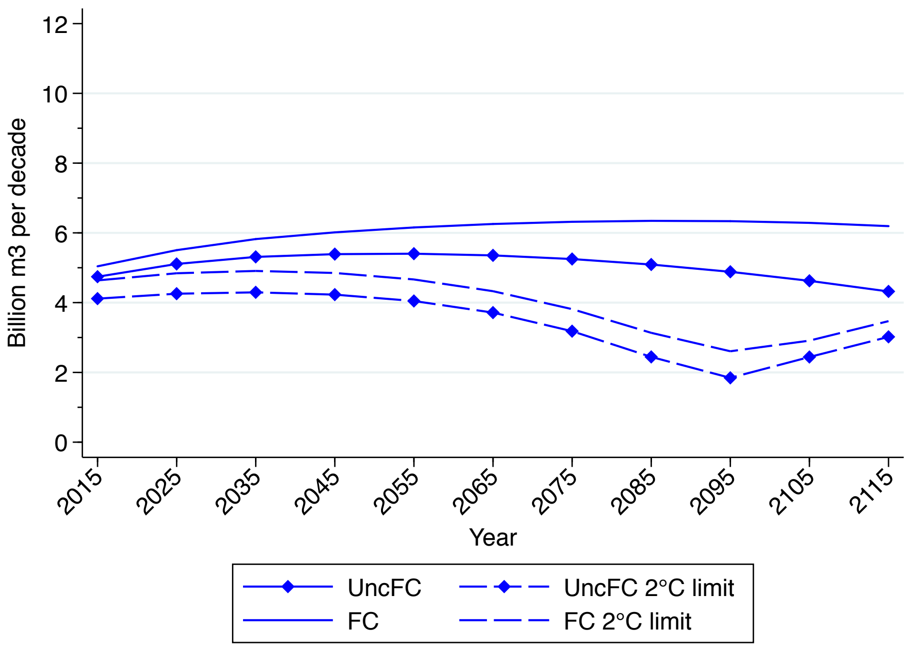

Figure 16: Temperate harvest to bioenergy production, billion m^3 per decade

Afforestation is higher for both the tropical and the temperate forest when we impose a 2°C limit, as shown in Figure 17 and Figure 18. Uncertainty under the 2°C limit leads to lower tropical and temperate afforestation in the medium and long run. This occurs because it is relatively more cost efficient to reduce emissions via other controls given the already high afforestation levels under the 2°C limit. As previously mentioned, uncertainty under the 2°C limit leads to higher avoided deforestation, a higher carbon control rate, and a lower bioenergy harvest, which gives a direct reduction in the carbon emissions, in contrast to forest planting, which only reduces emissions through sequestration.

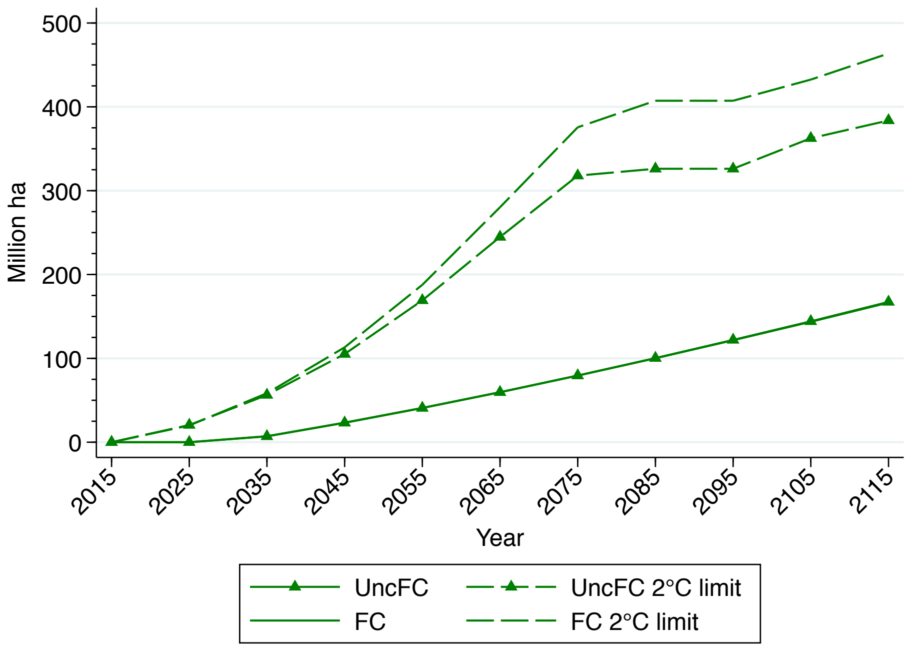

Figure 17: Tropical afforestation, million ha

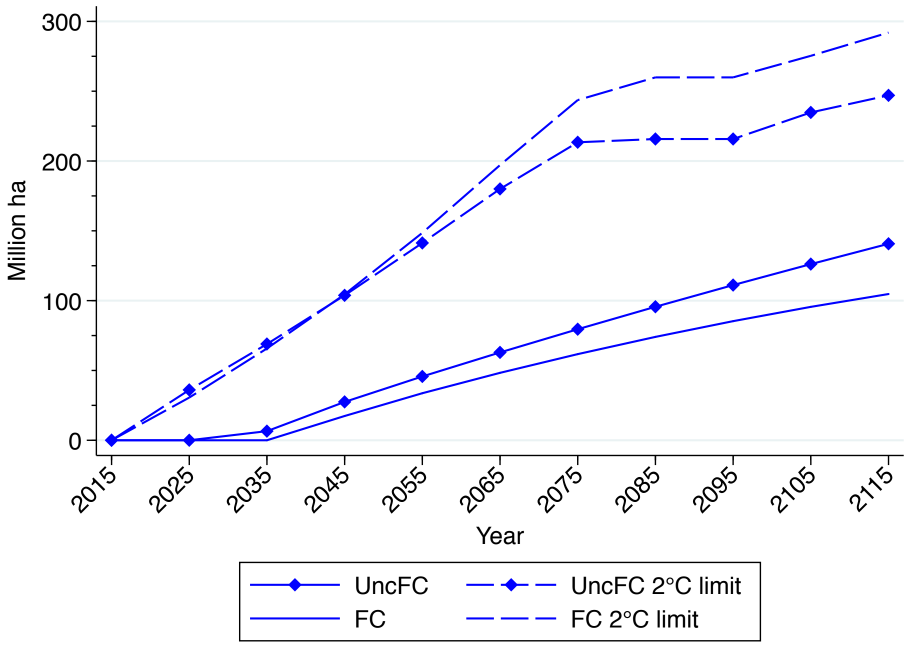

Figure 18: Temperate afforestation, million ha

Table 8 shows the expected value of carbon price for different scenarios under a 2°C temperature limit. Comparing these values to those in Table 4, we can see that imposing a temperature limit leads to higher carbon prices. A 2°C limit increases the importance of including the forest climate policy even if uncertainty is not taken into account. In line with previous results, uncertainty in the 2°C limit leads to higher carbon prices. Also as before, the rebalancing of the forest controls mitigates the effects of uncertainty but not to the same extent.

Table 8: Expected value carbon prices under a 2°C temperature limit, 2005 U.S. dollar per tC

	2015	2035	2055	2075
NFC 2°C limit	64.0	125.7	251.2	506.9
FC 2°C limit	55.2	102.7	192.9	369.3
UncNFC 2°C limit	68.8	138.2	282.6	587.1
UncFC 2°C limit	58.3	110.8	213.8	417.8

Appendix E: Sensitivity Analysis

This section explores the sensitivity of the results to the level of uncertainty. Specifically, we investigate the sensitivity of our results with respect to the size of the standard deviation. The figures in the sensitivity analysis include those of the temperate forest controls. As mentioned, the level of mitigation and the forest controls for the tropical and boreal forest are not sensitive to uncertainty.

Standard deviation of the initial intrinsic growth rate

The sensitivity of the level of uncertainty is tested by running the UncFC scenario with two alternative standard deviations of the initial intrinsic growth rate distribution. The original standard deviation in the UncFC scenario is 0.022. The low and the high standard deviations are 0.018 and 0.026, respectively. Figure 19 shows the cumulative temperate afforestation, and Figure 20 shows the temperate harvest for bioenergy production, under different standard deviations. The results show that reducing the level of uncertainty leads to less afforestation and more bioenergy harvest, and vice versa.

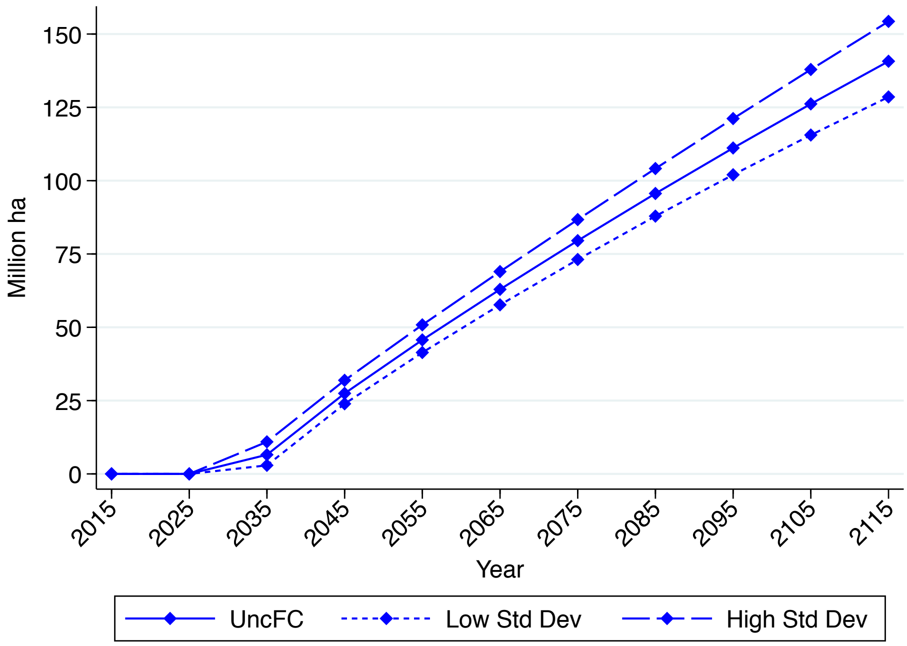

Figure 19: Cumulative temperate afforestation, million ha

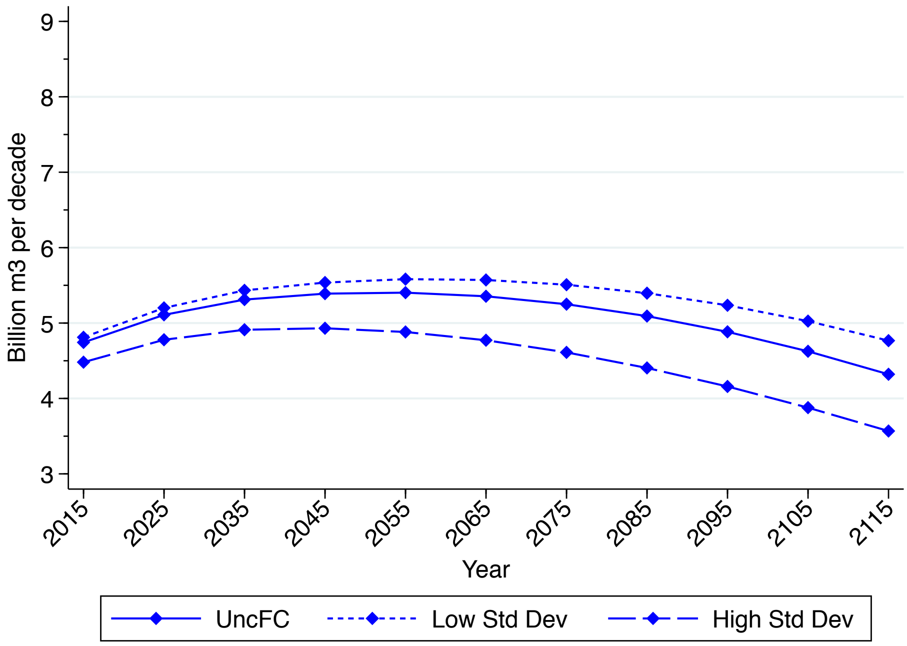

Figure 20: Temperate harvest to bioenergy production, billion m^3 per decade

Standard deviation of the climate effect on the forest cover

The sensitivity of the level of the climate effect on the forest cover is tested by running the UncFC scenario with two alternative standard deviations of the temperature-forest cover parameter distribution. For all forest zones, the low and the high standard deviation are 15% lower and 15% higher than the original standard deviation. As shown in Figure 21 and Figure 22, the temperate forest controls respond to a lower standard deviation but are insensitive to an increase in the standard deviation.

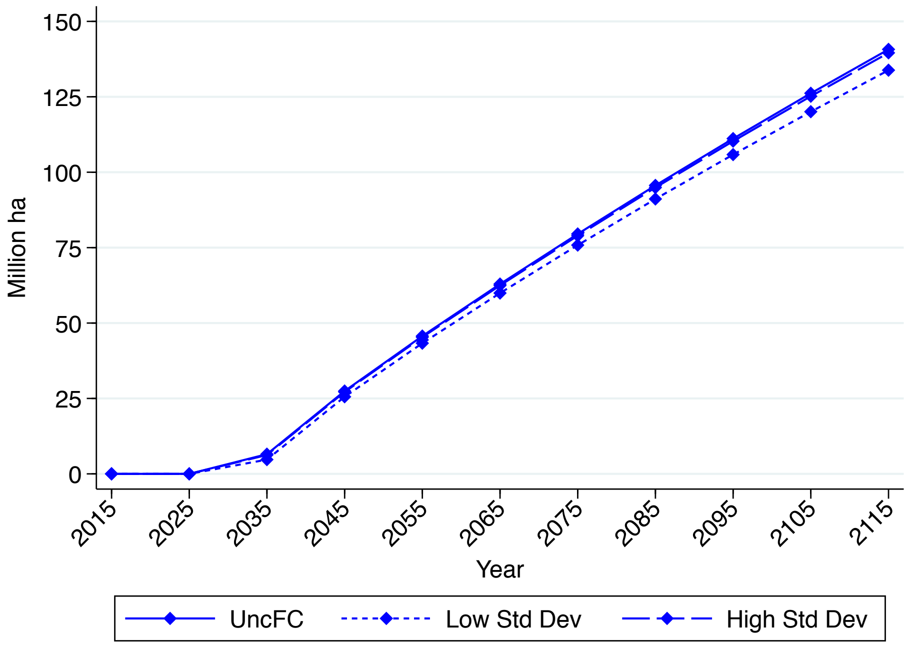

Figure 21: Cumulative temperate afforestation, million ha

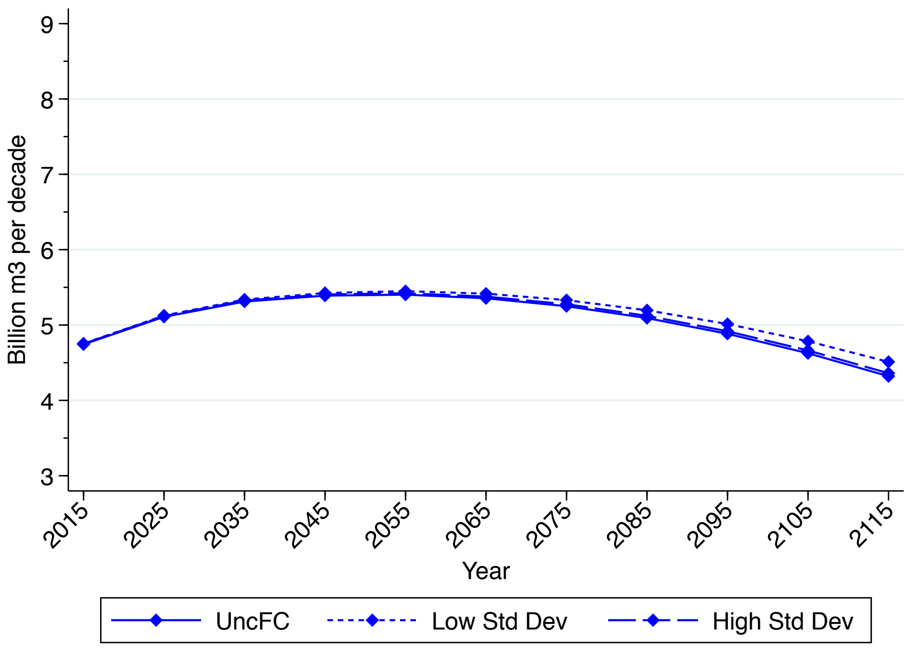

Figure 22: Temperate harvest to bioenergy production, billion m^3 per decade

Standard deviation of the climate effect on the intrinsic growth rate

The sensitivity of the level of the climate effect on the intrinsic growth rate is tested by running the UncFC scenario with two alternative standard deviations of the temperature-forest growth parameter distribution. For all forest zones, the low and the high standard deviation are 15% lower and 15% higher than the original standard deviation. Figure 23 shows the cumulative temperate afforestation, and Figure 24 shows the temperate harvest to bioenergy production, under different standard deviations. The results show that reducing the level of uncertainty leads to less afforestation and more bioenergy harvest, and vice versa.

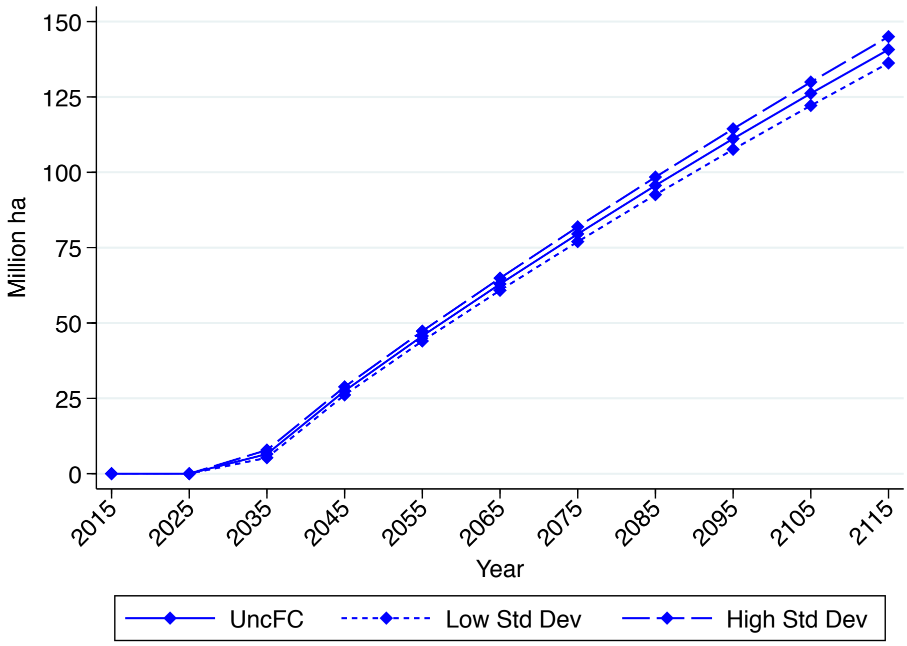

Figure 23: Cumulative temperate afforestation, million ha

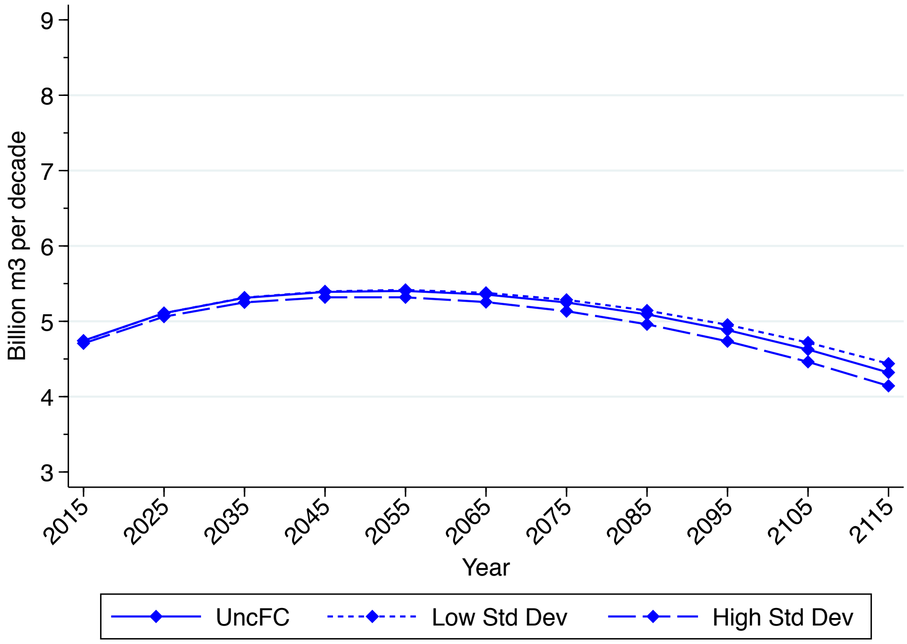

Figure 24: Temperate harvest to bioenergy production, billion m^3 per decade