The Role of the Forest in Climate Policy

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To My Family
Abstract

This thesis consists of an introductory part and four papers related to the optimal use of forest as a mitigation strategy.

In Paper [I], I develop the FOR-DICE model to analyze optimal global forest carbon management. The FOR-DICE is a simple framework for assessing the role of the boreal, tropical, and temperate forests as both a source of renewable energy and a resource to sequester and store carbon. I find that forests play an important role in reducing global emissions, especially under ambitious climate targets. At the global level, efforts should focus on increasing the stock of forest biomass rather than increasing the use of the forest for bioenergy production. The results also highlight the important role of reducing tropical deforestation to reduce climate change.

In Paper [II], I develop the FRICE to investigate the role of two key efforts to increase the stock of forest biomass, namely, afforestation and avoided deforestation. FRICE is a multi-regional integrated assessment model that captures the dynamics of forest carbon sequestration in a transparent way and allows me to investigate the allocation of these actions across space and time. I find that global climate policy can benefit considerably from afforestation and avoided deforestation in tropical regions, and in particular in Africa. Avoided deforestation is particularly effective in the short run while afforestation provides the largest emissions reductions in the medium run. This paper also highlights the importance of not solely relying on avoided deforestation as its capacity to reduce emissions is more limited than afforestation, especially under more stringent temperature targets.

In Paper [III], we investigate how uncertainties linked to the forest affect the optimal climate policy. We incorporate parameter uncertainty on the intrinsic growth rate and climate effects on the forest by using
the state-contingent approach. Our results show that forest uncertainty matters. We find that the importance of including forest in climate policy increases when the forest is subject to uncertainty. This occurs because optimal forest response allows us to reduce the costs associated with uncertainty.

In Paper [IV], we explore the implications of asymmetries in climate policy arising from not recognizing forest carbon emissions and sequestration in the decision-making process. We show that not fully including carbon values associated with the forest will have large effects on different forest controls and lead to an increase in emissions, higher carbon prices, and lower welfare. We further find, by investigating the relative importance of forest emissions compared to sequestration, that recognizing forest emissions from bioenergy and deforestation is especially important for climate policy.

**Keywords:** climate change; integrated assessment; forest carbon sequestration; forest bioenergy; avoided deforestation; afforestation; uncertainty; dynamic modeling; DICE; RICE
Acknowledgements

I am deeply grateful to my supervisors Runar Brämlund and Tommy Lundgren. Your advice and guidance have truly been fundamental to my research. Thank you for always having your office open and taking the time to read and give insightful comments on my work.

Writing these acknowledgments makes my mind wander back to how it all started. Runar, without your inspiration and encouragement I would not have ventured to the world of academia. All the way back from my undergrads, and throughout these years, I have learned much from you and hope to continue doing so in the future. I am also deeply indebted to Kenneth Backlund for introducing me into the world of modeling, the world that was to become a part of my everyday life. Runar and Kenneth, without your early encouragement I would not have entered this journey, and this thesis would not exist.

Over these years, I have also received valuable support from other researchers at the department of economics and CERE. Thank you all for creating such a great work environment. I am also very grateful for all the people I got to know during my time at UC Berkeley and Paris School of Economics. Many thanks for all the feedback and inspiring discussions. I consider myself very privileged to have had the opportunity to write this thesis at three rather contrasting institutions. I strongly believe that my research has benefited greatly from this experience.

I would also like to thank the former and current PhD-students in Umeå for all the great times both on and off work. You truly made this experience great! Naturally, I am also very thankful for my wonderful friends outside of academia who lift my gaze far beyond economics.

Finally, I would like to thank my family to whom this dissertation is dedicated. Your endless love and support made this thesis possible.

Paris, April 2016

Mathilda
This thesis consists of a summary and the following papers:


1 Introduction

Anthropogenic climate change is unlike any other public policy challenge that we have faced. In the words of Wagner and Weitzman (2015), climate change is a problem that is “almost uniquely global, uniquely long-term, uniquely irreversible, uniquely uncertain, and certainly unique in the combination of all four.”

At the time of writing this introduction, the concentration in the atmosphere of the heat-trapping gas carbon dioxide (CO\textsubscript{2}) is 403 ppm.\textsuperscript{1} Given business as usual trends, we could be in the 750 ppm region by the turn of the century. This level of CO\textsubscript{2} was last experienced three million years ago when temperatures were regularly 4°C above preindustrial levels (Pagani et al., 2010). As predicted by climate models, this levels of CO\textsubscript{2} could once again lead to a temperature increase of a similar magnitude (Rogelj et al., 2012). At this temperature range the related climate effects are likely to be so disruptive that they may pose an existential threat to our species, or at the very least, alter where and how we live.\textsuperscript{2}

At the root of the climate change problem is the fact that it does not matter where carbon is being emitted. Climate change is a global externality, where the benefit of activities that create emissions are local while the impact of emissions on temperature are global. At the country level, the problem is further compounded by the fact that low-income countries that have contributed the least to emissions are usually those most vulnerable to its negative effects (Tol, 2009). Additionally, climate change is a particular vexing problem because of its long term horizon. This occurs because the lifetime of some of the heat-trapping gases is in tens of thousands of years (Archer, 2005). Thus current actions might lock us onto specific paths that are irreversible on human time scales (IPCC, 2013). Which in turn implies that the bulk of the climate related effects

\textsuperscript{1}Monthly mean CO\textsubscript{2} for January, 2016 (Last updated: March 7, 2016). See NOAA http://www.esrl.noaa.gov/gmd/ccgg/trends/global.html

\textsuperscript{2}See Stern (2013) for a review of the damages that are likely to occur at 4°C.
will affect future generations which are not physically present today to influence our policy choices.

This global, long-term, and irreversible problem is further compounded by deep uncertainties, both on the scientific and economic side. These include uncertainties about the relationship between: emissions and accumulation of heat-trapping gases, the concentration of these gases and temperatures, higher temperatures and the related climate effects, climate effects and damages, and damages and human behavior. This behavioral response is at the heart of the problem because our actions, both regarding mitigation and adaptation, will ultimately determine the total cost of climate change, and will partly determine how these costs are shared across countries and generations.

This thesis focuses on the role of forests in controlling climate change. Forests play a crucial part in the global carbon cycle. The growth of forest biomass can reduce global carbon concentrations by absorbing carbon from the atmosphere and storing it in its biomass. Conversely, decreasing the forest biomass leads to carbon emissions. Globally the stocks of carbon in the forest are decreasing due to the loss of forest biomass. Deforestation and forest degradation is today the second largest anthropogenic source of global carbon emissions, after use of fossil fuels (IPCC, 2007).

This thesis consists of four papers. My aim with these papers is to contribute to the understanding of the role of the forests as a mitigation strategy in global climate policy. In the first two papers, I develop global frameworks, one single regional and one multi-regional, to investigate how forest climate tools, such as avoided deforestation, afforestation, and forest bioenergy can be used in conjunction with traditional carbon abatement strategies. In paper three, I investigate along with Vesterberg, how the optimal climate policy is affected by uncertainties linked to the forest. In the last paper, I investigate along with Brännlund and Lundgren, the consequences of asymmetric carbon policies.
The rest of this introductory part of the thesis is outlined in the following way: Section 2 provides a short overview of integrated assessment modeling (IAM), which have been influential in guiding the decisions of policymakers. Section 3 presents an introduction to the DICE/RICE family of IAMs on which I base my frameworks. Section 4 provides a summary of the four papers of the thesis.

2 Integrated Assessment Models (IAMs)

The primary purpose of Integrated assessment models (IAMs) is to improve our understanding of different policy options to tackle climate change. To assess climate policies we need to combine environmental science, that quantifies the relationship between emissions and their impact on temperature, with economics, that quantifies the value of climate damages and the cost of reducing emissions. By quantifying these values in a single framework, these models can be a useful pedagogical device that allows us to think about the relationships between the climate, the economy, and climate policy. Ultimately, IAMs can be used to inform policymakers about different courses of action.

In fact, these models have been very influential over the last decades. Since externalities, even global ones, can be resolved by pricing the damage caused by the externality. Policymakers attention has focused on a single metric produced by these models: the social cost of carbon. This figure represents the marginal cost of carbon emissions along the optimal emissions path. In practice, it is also the level at which a Pigouvian tax capable of solving the climate change problem should be set.

A particularly influential set of estimates of the social cost of carbon are those derived by the US government through the Interagency Working Group on Social Cost of Carbon. Initial estimates by the workgroup place the social cost of carbon in the order of $20 per ton, with those figures being recently revised to roughly $40 per ton. The working group derives its estimates by averaging the results from three well
known IAM’s. These include two welfare maximization IAM’s: the Dynamic Integrated model of Climate and the Economy model (DICE), and the climate Framework for Uncertainty, Distribution, and Negotiations model (FUND). As well as a simulation IAM: the Policy Analysis of the Greenhouse Effect model (PAGE).

Broadly, welfare maximizations IAM’s can be characterized by two blocks: the economic growth block which determines how production leads to emissions, and the climate model which relates emissions to the concentration of heat-trapping gases, and in turn to increases in temperatures. These blocks interact with each other through two functions. The abatement function which generally refers to the cost and effectiveness with which policy curbs emissions, and the damage function which models how increased temperature leads to economic damages.

Characterizing the DICE and FUND at a more detailed scale, reveals a number of fundamental differences: from the algorithm used to solve the maximization problem, to the time steps and the time horizon taken into account. Perhaps, more substantially the models vary considerably in the way they capture damages. While DICE takes an aggregated approach where temperature affects output, FUND models damages at the sector level.

Simulation IAM’s, like PAGE which is primarily concerned with modeling uncertainty, take a different structure. Their starting point is to assume that the path of emissions and the related changes in temperature are exogenous. They do not aim to determine the optimal policy mix, as they do not maximize welfare. Instead, these models aim to estimate the cost under various scenarios.

While there are many more IAM’s worth noting, a detail survey of the literature exceeds the scope of this introduction. Interested readers are instead directed to Stanton et al. (2009) who review 30 of the most commonly used models.

In essence, IAM’s are our best approximation to a very complex problem.
These models are the product of a number simplifying assumptions, and reflect the judgment of each author on how best to summarize the evolving scientific consensus on a wide range of environmental and economic issues. Accordingly, we cannot expect these models to produce estimates of key metrics, such as the social cost of carbon, along a narrow interval. Instead, we must interpret each estimate together with the assumptions on which the model is built. Frequently debated key assumptions include the discount rate, exogenous growth of production, construction of the damage function, and the role of uncertainty.

Perhaps the most discussed assumption in IAMs is the discount rate, which concerns how we value the well-being of future generations (e.g., Ackerman et al. (2009); Stern (2007); Portney and Weyant (1999); Arrow et al. (1996)). Given the long time horizon that characterizes the climate change problem, the discount rate is a critical assumption with large impacts on the estimates of the social cost of carbon. As the bulk of the cost of climate change takes place in distant future, a higher discount rate generally leads to lower rates of mitigation in IAMs. Another related assumption that has not received as much attention is how we value consumption between regions. Most multi-regional IAMs use Negishi weights (Stanton, 2011). These weights equalize the marginal utility of consumption across regions preventing any possible Pareto improvement from income redistribution (Negishi, 1960).

Another crucial debate as pointed out by Stern (2013), is that most IAM’s combine exogenous drivers of growth with damages functions that are naturally limited by our lack of knowledge about damages at 5°C or more. In fact, our gaps in knowledge exist at even lower temperatures. For example, Nordhaus accentuates that we should be cautious when extrapolating damages beyond 3°C. The very influential work of Weitzman (2009, 2012) illustrates paths forward to better model the uncertainty related to the damages created by climate change. Nonetheless, is still the case that current models do not take into account damage from omitted factor such as mass migrations or conflict (Stern, 2013). All in all,
the combination of exogenous growth and possibly weak damages functions, suggest that IAM’s predictions of the cost of carbon might be too conservative.

These debates, and more broadly the contingency of results on the ability of models to adequately summarize current scientific knowledge, has recently sparked some constructive criticism. Despite the IAM’s shortcomings, best outlined by Pindyck (2013), we should follow the example of environmental sciences and continue to develop the economic side of IAM’s. When pushing forward, however, it is my view that we should remember that IAM’s are primarily designed to inform policy. Given their purpose, it is important that the models not become too complex and risk being viewed as a black box by policymakers. One constant challenge of IAMs is finding the balance between detail/accuracy and simplicity/transparency. Rather than attempting to capture all features of reality and provide detailed predictions, we should instead prioritize capturing only the most essential features and prioritize transparency. With this thought in mind, I have chosen one of the most well know and well-studied families of IAM’s as the basis for the models I develop in this thesis.

3 The DICE and RICE models

The DICE/RICE family of models is one of the earliest and most well-known within the IAM literature. The DICE (Dynamic Integrated model of Climate and the Economy) was first developed and described by Nordhaus (1994) and the RICE (Regional Integrated model of Climate and the Economy) was first developed by Nordhaus and Yang (1996). These models have subsequently been updated and extended by William Nordhaus (Yale University) but also by many other researchers. In addition to the models being publicly available since their early development, the popularity of the models largely stems from their theoretical transparency. Compared to many other IAMs, the relationships within the
DICE/RICE are relatively simple making the models computationally and empirically tractable. This is especially true for the DICE model, which has gained the largest attraction because of its simplicity and straightforward optimization problem as a globally aggregated model. While both DICE and RICE are designed as welfare optimization models with essentially the same structure, the regional disaggregation in RICE creates a significant larger model. The global economy in the latest versions of the RICE model is composed of 12 different regions. The regions are chosen based on their regional or economic similarity, some of the regions consist of a single country while other regions consist of many countries.\(^3\)

The DICE/RICE models are based on the foundations of neoclassical economic growth theory. In these models, economies can reduce consumption today via investment in order to increase the capital stock and future consumption. DICE/RICE expands this traditional neoclassical theory by including the greenhouse gas concentration as negative environmental capital. By investing in abatement to reduce greenhouse gas emissions, economies can reduce consumption today in order to avoid future loss in consumption from climate damages.

A climate block, consisting of a set of geophysical equations, describes how emissions via the carbon concentration increase atmospheric temperature. The temperature increase, in turn, affects regional economic output through a damage-output function and, in later vintages of the models, a sea-level rise damage function. Economic output comes from a Cobb-Douglas production function of labor, capital, and energy. Energy needed in the production is either based on fossil fuel, which create emissions, or on non-carbon based technologies, which represent abatement. Technological change is exogenous both for the total factor productivity and the carbon-saving technological change. In the RICE model, there are regional specific structures for economic output, labor, emissions,

\(^3\)The 12 regions in the RICE-2010 are: Africa, China, EU, Eurasia, India, Japan, Latin America, Middle East, Russia, USA, Other High-Income countries, and Other Non-OECD Asia.
Designed as policy optimization models, the DICE/RICE models finds the optimal path of abatement and investment that maximize the economic objective function. The objective function refers to the present value of all future utilities from consumption. The welfare of each generation increases with the size of the population and per capita consumption, with diminishing marginal utility of consumption. The elasticity of the marginal utility of consumption together with the discount rate affects the relative importance of different generations. In the RICE model, each region has a welfare function and the objective of the model is to maximize the sum of these welfare functions, weighted by region-specific weights. This is done in the RICE model by solving for the optimal path of abatement and investment in each region.

A key determinant of welfare is the efficiency with which societies can reduce emissions. Total emissions in the DICE/RICE models are composed by exogenous emissions from land, and endogenous emissions from the production of energy from fossil fuels. In this setup, emissions can only be directly reduced by abatement, that is, production of non-carbon based energy. Forests have so far not been explicitly included in these models in spite of the key role that they can play to reduce emissions and thus to mitigate climate change.

3.1 The FOR-DICE and FRICE models

In order to investigate the role that forests can play in climate policy, I extend the DICE-2007 (Nordhaus, 2008) and RICE-2010 (Nordhaus, 2010) models by including a number of key strategies through which forests can mitigate climate change. My work attempts to accurately capture some of the key features of forests, while maintaining the simplicity and transparency of the frameworks. The result is FOR-DICE and FRICE.

In the FOR-DICE model, developed in Paper [I], I explicitly model the
stock of growing forest biomass. The global biomass is divided into tropical, temperate and boreal forest according to its ecological characteristics. I explore the use of forest biomass both as a source of energy and as a resource to sequester and store carbon. The forest controls of the model are harvest of biomass to produce energy and avoided deforestation in the tropics, which makes the emissions from land of the DICE-2007 model endogenous. In the later version of the FOR-DICE, used in Paper [III] and [IV] of this thesis, I extend the forest controls to include the possibility of increasing forest land through afforestation.

In the FRICE model, developed in Paper [II], I include forest controls to increase the sequestration and storage of forest carbon by including avoided deforestation and afforestation. These forest controls are chosen at the regional level, where the regional division of the world follows the one in RICE-2010. In contrast to the FOR-DICE, which models the effects of forest controls through the stocks of forest biomass, the effects of the forest controls in FRICE are directly modeled in terms of emissions and sequestration. For regions with emissions from land of the RICE-2010 model, the forest control avoided deforestation make these emissions endogenous. The forest control afforestation sequestrates carbon over time following regional sequestration curves.

In what follows, I provide further details on the models, the contribution, and the results of each of the papers.

4 Summary of the papers

Paper [I]: The Role of the Forest in an Integrated Assessment Model of the Climate and the Economy

The objective of this paper is to investigate the role the global forest can play to mitigate climate change. To do this, I develop the FOR-DICE model. The FOR-DICE extends the DICE-2007 (Nordhaus, 2008) by incorporating the global boreal, temperate, and tropical forest biomass.
These three types of forest biomass are modeled as endogenous state variables, controlled by avoided deforestation and bioenergy harvest. This simple framework allows me to model the global forest both as a source of renewable energy and as a carbon sink. The dynamics of each type of biomass follows a logistic growth function formulation. The parameters regarding the forest biomass stocks, carbon, and harvest are primarily based on data from the Food and Agriculture Organization of the United Nations (FAO, 2010). Energy values are derived from data from the International Energy Agency (IEA (2014c), IEA (2014a), IEA (2014b)) and the United Nations Statistical Division (UNSD, 2014). Baseline deforestation in FOR-DICE follows the path of emissions from land in the DICE-2007 model. The cost of avoiding this baseline deforestation is derived from estimates by Kindermann et al. (2008).

The results show that forests can play an important role in reducing global emissions, and increasingly so under more stringent climate policies. In accordance with previous literature, I find that avoiding deforestation in the tropical forest is a cost-efficient instrument to mitigate climate change. My main result at the global level shows that policy efforts should focus on increasing the stock of growing forest biomass rather than increasing the use of forest biomass to produce energy. This occurs because the release of carbon associated with the use of biomass is not offset by avoided fossil fuel emissions. However, the results differ between forest zones due to differences in the carbon content of biomass, the bioenergy efficiency, and the growth rate of the biomass. Bioenergy harvest is increasing for the temperate forest while decreasing for the boreal and tropical forest. Consistent with previous literature, these results highlight that forest bioenergy should not be treated as carbon neutral. Policies that promote the production of forest bioenergy without taking the dynamics of the carbon flows into account may lead to negative climate effects. By and large, my findings show that forest can be an important tool to contribute to emission reductions but should be viewed as a complement to mitigation efforts to produce non-carbon-based energy.
Paper [II]: Mitigating Climate Change with Forest Climate Tools

In this paper, I develop the FRICE model to analyze how the optimal paths of forest climate tools are related to the stringency of the global temperature target. More specifically, FRICE estimates the potential role, and spatial allocation, of two key forest climate tools, namely, afforestation and avoided deforestation. This multi-regional integrated assessment model is an extension of the RICE-2010 model (Nordhaus, 2010).

The baseline carbon emissions from land in the RICE-2010 model are used as approximations of the regional baseline deforestation paths. The costs of avoiding these deforestations are derived from estimates by Kindermann et al. (2008). The climate benefit of avoiding deforestation occurs directly through the reduction of baseline emissions from deforestation. The benefit from afforestation, on the other hand, takes place over time through sequestration from forest growth. This carbon accumulation over time is described by a sigmoidal function. The marginal costs of afforestation are derived from the total agricultural production value per hectares from the Global Agro-Ecological Zones (GAEZ v3.0) (Fischer et al., 2012) geospatial dataset.

The main result of this paper is that avoided deforestation and afforestation provide a cost-effective way to enhance global climate policy. However, the geographical allocation of these tools varies greatly due to different costs and forest characteristics between regions. The largest potential for cost-effective avoided deforestation and afforestation lies in the tropical forests of Africa, Asia, and Latin America. This paper also shows that avoided deforestation provides the largest short-run benefits while afforestation is most effective in the medium to long run. The results further demonstrate that stringent temperature targets will increase the relative importance of using afforestation to reduce emissions, as the potential to reduce emissions with avoided deforestation is limited
and will be quickly exhausted.

**Paper [III]: When Not in the Best of Worlds: Uncertainty and Forest Carbon Sequestration**

Many aspects of the dynamics of the forest and its interaction with climate change are still unknown. Despite these gaps in knowledge, uncertainty has largely been neglected in studies investigating the role of forests to mitigate climate change. In this paper, we explicitly model some of the key uncertainties linked to the forest and investigate their impact and importance in climate change policy.

We use the FOR-DICE (Eriksson, 2015) framework and implement parameter uncertainty with the state-contingent approach. In this approach, drawings from probability distributions of unknown parameters create possible states of the world. As it is not known which of these possible states that will occur, the optimal policy under uncertainty is found by maximizing the sum of utility for each of these possible states. In this paper, the unknown parameters are directly linked to the growth of forest biomass and to climate change effects on forests growth and geographical distribution.

We analyze the importance of including uncertainty by comparing the results from the optimal climate policy under uncertainty to the results derived from a deterministic optimization. Our overall result shows that uncertainty matters. Not taking uncertainty into account will lead to misleading carbon prices and non-optimal policies. Interestingly, we also find that including the forest in climate policy becomes more important when the forest is subject to uncertainty. Moreover, recognizing the forest in climate policy makes us more resilient to uncertainty, as optimal forest policy response allows us to reduce the costs associated with uncertainty. Without the forest controls in the set of mitigation tools, uncertainty will instead lead to high costs of reducing emissions by a large increase in non-carbon energy.
Paper [IV]: Pricing Forest Carbon: Implications of Asymmetry in Climate Policy

Currently, most countries with an active climate policy have focused their efforts on providing incentives to reduce the use of fossil fuels. These policies create asymmetric incentives for the use of different sources carbon, and can lead to an inefficient climate policy. The purpose of this paper is to examine the implications of asymmetric carbon policies that arise from imperfect accounting of forest carbon. To do this, we use an extended version of the FOR-DICE model and investigate two types of asymmetric carbon policy regimes. Compared to the symmetric carbon policy, the forest controls in the asymmetric regimes are set without, or with only partially, including the carbon values associated with the forest. In the first regime, we investigate the asymmetry between pricing fossil carbon and forest carbon, that is, policymakers take into account carbon emissions from fossil fuels but not emissions or sequestration from forests. In the second regime, we investigate the asymmetry that occurs when policymakers, in addition to fossil fuel emissions, only take into account either forest carbon emissions or sequestration from changes in forest biomass.

We show that the distortion in costs and benefits that arise under the asymmetric carbon policies leads to inefficient levels of forest controls and lower welfare. Overall, the results demonstrate that not recognizing forest emissions induce the largest deviation from the optimal levels of bioenergy harvest and avoided deforestation, while not recognizing sequestration induce the largest discrepancy for afforestation. Among the asymmetric carbon policies that we explore, the highest levels of total emissions, the highest carbon prices, and the lowest welfare, arise when policymakers neither recognize emissions or sequestration from forests. Specifically, not including the emissions or sequestration from forests in the decision-making process will lead to levels of bioenergy harvest that are too high, and to levels of afforestation and avoided deforestation that are too low. Results from the second policy regime indicate that
the welfare cost of not recognizing forest emissions are higher than not recognizing sequestration in climate policy.

We also provide a back of the envelope calculation on the magnitude of the required taxes and subsidies under the symmetric carbon policy. This calculation shows that the optimal subsidy payment for sequestration will exceed the optimal tax revenue from forest emissions for all forest types. However, the overall subsidy can be financed when including the optimal tax revenue from fossil fuels.
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The Role of the Forest in an Integrated Assessment Model of the Climate and the Economy

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Abstract

This paper develops the FOR-DICE model to explore the potential role of the global forest in reducing climate change. It presents a basic framework for assessing the boreal, tropical, and temperate forests as both a source of renewable energy and a resource to sequester and store carbon. The focus of the paper is to explore whether climate policies should focus on increasing the forest biomass, to sequester and store carbon, or on increasing the use of the forest biomass as a source of energy, to substitute fossil fuels. The paper shows that the global forest can play an important role in reducing atmospheric carbon. The main finding at the global level is that it is better to increase the forest biomass rather than increase the use of forest bioenergy. The reason for this is that the decrease in forest carbon stock created by increased bioenergy harvests is not offset by avoided fossil fuel emissions. This finding suggests that setting high bioenergy targets, without considering the dynamics of the forest stock and the efficiency of bioenergy, will be detrimental to climate change mitigation.

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1 Introduction

This paper develops the FOR-DICE model, which is an integrated assessment model for evaluating the potential role of the global forests in reducing climate change. Forests can be managed to reduce global carbon emissions in at least two ways: forest biomass can be increased in order to sequester and store carbon, and the forest biomass can replace fossil fuels as a source of renewable energy. The aim of this paper is to provide insights on the balance between these potentially conflicting forest management objectives in the context of climate change.

The global forest plays a key role in determining the amount of atmospheric carbon and thereby the climate. Several studies provide evidence that forest carbon sequestration can reduce a significant amount of carbon and provide a cost-efficient way to curb climate change (e.g., Tavoni et al. (2007); Bosetti et al. (2011)). Richards and Stokes (2004) perform a comprehensive review of existing carbon sequestration studies and different forestry practices to increase carbon sequestration on forestland.\(^1\) They conclude that several sequestration strategies can be used as effective tools to reduce climate change.

A key sequestration strategy is to avoid deforestation. Global deforestation, currently amounting to approximately 13 million hectares annually, accounts for as much as one-quarter of all anthropogenic carbon emissions (Kindermann et al., 2008). Deforestation is mainly caused by conversion of forest to agricultural land in tropical regions. Solhngen et al. (2009) show that reduction of deforestation has the largest sequestration potential in both the short and long run. Other research shows that reducing the tropical deforestation can be one of the least costly mitigation strategies (e.g., Gullison et al. (2007); Tavoni et al. (2007); Bosetti et al.\(^1\))

\(^1\)These practices include afforestation of agricultural land, reforestation of harvested or burned timberland, modification of forestry management practices to emphasize carbon storage, adoption of low-impact harvesting methods to decrease carbon release, lengthening forest rotation cycles, preservation of forestland from conversion and adoption of agroforestry practices.
As an alternative to sequestration strategies, atmospheric carbon can be reduced by substituting fossil fuels with forest biomass in energy production. However, such substitution also implies an immediate reduction in the forest biomass - a reduction that, at least in the short run, counteracts sequestration efforts aimed at increasing the carbon sink. Even if all bioenergy in the long run may be viewed as carbon neutral, it is important to acknowledge that the release of carbon is instantaneous when converted to energy, while sequestration occurs over time. Thus, the positive effects of biofuels may be overestimated if we do not account for the use of biofuels in the carbon cycle (Lundgren et al. (2008); Lundgren and Marklund (2013)).

One way to model forest carbon sequestration potential is to use partial equilibrium models of forestry. These models are useful in estimating how different carbon policy scenarios affect the optimal response of the forest sector (e.g., Sathaye et al. (2006)). A more common approach is soft-linking modeling, where results from a partial equilibrium forestry model are fed into a general equilibrium model (e.g., Hertel et al. (2009); Golub et al. (2009)). More broadly, there are also several integrated assessment models that include competition with other land use activities. Rose et al. (2012) provide a comprehensive analysis of current approaches to including different mitigation options in land modeling.\footnote{Rose et al. (2012) evaluate four integrated assessment modeling frameworks: GRAPE, IMAGE, MESSAGE, and GTEM.}

In a seminal paper using the soft-linking approach, Sohngen and Mendelsohn (2003) derive the optimal control of forest carbon sequestration by solving iteratively between a global timber model (Sohngen et al., 1999) and the DICE model (Nordhaus and Boyer, 2000). Their results show that land-use change and longer rotation periods can potentially sequester a considerable amount of carbon, but large carbon sequestration programs may also be costly due to the effects on land and timber prices. However, they do not consider the use of forest biomass to sub-
stitute fossil fuels.

The purpose of the present paper is to develop a model to analyze optimal forest carbon management. To this end I construct a simple framework that models the global forest both as a source of renewable energy and as a carbon sink. This is done by incorporating boreal, temperate, and tropical forest biomass into the DICE-2007 model created by Nordhaus (2008). These three types of forest biomass are modeled as endogenous state variables, controlled by avoided deforestation and bioenergy harvest.

The paper provides three key findings. First, forests have an important role in reducing global emissions, and increasingly so under ambitious climate targets. This finding, however, does not indicate that efforts to produce non-carbon-based energy should be reduced. Second, forest management should focus on increasing the stock of forest biomass rather than increasing the use of forest for bioenergy production. The reason for this is that the decrease in the forest carbon sink associated with increased harvests for bioenergy cannot be offset by avoided fossil fuel emissions under existing conditions. This finding at the global level is driven by a decrease in bioenergy harvest in the tropical and boreal forest that dominates the increase in the temperate forest. The conditions that determine the optimal bioenergy harvest include: the carbon content of biomass, the bioenergy efficiency, and the growth rate of the biomass in each forest zone. The third key finding in this paper is that reducing deforestation in the tropical forest is a cost-efficient instrument to reduce climate change.

On the whole, the present paper highlights that accounting for forest carbon, both in terms of emissions and sequestration, leads to higher welfare. In accordance with previous literature (e.g., Searchinger et al. (2009); McKechnie et al. (2010)), it also highlights that policies encouraging the use of forest bioenergy without taking carbon flows into account may lead to negative climate effects.
2 The model

The FOR-DICE model is based on a widely known model linking the climate system to the economy, i.e., the DICE model. The DICE model was first developed and described in Nordhaus (1994) but was subsequently updated in Nordhaus and Boyer (2000) and Nordhaus (2008). The DICE model is constructed as a neoclassical economic growth model where greenhouse gases lead to a temperature rise that affects the economic output through a damage function. It is a global one-decision-maker optimization model that maximizes the present value of the social welfare by choosing optimal levels of investment and abatement.\(^3\)

The DICE-2007 model, however, does not account for how different uses of forests affect the carbon cycle. To correctly choose an optimal climate policy pathway, it is necessary to explicitly integrate the forest resource as a carbon sink and a source of emissions in integrated assessment modeling. The present paper incorporates three types of forest biomass as endogenous state variables into the DICE-2007 model. The forest zone of the biomass is indicated by \(n\), where \(n = \{bor, tem, tro\}\) represents the boreal, the temperate, and the tropical forest zone, respectively. The total global forest is divided into these three forest zones according to the ecological characteristics of the forest biomass. The classification of the forest zones is described in Note 1 in Appendix A. Boreal and temperate forest biomass is solely affected by roundwood and bioenergy harvest, while tropical forest biomass is also affected by deforestation. The optimization problem in FORE-DICE is solved by choosing bioenergy harvest and avoided deforestation, besides choosing the controls of the DICE model. Appendix A contains a summarizing table of all variables and parameters.

\(^3\)There are several other well-established policy optimization models such as PAGE (Hope, 2006), FUND (Tol, 2002) and MERGE (Manne et al., 1995).
2.1 Forest growth, harvest, and deforestation

The dynamic modeling approach to estimate forest biomass is based on the logistic growth equation described in Clark (1990). The growth rate is at its upper limit when the stock is at its minimum and slows down as the size of the biomass approaches its carrying capacity. Harvest decreases the stock but at the same time increases the growth rate. Deforestation on the other hand does not change the growth rate but leads to a smaller stock of biomass. Note that deforestation is formulated in terms of biomass volume and not land area. The maximum forest biomass carrying capacity is modeled to decrease with deforestation in the following way:

\[
F_{MAX}^{n,t+1} = F_{MAX}^{n,t} - \frac{F_{MAX}^{n,t}}{F_{n,t}} D_{n,t},
\]

where the fraction \(\frac{F_{MAX}^{n,t}}{F_{n,t}}\) converts biomass deforestation, \(D_{n,t}\), to biomass carrying capacity. Hence, deforestation affects the biomass carrying capacity such that removing forest land does not change the dynamics of the remaining biomass. However, deforestation still affects the stock both directly through removal of forest biomass and indirectly via future growth restrictions. The dynamics of forest biomass are written as:

\[
F_{n,t+1} = F_{n,t} + \psi_n F_{n,t} \left[ 1 - \frac{F_{n,t}}{F_{MAX}} \right] - H_{n,t} - D_{n,t},
\]

where \(F_{n,t}\) is the stock of forest biomass, \(\psi_n\) is the maximum intrinsic growth rate, and \(H_{n,t}\) is biomass harvest. The intrinsic growth rate is constant over time and cannot be modified with fertilizers or affected by climate change. The dynamics of the forest are assumed to be unaffected by climate feedback due to the uncertainty regarding the net magnitude of increasing temperatures.\(^4\)

\(^4\)Increasing temperatures could affect both the stock and growth rate of the global forests. The distribution and magnitude of the effect at different temperature levels
Most of the current deforestation takes place in South America, Africa, and South and Southeast Asia (Murray et al., 2009). As the ongoing deforestation mainly concerns tropical forest, only tropical biomass is subject to deforestation in this model. Hence, maximum carrying capacity is only a variable for tropical biomass, while it is held constant for boreal and temperate biomass. The exogenous carbon emissions from land in the DICE-2007 model are used as an approximation of baseline deforestation. These baseline carbon emissions from land are written as:

$$\Gamma_{\text{tro},t} = \lambda_1 (1 - \lambda_2)^t,$$

where the parameter $\lambda_1$ represents carbon emissions in the first time period and $\lambda_2$ generates a declining carbon emissions over time. These baseline emissions from land are converted to tropical biomass deforestation by the tropical carbon intensity parameter, $\theta_{\text{tro}}$, which represents the average amount of carbon per volume of growing tropical forest biomass. The total biomass deforestation in any time period is then given by:

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

where $\frac{\Gamma_{\text{tro},t}}{\theta_{\text{tro}}}$ represents the baseline deforestation in terms of forest biomass and $RD_t$ is the deforestation control rate as a fraction of this baseline deforestation. Net deforestation is prevailing if $D_{\text{tro}} > 0$.

The cost of changing ongoing deforestation is difficult to estimate mainly due to the complexity in estimating the value of the economic activity underlying the deforestation. Estimating the opportunity cost of land is conditional on numerous variables, and this opportunity cost estimate is still highly uncertain. The net effect of a warmer climate is expected to be positive in colder regions and negative in warmer regions for moderate warming scenarios (IPCC, 2007). However, the effect highly depends on the degree of warming. It is likely that most forests will be negatively affected by high temperature increases due to rapid increases in forest dieback and disturbances (Scholze et al., 2006).

$^5$Afforestation and reforestation control is not considered in this model, i.e $D_{\text{tro}} \geq 0$. 

---
highly dependent on the size of the area (Grieg-Gran, 2008). All cost estimates of emissions reduction via avoided deforestation show upward-sloping marginal cost curves. Initial reduction of deforestation can cut carbon emissions at a low cost. Increasing the area of control progressively gets more expensive as a result of comparatively cheap alternatives are initially used (Murray et al., 2009). Forest land with relatively low potential for alternative economic use are initially hindered from conversion. The cost of reducing emissions by avoiding deforestation is approximately modeled to follow the marginal cost curves presented in Kindermann et al. (2008). Appendix B provides further information on the marginal cost estimation. The rental cost of avoiding direct release of carbon in one time period is given by the following marginal cost function:\footnote{The rental cost can be understood as the rental payment to the landowner to hinder conversion of forest land.}

\[
MC_t = \phi_1 R_E^{\phi_2} + \left[ (\phi_3 + \phi_4 t)^{\phi_5 R_E} - 1 \right],
\]

where the \(\phi\)s are the estimated cost parameters and the reduction of direct carbon emissions from deforestation is given by:

\[
R_E = \Gamma_{t,r,t} R_D.
\]

The marginal cost increases, over time, and with the level of reduction of carbon emissions because land with low opportunity cost is used first to avoid deforestation. The total cost of avoiding deforestation is given by:

\[
TC_{t+1} = TC_t + \int_0^{R_E} MC_{t+1}(x) dx.
\]
and forest land saved from conversion will not be deforested in future time periods.

As mentioned, wood for energy production together with wood for goods and services constitute the total harvest. Hence, the total harvest of biomass in each forest zone, i.e.,

$$H_{n,t} = HB_{n,t} + HS_{n,t},$$

is the sum of harvest dedicated to bioenergy production, $HB_{n,t}$, and industrial roundwood harvest, $HS_{n,t}$. The global industrial roundwood harvest has been quite stable in the last decade and is expected to increase only moderately according to FAO (2010). The future global demand for wood products will gradually increase due to higher income and a growing population. The relationship between industrial roundwood harvest and income and population will, however, diminish over time due to increased efficiency in production, as this will lower the input-output ratio. Hence, in order to maintain model simplicity, the demand for wood is assumed to be proportional to population size.\(^7\) The industrial roundwood harvest thus increases linearly with labor as:

$$HS_{t+1} = \sum_n \chi_n HS_t \eta \left[ \frac{L_{t+1}}{L_t} \right].$$

$HS_{n,t}$ is the sum of the industrial roundwood harvest from all forest zones, $\chi_n$ is the share of total harvest from each zone, $\eta$ is a preference parameter and $\frac{L_{t+1}}{L_t}$ represents the labor growth.\(^8\)

\(^7\)Solomon et al. (1996) project the global need for industrial roundwood to increase by 17% from 2000 to 2025 and by 25% from 2000 to 2050. This model projects a 16% increase 2005-2025 and a 26% increase 2005-2055.

\(^8\)The preference parameter is constant but can be modified to represent changes in demand due to consumer preferences.
2.2 Energy

In the FOR-DICE model, energy can either be carbon based or non-carbon based. The non-carbon-based energy technologies are represented by the carbon control rate. The carbon-based energy comes from use of fossil fuels and forest biomass. Energy is a perfect complement to the constant return to scale Cobb-Douglas production function of labor and capital. As energy is not explicitly modeled in the DICE-2007 model, the demand for energy is derived from the carbon emissions from production in the DICE-2007 model:

$$Π_t = Y_t σ_t [1 - µ_t] ,$$

where the production, $Y_t$, leads to carbon emissions through the carbon ratio, $σ_t$. The carbon emission output is declining over time due to an increase in carbon efficiency. This exogenous technology change also implies that the energy efficiency increases over time. The carbon emissions from production is further reduced by the carbon control rate, $µ_t$, which represents non-carbon-based technologies used to produce energy. These technologies include, for example, solar power, geothermal energy, and nuclear power. The carbon emissions from production are converted back to energy units by the energy-emissions parameter $ξ$. The energy from carbon-based sources is then:

$$Ξ_t = Π_t ξ.$$

This carbon-based energy is further modeled as a constant return to scale Cobb-Douglas function:\footnote{The Cobb-Douglas functions induce a non-perfect substitution and avoid unrealistic corner solutions. One general disadvantage of this functional form is the requirement that each type of input has to be strictly positive. However, this restriction is not considered to be unrealistic during at least the early time periods of the model.}
\[ \Xi_t = \zeta H B_{bor,t}^{\Phi_{bor}} H B_{tem,t}^{\Phi_{tem}} H B_{tro,t}^{\Phi_{tro}} FO_t^{1-\Phi_{bor}-\Phi_{tem}-\Phi_{tro}}, \]  

where \( \zeta \) is a scale parameter, \( FO_t \) is fossil fuel carbon, and \( HB_{n,t} \) is forest biomass harvest intended for energy production. \( \Phi_n \) is the bioenergy elasticities of the three types of forest biomass dedicated to bioenergy and \( (1 - \Phi_{bor} - \Phi_{tem} - \Phi_{tro}) \) is the energy elasticities of fossil fuel carbon. Fossil fuel is subject to a resource constraint and consumption of fossil energy is allocated over time, producing Hotelling rents. The constraint on fossil fuel carbon is:

\[ \kappa \geq \sum_{t=0}^{T} FO_t, \]  

where \( \kappa \) is the estimated available world fossil fuel carbon reserve.

### 2.3 Carbon emissions

The total carbon emissions come from three main sources, i.e., from energy conversion, \( EE_t \), from harvest and decay of wood products, \( ES_t \), and from the change of the forest biomass stock, \( EF_t \). The carbon emissions from carbon-based energy conversion is written as:

\[ EE_t = FO_t + \sum_{n} HB_{n,t} \theta_n, \]  

where \( FO_t \) is emissions from fossil fuel and \( HB_{n,t} \theta_n \) is emissions from forest bioenergy. Hence, the total carbon content in both fossil and forest fuel will be released when used to produce energy. This paper does not include the possibility to adopt the carbon capture and storage (CCS) technology to reduce the emissions from use of fuels in power plants.\(^{10}\)

\(^{10}\)Negative emissions can be generated by using forest bioenergy together with carbon capture and storage (biomass energy with carbon capture and storage, BECCS).
Both fossil fuels and biofuels immediately release the carbon from its biomass when used in energy production while forest biomass reserved for wood products can store the carbon for a considerable amount of time. Thus, the carbon storage time will depend on the final use of the biomass and the associated lifetime of that product. The half-life for wood products, $HL$, namely the number of time periods it takes for half of the initial amount of carbon to be released, is frequently used to describe at what rate the wood product will be discarded. The decay equation

$$\delta_{CH} = \frac{Ln(2)}{HL}$$

(15)

reflects the fraction of the carbon lost in each time period. The stock of wood products releases carbon at a constant percentage rate. This follows the IPCC method of estimating the amount of carbon to leave the pool (IPCC, 2006). The stock of carbon in wood products, $CH_t$, is modeled to decrease with the decay equation, $\delta_{CH}$, and increases with carbon inflow, $CI_t$, as follows:

$$CH_{t+1} = [1 - \delta_{CH}]CH_t + CI_{t+1}.$$  

(16)

The inflow of carbon to the stock is

$$CI_t = v \sum_n HS_{n,t} \theta_n,$$

(17)

where $v$ reflects the share of the carbon content in the harvested biomass that goes into long-lived wood products. Most of the biomass volume of harvested wood, and hence carbon, is lost in the processing chain (Ingerson, 2009). The total release of carbon from industrial roundwood harvest in each time period is given by:

However, a high carbon price is needed for BECCS to be cost efficient with forest biomass as fuel (Favero and Mendelsohn, 2014).
\[ ES_t = CH_t \delta CH + [1 - \nu] \sum_n HS_{n,t} \theta_n, \quad (18) \]

which is the sum of the release of carbon from the carbon stock in wood products and the direct release of carbon from the harvest process. The carbon sequestration or emissions from the stock of forest biomass is written as:

\[ EF_{n,t} = [F_{n,t-1} - F_{n,t} - H_{n,t}] \theta_n. \quad (19) \]

\[ EF_{n,t} \] represents the change in biomass multiplied by a forest carbon intensity parameter, \( \theta_n \). \( H_{n,t} \) is subtracted to avoid double counting of the emissions from harvest.

Total carbon emissions in each time period consist of emissions from energy conversion, \( EE_t \), emissions from harvest and carbon stored in wood products, \( ES_t \), and emissions or sequestration from change in forest biomasses, \( EF_{n,t} \). The total carbon emissions are then:

\[ E_t = EE_t + ES_t + \sum_n EF_{n,t}. \quad (20) \]

Equation 20 enters the unchanged geophysical equations of the DICE-2007 model, causing the temperature to change. The reader is referred to Nordhaus (2008) for the geophysical equations of the DICE-2007 model.

The change in temperature affects economic output through the polynomial damage function in DICE-2007. The output, net of abatement and damages, is given by:

\[ Q_t = \frac{[1 - \Lambda_t] Y_t}{[1 + \pi_1 TA_t^{\pi_2}]} - TC_t, \quad (21) \]

where \( \Lambda_t \) is the cost of non-carbon energy as a fraction of world output, \( Y_t \) is production, \( TA_t \) is the global mean surface temperature, \( \pi_1, \pi_2 \) are
damage scalars, and $TC_t$ is the cost of avoiding deforestation. As mentioned, the forest biomass is not affected by changes in temperature. If, alternatively, we were to assume that rising temperatures are damaging to the forest biomass, it would increase the incentives to reduce climate change. The reason for this is that we want to avoid a scenario where a smaller or slower growing stock reduces the capacity of the forest to sequester carbon. On the other hand, if we were to assume a positive temperature effect, it would slightly decrease the incentives to reduce climate change as increased temperatures would be attenuated by the increased sequestration.

The production function is written as:

$$Y_t = A_t L_t^{(1-\gamma)} K_t^\gamma,$$  \hspace{1cm} (22)

where $A_t$ is the total factor productivity, $\gamma$ is the production elasticity with respect to physical capital and $(1 - \gamma)$ is the output elasticity of labor. The capital accumulation equation is written as:

$$K_{t+1} = (1 - \delta_K)K_t + I_t,$$  \hspace{1cm} (23)

where $\delta_K$ is the rate of depreciation of capital and $I_t$ is investment. Consumption per capita in any period equals output net of abatement and damages minus investment divided by labor,

$$c_t = \frac{Q_t - I_t}{L_t}.$$  \hspace{1cm} (24)

Social welfare is defined as the present value of current and future utility from consumption, where the utility function is a standard constant relative risk aversion function discounted with the pure rate of time preference, $\rho$. Hence, the welfare function is written as:
\[ W = \sum_{t=1}^{T} L_t \left[ \frac{c_t^{1-\alpha}}{1 - \alpha} \right] (1 + \rho)^{-t}, \]  
\[(25)\]

where \( \alpha \) is the constant elasticity of the marginal utility of per capita consumption.

3 Numerical analysis

This section numerically develops the theoretical model described in Section 2.

3.1 Model setup

The objective is to maximize the present value of the social welfare function from the year 2005 to sixty 10-year periods ahead. The optimization problem is solved with the GAMS CONOPT solver. The freely available GAMS code for the DICE-2007 model is used as a base structure. Parameter values used in the extension of the model originate from various sources. The parameters regarding the forest biomass stocks and carbon are primarily based on data from the Food and Agriculture Organization of the United Nations (FAO). Energy values are derived from data from the International Energy Agency (IEA) and the United Nations Statistical Division (UNSD). Cost estimates for avoided deforestation are calibrated to approximately match the mean global marginal cost estimates of emissions reduction from avoided deforestation presented by Kindermann et al. (2008). Appendix A contains a table that summarizes the parameters and variables used in the paper. Appendix B contains detailed information regarding the cost estimates.
3.2 Results

I run three main scenarios: Optimal Control, Baseline, and No Forest Control. The Optimal Control scenario represents utility maximization when all control variables are determined simultaneously, i.e., investment, carbon control rate and the forest controls (bioenergy harvest and tropical deforestation control rate) are optimally chosen. The Baseline scenario represents the optimal control scenario without climate damages to the economy from increased temperatures. This scenario implies that controls are chosen without consideration of the impact on the climate through emissions and sequestration. Energy abatement is only determined by the fossil fuel resource constraint through the Hotelling rent. The No Forest Control scenario has a deforestation control rate of zero and a bioenergy harvest growth rate equal to the growth of labor.\textsuperscript{11}

To shed light on the relative importance of forest controls, I also run two variations of the Optimal Forest Control scenario. Deforestation is exogenous in the Bioenergy Harvest Control scenario and bioenergy harvest is exogenous in the Deforestation Control scenario. I also run the Optimal Forest Control and No Forest Control scenarios imposing a 2°C global mean temperature increase limit, as suggested by the Copenhagen United Nations Climate Change Conference. Table 1 gives brief definitions of the scenarios.

Figure 1 shows the evolution of forest biomass stocks under the Optimal Control and the No Forest Control scenario. The tropical forest stock increases over time when deforestation and bioenergy harvest is determined optimally. The figure reveals that the total stock of growing global forest biomass is increasing under Optimal Control. This increase is driven by the growth of the tropical forest stock and the small increase in the boreal forest, which dominates the decrease in the temperate forest stock.

\textsuperscript{11}This exogenous harvest initially grows by 5.7 percent per decade. This rate slows down to 3.8 percent per decade by 2205 and approximately zero percent per decade by 2505.
Table 1: Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Optimal Control</strong></td>
<td>Saving, carbon control rate, and forest controls</td>
</tr>
<tr>
<td><strong>Baseline</strong></td>
<td>Saving, carbon control rate, and forest controls, no climate damages</td>
</tr>
<tr>
<td><strong>No Forest Control</strong></td>
<td>Saving and carbon control rate</td>
</tr>
<tr>
<td><strong>Deforestation Control</strong></td>
<td>Saving, carbon control rate, and deforestation control rate</td>
</tr>
<tr>
<td><strong>Bioenergy Harvest Control</strong></td>
<td>Saving, carbon control rate, and bioenergy harvest control</td>
</tr>
<tr>
<td><strong>2°C Optimal Control</strong></td>
<td>Saving, carbon control rate, and forest controls, 2°C limit</td>
</tr>
<tr>
<td><strong>2°C No Forest Control</strong></td>
<td>Saving and carbon control rate, 2°C limit</td>
</tr>
</tbody>
</table>

Figure 1: Growing stock, billion m$^3$

The large deviation in the size of the tropical forest stock between the Optimal Control and the No Forest Control scenario is caused by both a change in deforestation and bioenergy harvest. Conversely, for temperate and the boreal forests, the difference in the size of the stocks between the scenarios is solely driven by changes in the bioenergy harvest control. Figure 2 shows the evolution bioenergy harvest for the Optimal Control and the No Forest Control scenario. The tropical and boreal bioenergy
harvests are lower under Optimal Control than under No Forest Control while the temperate bioenergy harvest is higher.

The evolution of the bioenergy harvest in Figure 2 indicates that the size of the initial harvest level is non-optimal. In the case of the tropical forest, the initial bioenergy harvest is high due to extensive use of wood fuel in tropical regions. The optimal bioenergy harvest drops to 50% of the initial size in the first decade, but then gradually increases following the trend of the No Forest Control prediction. The tropical bioenergy harvest is by 2105 approximately 80% of the initial level and 60% of the No Forest Control prediction. The tropical forest stores a vast amount of carbon in its biomass that will be released when used for bioenergy production. This release of carbon in combination with a low net biomass growth rate leads to lower harvest under Optimal Control.

In the case of the boreal forest, the initial bioenergy harvest is small due to the small direct forest removals for energy production in the boreal region. The optimal boreal bioenergy harvest drops by approximately 50%
from the initial level, although the difference is small in absolute terms. Conversely, in the case of the temperate forest, the optimal bioenergy harvest increases by almost 80% of the initial size in the same period, and then remains higher than the No Forest Control prediction. This increase occurs primarily because the temperate forest biomass has the highest net biomass growth rate and the highest efficiency in bioenergy conversion.

As mentioned, the reduction in deforestation also contributes to the increase in the stock of tropical biomass under Optimal Control. Table 2, which shows the deforestation control rate and the carbon control rate for the Optimal Control and the No Forest Control scenario, indicates that it is optimal to reduce the baseline deforestation by almost 10% in the first time period. The reduction increases over time until reaching 100% of baseline deforestation in 2115. Note that baseline deforestation is declining over time. The optimal carbon control rate is 16.5% in the first time period and increases almost linearly over time until it reaches 97% in 2195. Table 2 also shows that the carbon control rate is slightly higher in the Optimal Control scenario than in the No Forest Control scenario. This higher rate of non-carbon energy indicates that the use of carbon-based energy is lower. Total energy from forest biomass is lower because it is optimal to progressively substitute forest bioenergy for non-carbon energy.

<table>
<thead>
<tr>
<th></th>
<th>2015</th>
<th>2035</th>
<th>2055</th>
<th>2115</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deforestation control rate Optimal Control</td>
<td>0.0959</td>
<td>0.2963</td>
<td>0.5048</td>
<td>1</td>
</tr>
<tr>
<td>Carbon control rate Optimal Control</td>
<td>0.1648</td>
<td>0.2188</td>
<td>0.2788</td>
<td>0.5041</td>
</tr>
<tr>
<td>Carbon control rate No Forest Control</td>
<td>0.1633</td>
<td>0.2175</td>
<td>0.2779</td>
<td>0.5030</td>
</tr>
</tbody>
</table>

One key prediction of the model is that direct emissions from land are decreasing over time. Figure 3 shows the emissions path from baseline deforestation and the avoided deforestation under Optimal Control. The path of the baseline emissions occurs both under No Forest Control and
Baseline. Note that the direct emissions from baseline deforestation are equal to the baseline emissions from land in the DICE-2007 model and are the only source of land-use emissions. The difference between these two curves illustrates the direct emissions from deforestation under Optimal Control. These emissions are decreasing over time both because the avoided deforestation is increasing and because the baseline deforestation is declining. The total reduction in emissions occurs not only through a instant reduction of emissions released from the removed forest, but also through increasing its sequestration potential. This implies that even if the actual amount of biomass saved through reducing deforestation is low compared with the growing stock, the overall effect is potentially high due to the increase in the relative growth rate and the larger forest stock potential.

![Graph showing emissions over time](image)

Figure 3: Emissions from baseline deforestation and reduced emissions from deforestation control, GtC per decade

The model predicts that optimal use of forest contributes to the reduction of overall emissions. Figure 4 compares the evolution of carbon
emissions for four scenarios: No Forest Control, Optimal Control, and its two variations, Deforestation Control and Bioenergy Harvest Control. The figure shows that the use of optimal bioenergy harvest and avoided deforestation leads to lower total emissions. The figure also illustrates that in the short run, each of the forest controls is almost equally good at lowering emissions. However, in the long run, avoided deforestation is by itself the key control to reducing emissions.

![Figure 4: Total carbon emission, GtC per decade](image)

Total carbon emissions are the net of emissions from energy conversion, forest carbon sequestration, and emissions from harvest and decay of wood products. Figure 5 illustrates the evolution for each of these components of the total emissions in the Optimal Control scenario. Emissions from energy conversion represent carbon from fossil fuels and forest fuels. Emissions from energy conversion are increasing over the next 100 years due to increased use of carbon energy. Forest carbon sequestration, displayed in the figure as negative emissions, represents the change in the carbon in the forest biomass. The optimal accumulation of car-
bon in forest biomass is positive and increasing until 2115. The release of carbon from the carbon stock in wood products and the direct release of carbon from roundwood harvest are constant over time.

![Graph showing carbon emissions and sequestration under Optimal Control](image)

**Figure 5:** Carbon emissions and sequestration under Optimal Control, GtC per decade

In terms of temperature, the implication of lower emissions under optimal control is a slight reduction in global mean temperature. Table 3 shows the global mean temperature increase under Optimal Control, No Forest Control, Baseline and the values of the DICE-2007 model. The temperature in the Optimal Control scenario is $0.2 \degree C$ lower than in the Baseline scenario by 2055 and $0.74 \degree C$ lower by 2115. As shown in the table, the difference in temperature between the Optimal Control scenario and the No Forest Control scenario is small but increasing over time. Note that explicitly including the forest biomass in the global carbon cycle leads to lower total global carbon emissions compared with the original DICE-2007 model results. The global mean temperature increases under optimal control of this model and peaks at $3.25 \degree C$ by 2185, while the optimal run of the DICE-2007 model shows a peak at $3.47 \degree C$. 


one decade later.

Table 3: Mean temperature increase, °C

<table>
<thead>
<tr>
<th></th>
<th>2015</th>
<th>2035</th>
<th>2055</th>
<th>2115</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal Control</td>
<td>0.927</td>
<td>1.301</td>
<td>1.673</td>
<td>2.694</td>
</tr>
<tr>
<td>No Forest Control</td>
<td>0.928</td>
<td>1.313</td>
<td>1.700</td>
<td>2.763</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.938</td>
<td>1.386</td>
<td>1.875</td>
<td>3.432</td>
</tr>
<tr>
<td>DICE-2007 Optimal Control</td>
<td>0.951</td>
<td>1.376</td>
<td>1.783</td>
<td>2.840</td>
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<tr>
<td>DICE-2007 Baseline</td>
<td>0.960</td>
<td>1.445</td>
<td>1.945</td>
<td>3.437</td>
</tr>
</tbody>
</table>

Lower temperatures under optimal forest controls also lead to a lower carbon price, with larger differences between scenarios when the climate target is low. Table 4 shows the price of carbon for different scenarios. The first column represents the social cost of carbon in 2005. The social cost of carbon is the discounted change in utility caused by an additional ton of carbon emissions in the first time period. The next three columns represent the optimal carbon price in 2025, 2045, and 2105. The optimal carbon price is the price that balances the marginal cost of reducing emissions with the marginal benefit of reducing damages. The table indicates that the predictions of the DICE-2007 model are higher than those under Optimal Control and No Forest Control. These higher predictions are the result of not taking into account forest carbon sequestration. The table also shows that the carbon price prediction in the Optimal Control scenario is only slightly lower than the No Forest Control scenario in the optimal run of the model. This is partly due to the low climate damages in the DICE model. However, if we impose a 2°C global mean temperature target, the benefit of an optimal forest control is much larger. The carbon price is approximately $13 lower by 2025 and $33 lower by 2045 compared with the No Forest Control scenario.
Table 4: Carbon prices, 2005 U.S. dollar per tC

<table>
<thead>
<tr>
<th></th>
<th>2005</th>
<th>2025</th>
<th>2045</th>
<th>2105</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal Control</td>
<td>26.70</td>
<td>52.07</td>
<td>79.30</td>
<td>211.44</td>
</tr>
<tr>
<td>No Forest Control</td>
<td>26.84</td>
<td>52.38</td>
<td>79.76</td>
<td>211.94</td>
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<tr>
<td>DICE-2007 model</td>
<td>27.27</td>
<td>53.18</td>
<td>80.73</td>
<td>212.64</td>
</tr>
</tbody>
</table>

2°C temperature limit

<table>
<thead>
<tr>
<th></th>
<th>2005</th>
<th>2025</th>
<th>2045</th>
<th>2105</th>
</tr>
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<tr>
<td>Optimal Control</td>
<td>35.38</td>
<td>75.50</td>
<td>141.44</td>
<td>683.51</td>
</tr>
<tr>
<td>No Forest Control</td>
<td>40.20</td>
<td>88.31</td>
<td>174.37</td>
<td>876.50</td>
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<tr>
<td>DICE-2007 model</td>
<td>45.30</td>
<td>101.87</td>
<td>208.45</td>
<td>797.94</td>
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</tbody>
</table>

The results of FOR-DICE are contingent on the value of some parameters for which there is considerable uncertainty. This uncertainty stems from data limitations and discrepancies in the values reported in the literature. Appendix C provides a detailed sensitivity analysis in order to test the importance of these uncertainties. The sensitivity is examined with respect to the discount rate, the intrinsic growth rate, the carrying capacity, the cost of avoiding deforestation, and the energy elasticity.

The first key result from the sensitivity analysis is that the optimal bioenergy harvest is mainly affected by the energy elasticity, the intrinsic growth rate, and the carrying capacity. The use of a logistic growth equation implies that the optimal bioenergy harvest is sensitive to the maximum carrying capacity and the intrinsic growth rate assumptions. Specifically, a large harvest is optimal when the growth rate is high and the size of stock is close to its resource limit and vice versa. Note, however, that the magnitudes of the changes required to alter the main findings are considerable. The second key result from the sensitivity analysis is that the avoided deforestation is mainly affected by changes in its cost and the discount rate. The changes in avoided deforestation are consistent with previous literature.
4 Concluding remarks

This paper develops the FOR-DICE model, which is an extension of the DICE-2007 model by Nordhaus (2008). FOR-DICE provides a basic framework that includes boreal, temperate and tropical forest biomass as both a source of renewable energy and storage of carbon. In addition to the controls of the DICE model, the paper extends the optimal carbon management to include forest carbon management. First, the paper endogenizes land emissions of the DICE model by adding the possibility of reducing deforestation in the tropical forest. Second, the paper extends the source of energy to include forest bioenergy as a substitute for fossil fuel. This allows us not only to establish the importance of including the forest carbon in climate policy, but also to explore whether climate policy should focus on preserving or using the forest biomass as a source of energy.

The results of this paper show that the optimal use of forest leads to an increase in carbon sequestration and a reduction in global carbon emissions, especially under an ambitious climate target. However, forest carbon management does not alter the importance of deriving energy from non-carbon-based sources. The results also indicate that forest climate policy should focus on increasing the stock of forest biomass rather than increasing the use of forest bioenergy. At the global level, the decrease in forest carbon stock associated with increased harvests for bioenergy cannot be offset by avoided fossil fuel emissions. At the forest zone level, bioenergy harvest is decreasing for the boreal and tropical forest while increasing for the temperate forest. These results follow from differences in the carbon content of biomass, the bioenergy efficiency and the growth rate of the biomass in each forest zone. Thus, on the whole, and in accordance with previous literature, these results highlight that forest bioenergy cannot be treated as carbon neutral. Last, and also in line with previous studies, I find that reducing deforestation in the tropical forest is a cost-efficient instrument to reduce climate change.
Like the DICE model, one of the main limitations of the FOR-DICE stems from the highly aggregated approach and the simple model setup. This setup, nevertheless, captures the key features of the relationships between the forest and the climate, and allows for a transparent analysis. The insights of this paper should therefore be viewed as complementary to those of more disaggregated models, whose insights cannot be derived through this approach. Irrespective of its simple structure, FOR-DICE allows me to draw two important policy conclusions. First, accounting for forest carbon in climate policy is important for welfare because it allows us to reduce climate change at a lower cost. Practically, this implies that it is important to attach a price to forest carbon. Second, without policies aimed at improving the efficiency of forest bioenergy and the growth rate of forest biomass, ambitious forest bioenergy targets will lead to an increase in atmospheric carbon.
References


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Appendix A: Parameters and variables of the model

Table 5: Variables

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_{n,t}$</td>
<td>Stock of forest biomass (billion m$^3$)$^1$</td>
</tr>
<tr>
<td>$F_{n,t}^{MAX}$</td>
<td>Forest biomass carrying capacity (billion m$^3$)$^2$</td>
</tr>
<tr>
<td>$H_{n,t}$</td>
<td>Total harvest (billion m$^3$)$^3$</td>
</tr>
<tr>
<td>$D_{n,t}$</td>
<td>Forest biomass deforestation (billion m$^3$)</td>
</tr>
<tr>
<td>$\Gamma_{tro,t}$</td>
<td>Baseline carbon emissions from land (Gtc)$^4$</td>
</tr>
<tr>
<td>$RD_{n,t}$</td>
<td>Deforestation control rate (fraction of uncontrolled deforestation, $0 \leq RD_{n,t} \leq 1$)</td>
</tr>
<tr>
<td>$RE_t$</td>
<td>Reduced carbon emissions through deforestation control (Gtc)$^5$</td>
</tr>
<tr>
<td>$MC_t$</td>
<td>Marginal cost of avoiding deforestation (trillion U.S dollars)$^6$</td>
</tr>
<tr>
<td>$TC_t$</td>
<td>Total cost of avoiding deforestation (trillion U.S dollar)</td>
</tr>
<tr>
<td>$HB_{n,t}$</td>
<td>Harvest for bioenergy production (billion m$^3$)$^7$</td>
</tr>
<tr>
<td>$HS_{n,t}$</td>
<td>Roundwood harvest (billion m$^3$)$^8$</td>
</tr>
<tr>
<td>$Y_{t}$</td>
<td>Production (trillion U.S dollar)</td>
</tr>
<tr>
<td>$\sigma_t$</td>
<td>Carbon emissions per output (tc/output)</td>
</tr>
<tr>
<td>$\mu_t$</td>
<td>Carbon control rate (fraction of uncontrolled carbon emission, $0 \leq \mu_t \leq 1$)</td>
</tr>
<tr>
<td>$\Pi_t$</td>
<td>Carbon emissions from production (Gtc)</td>
</tr>
<tr>
<td>$\Xi_{t}$</td>
<td>Carbon-based energy function$^9$</td>
</tr>
<tr>
<td>$FO_{t}$</td>
<td>Fossil fuel carbon (Gtc)</td>
</tr>
<tr>
<td>$EE_{t}$</td>
<td>Emissions from energy conversion (Gtc)</td>
</tr>
<tr>
<td>$CH_{t}$</td>
<td>Carbon stock in wood products (Gtc)$^{10}$</td>
</tr>
<tr>
<td>$CI_{t}$</td>
<td>Inflow to the carbon stock in wood products (Gtc)</td>
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<tr>
<td>$ES_{t}$</td>
<td>Emissions from harvest and carbon in wood products (Gtc)</td>
</tr>
<tr>
<td>$EF_{t}$</td>
<td>Emissions from change in stock of forest biomass (Gtc)</td>
</tr>
<tr>
<td>$E_{t}$</td>
<td>Total carbon emissions (Gtc)</td>
</tr>
<tr>
<td>$Q_{t}$</td>
<td>Output net of abatement and damages (trillion U.S dollar)</td>
</tr>
<tr>
<td>$N_{t}$</td>
<td>Cost of non-carbon energy (fraction of world output)</td>
</tr>
<tr>
<td>$TA_{t}$</td>
<td>Global mean surface temperature (°C increase from year 1900)</td>
</tr>
<tr>
<td>$I_{t}$</td>
<td>Investment (trillion U.S dollar)</td>
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<tr>
<td>$K_{t}$</td>
<td>Capital stock (trillion U.S dollar)</td>
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<tr>
<td>$L_{t}$</td>
<td>Labor (trillion)</td>
</tr>
<tr>
<td>$c_{t}$</td>
<td>Per capita consumption (trillion U.S dollar)</td>
</tr>
</tbody>
</table>

1. Year 2005 boreal, temperate and tropical stocks of growing biomass are derived from region and country-level data from FAO (2010). The FAO Global Ecological Zone map is used to classify countries into the different forest zones (FAO, 2012). The subtropical forest zone of the Global Ecological Zone is merged into the temperate forest zone. This aggregation is an approximation of the true ecological zones as I use this country level data. FAO regions or countries included in the boreal forest zone: Canada, Finland, Norway, Russia, and Sweden; in the temperate forest zone: Eurasia, Western and Central Asia, United States, Argentina, Chile, Uruguay, New Zealand, and Europe (except Finland, Norway, Russia, and Sweden); and in tropical forest zone: Africa, South and Southeast Asia, the Caribbean, Central America, South America (except Argentina, Chile, and Uruguay), Mexico, Oceania (except New Zealand). Year 2005 total growing forest biomass was approximately 525 billion m$^3$. $F_{bor,t=0} = 120$, $F_{tem,t=0} = 96$, $F_{tro,t=0} = 309$. 

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2. The carrying capacity is constant for the boreal and temperate forests due to absence of land area changes and forest management that can alter the maximum amount of biomass. For the tropical forest, however, the carrying capacity can change through deforestation. No general estimates of the carrying capacity in m$^3$ per hectare exist for the boreal, temperate, and tropical forest. The carrying capacity is set to be twice as large as the existing stock of forest biomass at the initial year of the logistic growth function calibration. See Note 18 for further discussion regarding the carrying capacity and its relation to the intrinsic growth rate. $F_{bor,t=0} = 237, F_{tem,t=0} = 183, F_{tro,t=0} = 589$.

3. Billion m$^3$ biomass removed from the forest for production of energy and goods and services, i.e., $H_{n,t} = HB_{n,t} + HS_{n,t}$.

4. Baseline carbon emissions from deforestation is determined by the exogenous carbon emissions equation from land in the DICE-2007 model.

5. Avoided emissions from land through deforestation control. These emissions represent the avoided direct release of carbon stored in the forest biomass.

6. See Appendix B for cost of avoiding deforestation.

7. I use data from FAO (2010) on woodfuel removals (wood removed for energy production for industrial, commercial and domestic use) to estimate the year 2005 harvest for energy production in each forest zone. The year 2005 global woodfuel removals are 1.45 billion m$^3$. The actual removals are, however, unquestionably higher as informally and illegally removed wood rarely is included in the data (FAO, 2010). $HB_{bor,t=0} = 0.073, HB_{tem,t=0} = 0.250, HB_{tro,t=0} = 1.127$.

8. I use data from FAO (2010) on industrial roundwood removals (wood removed for production of goods and services) to estimate the year 2005 roundwood harvest in each forest zone. The year 2005 global industrial roundwood removals amounted to 1.762 billion m$^3$. $HS_{bor,t=0} = 0.7285, HS_{tem,t=0} = 0.6285, HS_{tro,t=0} = 0.4050$.

9. The carbon-based energy function is a constant return to scale Cobb-Douglas function with fossil fuel carbon and bioenergy harvest inputs. The year 2005 value of the carbon-based energy function corresponds to the total global energy production of 485.66 EJ (IEA, 2014d).

10. The year 2005 stock of carbon in forest products is 4.2 GtC. Due to lack of more recent estimates, this amount is equal to the one decade older estimate reported by IPCC. While the amount of carbon stored in forest products is highly uncertain, there is a consensus that the sink potential is relatively small compared with the existing carbon storage in living forest biomass (IPCC, 2001).
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
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<tr>
<td>$\lambda_1$</td>
<td>First decade emissions from deforestation (Gtc)&lt;sup&gt;11&lt;/sup&gt;</td>
<td>11.0</td>
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<td>$\lambda_2$</td>
<td>Deforestation decrease parameter</td>
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<td>$\phi_1$</td>
<td>Avoided deforestation cost parameter&lt;sup&gt;12&lt;/sup&gt;</td>
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<td>Avoided deforestation cost parameter</td>
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<td>Avoided deforestation cost parameter</td>
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<td>Avoided deforestation cost parameter</td>
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<td>Avoided deforestation cost parameter</td>
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<td>$\xi$</td>
<td>Energy-emissions parameter (EJ/Gtc)&lt;sup&gt;13&lt;/sup&gt;</td>
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<td>$\zeta$</td>
<td>Energy scale parameter&lt;sup&gt;14&lt;/sup&gt;</td>
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<td>$\delta_k$</td>
<td>Rate of depreciation of carbon in wood products</td>
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<td>$H_L$</td>
<td>Half-life years for carbon in wood products&lt;sup&gt;15&lt;/sup&gt;</td>
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<td>$\delta_{CH}$</td>
<td>Fraction of carbon lost from wood product per year&lt;sup&gt;16&lt;/sup&gt;</td>
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<td>$\nu$</td>
<td>Share of carbon in harvest to wood products&lt;sup&gt;17&lt;/sup&gt;</td>
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<td>$\kappa$</td>
<td>Maximum consumption fossil fuels (Gtc)</td>
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<td>Elasticity of marginal utility of consumption</td>
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<tr>
<td>$\rho$</td>
<td>Pure rate of social time preference</td>
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<table>
<thead>
<tr>
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<th>Temperate</th>
<th>Tropical</th>
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<td>$\psi_n$</td>
<td>Intrinsic growth rate of forest biomass&lt;sup&gt;18&lt;/sup&gt;</td>
<td>0.1128</td>
<td>0.3726</td>
<td>0.1989</td>
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<tr>
<td>$\theta_n$</td>
<td>Carbon intensity in forest biomass (tc/m&lt;sup&gt;3&lt;/sup&gt;)&lt;sup&gt;19&lt;/sup&gt;</td>
<td>0.406084</td>
<td>0.456057</td>
<td>0.637926</td>
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<tr>
<td>$\Phi_n$</td>
<td>Energy elasticity of bioenergy harvest&lt;sup&gt;20&lt;/sup&gt;</td>
<td>0.0017</td>
<td>0.0223</td>
<td>0.0394</td>
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<tr>
<td>$\chi_n$</td>
<td>Biomass share of total roundwood harvest&lt;sup&gt;21&lt;/sup&gt;</td>
<td>0.41</td>
<td>0.36</td>
<td>0.23</td>
</tr>
</tbody>
</table>

11. The first decade emissions from deforestation come from the carbon emissions from land in the DICE-2007 model. This amount corresponds well to estimates by FAO (2005).

12. See Appendix B for cost of avoiding deforestation.

13. I calculate the carbon emissions energy parameter by using the year 2005 global energy production from IEA (2014d) and the year 2005 carbon energy emissions in the DICE-2007 model. $\xi = 485.66/7.4 \approx 65.6297$.

14. The scale parameter of the carbon energy function is calibrated with the year 2005 values of the inputs and the elasticities. The value of the fossil fuel carbon is from the DICE-2007 model and the value of the bioenergy harvest is from FAO (2010). The elasticities are calculated with data from IEA (2014d), IEA (2014b), IEA (2014c), and UNSD (2014).

$$485.66/[0.073^{0.0017} 0.25^{0.0223} 1.127^{-0.394} 7.4^{(1-0.0017-0.0223-0.394)}] \approx 76.8285.$$
15. The half-life duration of carbon in wood products is a weighted average of different types of products, ranging from paper, which is discarded rapidly, to buildings, which have a significantly longer life cycle. Hence, the variation in the duration of carbon in wood products spans from one-year half-life carbon up to 100-year half-life carbon (Skog and Nicholson, 1998).

16. The decay rate for carbon in wood products is written as: $\delta_{CH} = \frac{ln(2)}{v}$.

17. The share of total carbon in the forest removals that goes into the carbon stock in wood products comes from estimates by Ingerson (2009).

18. I calculate the intrinsic growth rates of the forest by using data from FAO (2010) on forest biomass, total removals, and forest area. This region- and country-level data is aggregated to the forest zones and used to calibrate the intrinsic growth rate of the logistic growth function. The intrinsic growth rate for each forest zone is the average of the calibrated intrinsic growth rates for the decades 1990-2000 and 2000-2010. The initial carrying capacity in this calibration is assumed to be twice as large as the size of the stock. The intrinsic growth rates will depend on the size of the carrying capacity; a lower carrying capacity relative to the current stock size leads to a higher intrinsic growth rate and vice versa. Effects of changing the carrying capacity and of changing the intrinsic growth rate are shown in the sensitivity analysis in Appendix C. The intrinsic growth rate is calibrated from the net increment of the forest. The gross forest growth in the tropical forest is undoubtedly higher as unrecorded wood removals are expected to be high.

19. I use data from FAO (2010) on the total carbon in growing forest biomass and the stock of growing forests biomass to derive the carbon intensity in each forest zone. Carbon in soil is not included.

20. The energy elasticities of bioenergy harvest are defined by their share of the total global energy production. I derive these figures using data from IEA (2014d), IEA (2014b), IEA (2014c), and UNSD (2014). I aggregate these country-level datasets to the forest-zone level. I calculate terajoules from bioenergy harvest by taking the total production from solid biofuel and charcoal and then subtracting black liquor, other vegetal materials and residuals, animal waste, and bagasse. Terajoule data is not available for all categories. I use conversion factors from IEA (2014a) to convert charcoal data in kiloton from IEA (2014c) to terajoule. Similarly, I use the standard conversion factor of UNSD (2011) to convert the bagasse data in kiloton from UNSD (2014) to terajoule.

21. The roundwood harvest shares for the forest zones are derived from the region and country level data on the industrial roundwood harvest by FAO (2010). Year 2005 total industrial roundwood harvest is 1.762 billion m$^3$.

$HB_{bor,t=0} = 0.098, HB_{tem,t=0} = 0.204, HB_{tro,t=0} = 1.148$. 

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Appendix B: Cost of reducing deforestation

The functional form of the marginal cost of avoiding deforestation is modeled to approximately follow the marginal cost curves presented in Kindermann et al. (2008). They use three land use and management models, the dynamic integrated model of forestry and alternative land use (DIMA), the generalized comprehensive mitigation assessment process model (GCOMAP), and the global timber model (GTM) to examine the carbon emissions reduction potential and marginal cost of avoiding emissions from deforestation. The paper presents marginal cost results for the tree different models and a mean for the years 2010, 2020, and 2030. The functional form in Equation 5 is an approximation of their mean marginal cost curves of avoiding deforestation. Figure 6 illustrates, for three decades, this estimated marginal cost function of avoiding emissions from deforestation.

Figure 6: Marginal cost of reducing emissions from deforestation, US$ per TC
Appendix C : Sensitivity analysis

This section contains a sensitivity analysis that examines how the results change with different values of the discount rate, the intrinsic growth rate, the carrying capacity, the cost of avoiding deforestation, and the energy elasticities. All figures in the sensitivity analysis correspond to the Optimal Control scenario. The solid and dashed lines represent the parameter value of this model and the lines with symbols represent results for the alternative parameter values.

Discount rate

The optimal scenario is run with three alternative pure rate of time preference. The low rate is 50% of the original rate, and the high rate is 150% of the original rate, \( \rho = \{0.0075, 0.015, 0.0225\} \). Figure 7 shows the carbon control rate and the deforestation control rate. We can see in the figure that both control rates are higher with a low discount rate and lower with a high discount rate. Furthermore, bioenergy harvest decisions are insensitive to variations in the pure rate of time preference.
Figure 7: Deforestation control rate and carbon control rate, fraction of uncontrolled emissions

**Intrinsic growth rate**

Figure 8 displays the optimal bioenergy harvest decisions for three different intrinsic growth rates and unchanged carrying capacity. The low rate is 20% lower than the original growth rate and the high rate is 20% higher than the original growth rate. $\psi_{tro} = \{0.1591, 0.1989, 0.2387\}$, $\psi_{bor} = \{0.0902, 0.1128, 0.1354\}$, and $\psi_{tem} = \{0.2981, 0.3726, 0.4471\}$. The bioenergy harvest for the tropical and temperate forest is higher with a high intrinsic growth rate and lower with a low intrinsic growth rate. The boreal bioenergy harvest does not change when the growth rate varies. Moreover, the avoided deforestation is also insensitive to changes in the intrinsic growth rate.
Carrying capacity

Figure 9 displays the optimal tropical bioenergy harvest decisions for three different carrying capacities and intrinsic growth rates. The intrinsic growth rates are recalibrated by assuming different initial levels of the carrying capacity in the logistic growth function. The low carrying capacity represents an initial forest biomass at 75% of its carrying capacity, and the high carrying capacity represents an initial forest biomass at 25% of its carrying capacity. A lower carrying capacity leads to a higher intrinsic growth rate and vice versa. \( \psi_{\text{tro}} = \{0.4125, 0.1989, 0.1311\} \), \( \psi_{\text{bor}} = \{0.2270, 0.1128, 0.0750\} \), and \( \psi_{\text{tem}} = \{0.7832, 0.3726, 0.2451\} \). The figure shows that the optimal harvest levels are higher when the stock of biomass has a higher intrinsic growth rate and is close to its maximum capacity. When the carrying capacity is high and the intrinsic growth rate is low, it is instead optimal to decrease the harvest to increase the stock.
Figure 9: Bioenergy harvest, billion m$^3$ per decade

Cost of reducing deforestation

There are large uncertainties about the cost of reducing deforestation. Figure 10 displays the optimal deforestation control rate for three different cost levels. The low cost is 20% lower and the high cost is 20% higher than the integrated original marginal cost function. We can see in Figure 10 that a lower cost results in higher levels of avoided deforestation and vice versa.
Figure 10: Deforestation control rate, fraction of uncontrolled emissions

Energy elasticity

Figure 11 illustrates how the elasticities in the Cobb-Douglas carbon energy function affect the optimal bioenergy harvest. The bioenergy harvest generates a 20% higher amount of energy in the calculation of the high bioenergy elasticities and a 20% lower amount of energy in the calculation of the high bioenergy elasticities. The amount of energy produced by fossil fuel carbon will also vary since this total energy production is unchanged. \( \zeta = \{74.4271, 76.8285, 79.2720\} \), \( \Phi_{bor} = \{0.0013, 0.0017, 0.0020\} \), \( \Phi_{tem} = \{0.0179, 0.0223, 0.0268\} \), and \( \Phi_{tro} = \{0.0315, 0.0394, 0.0472\} \). We can see in Figure 11 that the higher bioenergy elasticity leads to a larger bioenergy harvest. While the harvest is increasing compared with the Optimal Control scenario, the total bioenergy harvest is still below the baseline prediction.
Appendix D: The 2°C global mean temperature target

The Copenhagen United Nations Climate Change Conference formed an agreement in December 2009 to reduce global emissions so that the increase in global temperature would not exceed 2°C (UNFCCC, 2010). In the model, meeting this global mean temperature target implies a lower temperature than under the optimal control scenario, which peaks at 3.25°C. Figure 12 shows how the emissions control rates are affected by a 2°C mean temperature goal. The goal increases both control rates in the short and the long run. We can see in Figure 12 that the carbon control rate rise steeper in the 2°C scenario, increasing the distance to the Optimal Control path over time. In the first decade, the deforestation control in the 2°C scenario is more than three times higher than the Optimal Control path. The baseline deforestation is fully avoided by year 2017 with a 2°C goal.
Figure 12: Deforestation control rate and carbon control rate, fraction of uncontrolled emissions

Figure 13 illustrates how the optimal bioenergy harvest is affected by an 2°C mean temperature goal. The goal leads to a large reduction of the temperate and tropical bioenergy harvest after year 2045 as the carbon energy dependence declines. The lower carbon energy dependence comes from the decline of the carbon emission-output ratio and the higher carbon control rate.
Figure 13: Bioenergy harvest, billion m³ decade

Figure 14 shows the carbon emissions from energy conversion, forest carbon sequestration, and emissions from harvest and decay of wood products for the Optimal Control and the 2°C Optimal Control scenario. The carbon energy emissions for the 2°C Optimal Control scenario display a large decrease due to a higher carbon control. The decrease comes from reduced emissions from both forest fuels and fossil fuels. The carbon sequestration from forest growth is only slightly higher with the 2°C temperature goal.
Figure 14: Carbon emissions and sequestration, GtC per decade
Mitigating Climate Change with Forest Climate Tools

Mathilda Eriksson

Abstract

This paper develops the FRICE, a framework that determines optimal levels of forest climate tools in the context of global climate policy. The paper integrates afforestation and avoided deforestation into the well-known global multi-regional integrated assessment model, RICE-2010. The paper finds that climate forest tools can play an essential role in global climate policy and that this role is increasingly important under stringent temperature targets. Under a 2°C temperature target, the model reveals that emission reductions from avoided deforestation are quickly exhausted whereas afforestation is capable of substantially reducing emission reductions in both the medium and long run. The model also indicates that the most significant reductions in emissions from avoided deforestation and afforestation can be achieved by focusing policy efforts on tropical forests.

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1 Introduction

The objective of this paper is to investigate the role of forest carbon policy in the broader context of climate policy. To do this, I derive a multi-regional integrated assessment model that allows me to estimate the spatial allocation of two key forest climate tools, namely, afforestation and avoided deforestation. I additionally, investigate how the optimal paths of forest climate tools are related to the stringency of the global temperature target.

Forests play a significant role in the global climate. One key mechanism through which forest affects the climate is through emissions and sequestration of carbon. Accordingly, forest climate tools such as avoided deforestation and afforestation should be included in the set of instruments to combat climate change. Richards and Stokes (2004) review numerous sequestration cost studies, including avoided deforestation and afforestation. They conclude that carbon sequestration could play an important part of an efficient carbon abatement strategy. However, their review highlights that the potential of forest climate tools depends on when and where these actions are introduced. For example, the efficiency of forest climate tools varies across regions, and sequestration opportunities are in general lower in the boreal regions than in both the temperate and tropical regions. Moreover, actions related to preservation of forests provides the largest carbon sequestration in the short run, while sequestration from afforestation is increasingly important in the long run. Furthermore, the results of Sohngen et al. (2009) are consistent with the idea that afforestation plays the biggest role in temperate regions while avoided deforestation is most important in the tropics. In the tropical forests, reduction of deforestation has the largest sequestration potential in both the short and long run.¹

A series of case studies have estimated the cost of these forest climate tools have argued by many others in the literature (e.g., Gullison et al. (2007); Tavoni et al. (2007); Bosetti et al. (2011)).

¹The argument that reducing deforestation can be one of the least costly mitigation policies has been argued by many others in the literature (e.g., Gullison et al. (2007); Tavoni et al. (2007); Bosetti et al. (2011)).
tools in particular countries or regions. For example, estimations of the cost of sequestration from afforestation are available for China (Xu et al., 2001), for the United States (Nielsen et al., 2014), and for Latin America (Benítez and Obersteiner, 2006). While these studies can illustrate the afforestation potential for each region, they fail to globally identify cost-efficient sites for afforestation. Another strand of the literature that takes a global approach, such as Benítez et al. (2007), deals with this concern but does not simultaneously evaluate forest climate tools with other climate mitigation policies. Accordingly, a policy-relevant approach requires a multi-regional optimization model that accounts for the simultaneous evaluation of sequestration activities in addition to other mitigation policies.

Current integrated assessment models that investigate the forest carbon sequestration potential are by and large soft linking models, where results from a partial equilibrium forestry model are fed into a general equilibrium model (e.g., Sohngen and Mendelsohn (2003); Tavoni et al. (2007); Hertel et al. (2009); Golub et al. (2009)). The upside of these models is that they provide detailed insights into the inner workings of the forest, and of its relationship to the climate and the economy. The downside is that given their complexity, the policy targets derived from them are at risk of being viewed by policy makers as being derived from a black box.

Given the importance of transparency during climate negotiations, it is of crucial importance to elaborate a framework that allows users to easily understand how different climate targets affect policy tools. The purpose of this paper is to develop such a framework and to derive targets for world carbon sequestration policy in the broader context of climate policy. To do this, I integrate afforestation and avoided deforestation into RICE, the well-known global multi-regional integrated assessment model by Nordhaus (2010). Specifically, I make emissions from land in the RICE model endogenous by adding the possibility to reduce deforestation. The cost of avoiding regional emissions from deforestation
follows the cost estimates provided by previous literature. In addition, I model regional sequestration from afforestation by combining regional forest data with a stylized forest growth function. The cost of afforestation is derived from geospatial data on the production value of land. The model is stated as an optimal control problem for efficient regional allocation of afforestation and avoided deforestation, together with the emission control variable of the original RICE model.

The main finding is that forest climate tools provide a cost-effective way to enhance global climate policy. Avoided deforestation is particularly effective in the short run while afforestation provides the largest emissions reduction in the medium and run. My results also indicate that forest climate policy should not solely rely on avoided deforestation as its capacity to reduce emissions is quickly exhausted. Limiting the increase in global temperature bolsters the previous findings and highlights that the importance of forest climate tools increases with the stringency of temperature targets. At the regional level, for both avoided deforestation and afforestation, priority should be given to tropical forests. The bulk of the potential for the reduction of global emissions lies in Africa.

The paper is organized as follows: Section 2 presents the FRICE model. Section 3 presents the main findings. Section 4 concludes.

2 Model

This paper develops the FRICE model, which is based on the well-known RICE model by Nordhaus (2010). This section describes the main features of the RICE-2010 model and the integration of the forest climate tools in the FRICE. To this date, the RICE-2010 model is only publicly available as an Excel model. Appendix A describes some aspects of the recoding of the model into the GAMS software.
2.1 RICE-2010

The RICE (Regional Integrated model of Climate and the Economy) model is as a multi-regional neoclassical economic growth model that includes climate change. A climate module describes how greenhouse gas emissions increase atmospheric temperature. The temperature increase, in turn, affects regional economic output through a damage output function and a sea-level rise damage function. The model consists of 12 regions: Africa, China, EU, Eurasia, India, Japan, Latin America (LA), Middle East (ME), Russia, USA, Other High-Income countries (OHI), and Other Non-OECD Asia (ASIA). Each region is endowed with an initial capital stock and has a region-specific level and trend of labor and technology. The regional production can be used for investment, consumption, and energy abatement. Total emissions come from production, net of energy abatement, and exogenous land-use emissions. The objective of the RICE model is to maximize a Negishi weighted aggregation of regional social welfare functions by choosing optimal regional levels of investment and energy abatement. The objective function is given by:

\[
W = \sum_{n=1}^{N} \sum_{t=1}^{T} \omega_{n,t} \left[ L_{n,t} \frac{c_{n,t}^{1-\alpha}}{1 - \alpha} (1 + \rho)^{-t} \right],
\]

where \( n \) denotes the region, \( \alpha \) is the elasticity of the marginal utility of per capita consumption, \( c_{n,t}, \omega_{n,t} \) is the Negishi weight, \( \rho \) is the pure rate of social time preference, and \( L_{n,t} \) is labor. Regarding equity across time, the pure rate of time preference, and the elasticity of marginal utility of consumption together with the growth of per capita consumption, gives a diminishing marginal utility of income over time. Regarding equity across space, the Negishi weights adjust so that the marginal utility of consumption in each period is equal across regions. Hence, these welfare weights eliminate any possible Pareto improvement from income redistri-
bution between regions (Negishi, 1960).\(^2\) The use of Negishi weights has been criticized on ethical grounds for preserving the global distribution of income between regions. The criticism hinges on whether it is reasonable to separate questions of efficient resource allocation from concerns over inequality. Stanton (2011) provides a comprehensive discussion on the implications of using Negishi weighting in integrated assessment modeling.\(^3\)

The reader is referred to Nordhaus (2010) including appendix for equations and key assumptions of the RICE-2010 model.\(^4\)

### 2.2 FRICE

Energy abatement, which represents non-carbon-based energy, is the only action that can be taken to reduce global carbon emissions in the RICE-2010 model. Emissions from land-use are exogenous and only exist in regions experiencing deforestation. The FRICE model extends the RICE-2010 model (Nordhaus, 2010) by including afforestation and avoided deforestation as actions to reduce global carbon emissions. The optimization problem in FRICE is solved by choosing afforestation and avoided deforestation for each region, in addition to the controls of the original RICE model.

**Avoided deforestation**

The exogenous carbon emissions from land for Latin America (LA), Africa, and Non-OECD Asia (ASIA) in the RICE-2010 model are used as

\(^2\)The weights can be identified through an iterative procedure where weights are adjusted until the shadow price of capital is equalized across regions Yang (2008).

\(^3\)Two alternatives to the Negishi approach include optimization without welfare weighting and the use of a cost-benefit approach where money is maximized instead of utility.

\(^4\)The Excel spreadsheet of the model is downloadable from Nordhaus website: http://www.econ.yale.edu/~nordhaus/homepage/RICEmodels.htm.
approximations of baseline deforestation. The RICE-2010 model baseline carbon emissions from land are given by:

$$BD_{n,t} = \lambda_1 n \lambda_2^t,$$

(2)

where the parameter $\lambda_1$ represents the first-period carbon emissions and the parameter $\lambda_2$ generates a declining carbon emissions over time. The baseline decline of emissions over time is in line with FAO (2015), which reports a tendency towards a global slowdown in deforestation. The paths of the baseline carbon emissions from land are shown in Figure 1.

![Figure 1: Baseline emissions from deforestation, GtC per year](image)

In the FRICE model, the baseline emissions from land can be reduced by the deforestation control rate. This control rate represents the fraction of the baseline deforestation that is avoided. The benefit of avoiding deforestation occurs only through this direct reduction of baseline emissions.

---

5The RICE-2010 total annual baseline emission from land at the year 2015 is 1.28 GtC (LA=0.48, Asia=0.56, and Africa=0.24).
from deforestation. Specifically, the deforestation control rate reduces the release of carbon stored in forest biomass.\textsuperscript{6} For simplicity, future sequestration on preserved forest land is not modeled. The accuracy of not including future sequestration in the modeling of forest carbon mainly depends on the age of the forest stand being preserved. This might be a close approximation of the carbon benefits of saving a mature forest while underestimating the benefits of saving a young forest with significant future sequestration potential.

Avoiding deforestation comes at a cost in terms of lost production. As land is implicit in the production function in the FRICE, avoiding the baseline conversion of forest land to other economic activities, such as agricultural production, will reduce the output. These cost estimates of avoiding deforestation in Latin America, Africa, and Other Non-OECD Asia are approximately calibrated to match the mean marginal cost estimates of emissions reduction from avoided deforestation in Central and South America, Africa, and Southeast Asia as estimated by Kindermann et al. (2008). The cost of avoiding deforestation can be seen as a rental payment to land owners in each period to prevent the conversion of forest land. Figure 11 in Appendix B shows the upward sloping FRICE marginal cost curves of avoiding emissions from deforestation. The cheapest avoided deforestation sites lie in Africa while the highest lie in Other Non-OECD Asia.

**Afforestation**

In FRICE, afforestation includes both reforestation and afforestation on never forested land. While the climate befits of avoiding deforestation is instant through avoided emissions, the benefit of afforestation takes

\textsuperscript{6}This paper does not consider the possibility of altering the baseline end use of the deforested biomass. The carbon balances could potentially be affected by actions to replace energy-intensive materials and fossil fuels with forest biomass. Moreover, the release of carbon from deforestation would be lower if a large share of the deforested biomass goes into long-lived wood products. However, this effect is expected to be small as the largest share of the biomass for wood products is lost in the process chain (Ingerson, 2009).
place over time through sequestration from forest growth. Forest growth, and sequestration over time, is non-linear and usually follows some logistic form. In FRICE, carbon accumulation over time is described by a sigmoidal function, which is a special case of the logistic function. The sigmoidal function is written as:

\[ S_{t,n} = \frac{1}{1 + e^{-(t-m_n)}} \]  

(3)

where \( m_n \) is the midpoint of the growth curve. This function describes how the average rate of carbon uptake per hectare is distributed over time. The carbon accumulation reflects the primary volume growth net of decay. Initially after afforestation, the net accumulation of carbon is relatively low. The accumulation rate accelerates as the trees ages, reaching maximum sequestration around its midpoint. As the plantation approaches maturity, the carbon sequestration rate slows down.

Figure 2 show the average rate of uptake of carbon per hectare over time for the different regions. Rotation periods for the regions reported in Nilsson and Schopfhauser (1995) are used as an approximation of the time that it takes to reach maximum carbon storage for the regions in the FRICE. The curve goes from zero to one, representing the share of the total sequestration potential. The afforestation has reached its carbon storage carrying capacity when the share is one. The average ton of carbon per hectare is derived from FAO (2015) and represents the carbon carrying capacity.\(^7\) Table 4 in Appendix C shows the regional value of the total carbon carrying capacity and the rotation lengths.\(^8\)

\(^7\)This carbon capacity might be a lower bound estimate as this reflects existing forests. Plantations and more intensive forest management can in many cases lead to a higher carbon storage per hectare than the average of the existing forests. However, as the quality of land for forest plantation in some cases might be lower than for the existing forest, this might be a realistic average of the carbon potential.

\(^8\)Both the carrying capacity and the growth rate of the forests are assumed to be unaffected by warmer climate to maintain model simplicity. It is well-known that higher temperatures and carbon concentrations can affect both the stocks and dynamics of global forests. In this model, including a climate feedback on the forests could impact both the potential of forests to mitigate, and the incentive to reduce, climate change. The distribution and the magnitude of the climate-related impact
As for avoided deforestation, the marginal costs of afforestation is increasing due to the increasing opportunity cost of land. However, besides the rental payment of land, afforestation efforts usually also require up-front investments in terms of plantation costs (Nabuurs and Masera, 2007). Due to this cost, it is likely that afforestation is more expensive than avoiding deforestation (van Kooten et al., 2004). There exist several different approaches to model the cost of afforestation in the literature and the estimates are quite diverse as the opportunity cost of land is the most important, but also most difficult cost to model (Richards and Stokes, 2004). I use total agricultural production value per hectares from the Global Agro-Ecological Zones (GAEZ v3.0) (Fischer et al., 2012) geospatial dataset to estimate the value of land. By using this high spatial resolution forests are, however, still highly uncertain. Forest climate tools might, for that reason, be a more uncertain way to reduce emissions than the use of non-carbon energy. Modeling these type of uncertainty, however, would require a much more complex model. Results by Eriksson and Vesterberg (2016) indicate that uncertainty related to the forest biomass can increase the importance including forest tools in climate policy.
tial resolution data on the agricultural production value of land, I can capture the opportunity costs of afforestation decisions. However, this approach does not take into account the rise in agricultural production values as increasing quantities of land are withdrawn from agricultural production. Hence, the cost associated with converting agricultural land to forest might be underestimated for extensive afforestation programs. I extract the geospatial data with Arc GIS and exclude land with high livestock density and agroforestry from the estimates of land area suitable for afforestation. With these values of land, I then use symbolic regression to estimate marginal cost curves for land available for afforestation for each region. Figure 12 and Figure 13 in Appendix B shows the estimated regional marginal cost curves of afforestation. Appendix B also provides more information about the afforestation cost estimation.

3 Results

This section presents some key results for four main scenarios: Optimal, Deforestation, Afforestation, and No Forest Tools. The Optimal scenario represents utility maximization when all control variables are determined simultaneously, i.e., investment, energy abatement and the forest climate tools (afforestation and avoided deforestation) are optimally chosen. To shed light on the relative importance of forest tools, I present two scenarios where only one of the forest tools is optimally chosen while the other one is set to zero. These are the Deforestation and the Afforestation scenarios. In the No Forest Tools scenario, both avoided deforestation and afforestation are set to zero. In addition, I run the four main scenarios under three different global mean temperature increase targets, namely, 1.75°C, 2°C, and 2.5°C. Table 1 summarizes the main scenarios.

9The symbolic regression analysis simultaneously searches for the parameters and the functional form that best fits a given dataset, while minimizing the complexity of the expression. This regression is performed with the mathematical software Eureqa by Nutonian, Inc.
Table 1: Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal</td>
<td>All controls</td>
</tr>
<tr>
<td>Deforestation</td>
<td>Saving, energy abatement, and deforestation control rate</td>
</tr>
<tr>
<td>Afforestation</td>
<td>Saving, energy abatement, and afforestation</td>
</tr>
<tr>
<td>No Forest Tools</td>
<td>Saving and energy abatement</td>
</tr>
</tbody>
</table>

Figure 3 shows the evolution of the total global emissions under the four main scenarios. The figure reveals that forest controls are cost-effective tools to reduce emissions. Specifically, I find that the scenario without forest tools leads to highest total emissions in both the short and the medium run. Moreover, consistent with previous literature I find that avoiding deforestation matters most for emissions in the short run, while afforestation plays a bigger role in the medium run. The combined use of the forest tools leads to the lowest emissions in the short and the medium run.

Figure 3: Total global emissions under different scenarios, GtC per year
Figure 4 shows the reduction in emissions from avoided deforestation and the sequestration that arises from afforestation. The carbon paths show that the reduction in emissions from avoided deforestation is initially larger, while the sequestration from afforestation grows over time. In cumulative terms, these results suggest that the global carbon gains from avoided deforestation exceed those of afforestation during the first four decades. Over five decades, for example, the cumulative reduction in emissions amount to 33 GtC, with roughly 17 GtC coming from afforestation and 16 GtC from avoided deforestation. More generally, the cumulative carbon gains predicted by this model are within the upper range of those previously estimated (e.g., Brown et al. (1996); Sohngen and Mendelsohn (2003); Sathaye et al. (2006)).

![Graph showing sequestration from afforestation and reduction of emissions through avoided deforestation under different scenarios, GtC per year](image)

Figure 4: Sequestration from afforestation and reduction of emissions through avoided deforestation under different scenarios, GtC per year

We can also see, in the long run, that the substitution effect between avoided deforestation and afforestation is non-symmetric. The path of emissions from avoided deforestation is not sensitive to whether afforestation-
tion is possible on not. Afforestation, on the other hand, is higher in the scenario where avoided deforestation is not feasible. The explanation for this non-symmetric response is that avoided deforestation is bounded by the level of baseline deforestation, while the upper afforestation bound is not binding in this case. Regional reduction in emissions from avoided deforestation and the sequestration from afforestation are provided in Appendix D, Figure 14 and Figure 15.

The optimal deforestation control rates are shown in Figure 5. The figure shows that the upper bound of avoided deforestation is binding in the medium run for the Optimal scenario. At the regional level, the avoided deforestation control rate is increasing for both Latin America, Asia and Africa until deforestation is fully avoided. In the short run, the highest fraction of baseline deforestation is reduced in Africa and the lowest fraction in Asia. Note that the level of baseline deforestation is different between regions and decreasing over time, as shown in Figure 1.

![Figure 5: Optimal scenario avoided deforestation, share of baseline deforestation](image-url)
Figure 6 shows the optimal cumulative regional afforestation in millions of hectares. The bulk of afforestation, both in the short and long run, occur in Africa. Significant contributions to afforestation are also provided by Asia, Latin America, Eurasia, and OHI (Australia and New Zealand). The contributions to afforestation from EU, India, USA, ME, and China are small in the global perspective. The difference in the levels of afforestation is driven by the amount of land available for afforestation at low cost and the rate of potential carbon accumulation. At the global scale, the results suggest, for example, that 276 million hectares of forest land could be added over five decades. These findings are within the upper range estimated by previous studies (e.g., Brown et al. (1996); Sohngen and Mendelsohn (2003)).

In addition to the forest tools, emissions in this model are also being reduced through energy abatement, that is, substitution from carbon energy to non-carbon energy. Figure 16 and 17 in Appendix D show that introducing afforestation and avoided deforestation reduces the level of
energy abatement. This finding highlights the existence of a substitution effect between forest climate tools and energy abatement in all regions.

Limiting the global mean temperature increase

To investigate how the role of the forest climate tools changes under a more stringent global temperature target, I begin by presenting results where the global mean temperature is limited to a 2°C increase. This limit follows the consensus of the Paris Agreement from December 2015 that reaffirms the 2009 Copenhagen Accord of keeping average warming below 2°C. In this model, meeting this target implies a lower temperature than under the Optimal scenario in the previous section, which peaks at around 2.9°C.\(^\text{10}\)

Figure 7 shows how the reduction in emissions from avoided deforestation and the sequestration from afforestation are affected by a 2°C target. We can see that the sequestration from afforestation is vastly higher in the medium run, and the reduction in emissions from avoided deforestation is slightly higher in the short run. In cumulative terms, over five decades the total carbon gains under the 2°C target amount to 54 GtC. This figure compares to 33 GtC without any temperature limit.

\(^\text{10}\)In the original RICE-2010 model, it is optimal to let temperatures increase to 3°C. The set of results in this paper is, besides the extension of the forest climate tools, based on the standard parameters from the RICE-2010 model. Politicians promoting the 2°C limit in Paris implicitly based their assessment on other economic parameters, such as lower discount rate or a different damage function than the RICE model.
Figure 7: Optimal scenario sequestration from afforestation and reduction of emissions through avoided deforestation with and without a 2°C target, GtC per year

Figure 8 explains the limited response in reduction of emissions from deforestation. The deforestation control rate has a steeper increase for all three regions under the 2°C target. This increase implies that the capacity of reducing emissions through avoided deforestation is exhausted one decade earlier for all regions.
In contrast to avoided deforestation, afforestation is not bounded to its upper limit in the Optimal scenario. Figure 9 illustrates that the optimal cumulative afforestation is much higher for most regions under a 2°C target, compared to the Optimal scenario shown in Figure 6. The largest increase, in absolute terms, occurs in Africa and Latin America. At the global scale, the 2°C target suggests that 711 million hectares of forest land could be added over five decades. This figure compares to 276 million hectares in the optimal scenario without any temperature limit.
The introduction of forest climate tools translates into a lower price of carbon. Table 2 shows the price of carbon at different points in time for the main scenarios. In addition to the optimal temperature scenario, the table also provides carbon prices for scenarios with the following temperature limits: 1.75°C, 2°C, and 2.5°C. The table shows that the difference in the price of carbon between Optimal and No Forest Tools increases with lower temperature limits. These prices clearly highlight that the importance of forest climate tools increases with the stringency of the temperature target. Moreover, among the forest tools, afforestation becomes particularly important under ambitious temperature targets. This result follows the previous discussion of the limited capacity of reducing emissions by avoiding deforestation.
Table 2: Carbon prices, 2005 U.S. dollar per tC

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>2015</th>
<th>2035</th>
<th>2055</th>
<th>2075</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Forest Tools</td>
<td>37.3</td>
<td>87.8</td>
<td>154.2</td>
<td>250.7</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>158.7</td>
<td>488.0</td>
<td>1271.6</td>
<td>2847.6</td>
</tr>
<tr>
<td>2°C target</td>
<td>89.1</td>
<td>260.3</td>
<td>634.1</td>
<td>1371.6</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>47.2</td>
<td>121.0</td>
<td>248.9</td>
<td>485.7</td>
</tr>
<tr>
<td>Optimal</td>
<td>36.1</td>
<td>84.0</td>
<td>143.6</td>
<td>223.7</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>76.8</td>
<td>217.9</td>
<td>488.8</td>
<td>811.0</td>
</tr>
<tr>
<td>2°C target</td>
<td>56.7</td>
<td>153.2</td>
<td>333.4</td>
<td>633.4</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>40.2</td>
<td>97.9</td>
<td>183.3</td>
<td>321.9</td>
</tr>
<tr>
<td>Deforestation</td>
<td>36.9</td>
<td>86.6</td>
<td>150.9</td>
<td>242.2</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>122.1</td>
<td>369.1</td>
<td>938.6</td>
<td>2072.2</td>
</tr>
<tr>
<td>2°C target</td>
<td>78.1</td>
<td>224.3</td>
<td>534.8</td>
<td>1140.2</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>44.8</td>
<td>113.0</td>
<td>226.7</td>
<td>433.2</td>
</tr>
<tr>
<td>Afforestation</td>
<td>36.3</td>
<td>84.5</td>
<td>145.0</td>
<td>227.3</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>84.7</td>
<td>243.2</td>
<td>548.5</td>
<td>888.8</td>
</tr>
<tr>
<td>2°C target</td>
<td>60.6</td>
<td>166.0</td>
<td>367.3</td>
<td>701.0</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>41.3</td>
<td>101.5</td>
<td>193.5</td>
<td>346.3</td>
</tr>
</tbody>
</table>

Table 3 provides the present value of global consumption under the main scenarios. Consistent with the carbon price results, I find that welfare increases with the use of forest climate tools. The global social welfare for the scenarios has the following ranking, from high to low: Optimal, Afforestation, Deforestation, and No Forest Tools. In accordance with previous results, the table also reveals that forest climate tools allow us to achieve climate targets with the highest level of welfare. Of the two forest climate tools, afforestation is the most welfare enhancing, in particular under the more stringent temperature limits. Again, this occurs because the upper bound of avoided deforestation is binding in the medium run, while afforestation is unconstrained to produce further reductions in emissions.
Table 3: Present value of global consumption and temperature increase

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>PV utility Trillions of 2005 U.S. $</th>
<th>Difference from Climate change °C from 1900 year 2115</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Forest Tools</td>
<td>2307.78</td>
<td>2.89</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>2298.00</td>
<td>-9.78</td>
</tr>
<tr>
<td>2°C target</td>
<td>2303.18</td>
<td>-4.60</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>2307.04</td>
<td>-0.74</td>
</tr>
<tr>
<td>Optimal</td>
<td>2308.31</td>
<td>0.53</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>2304.77</td>
<td>-3.01</td>
</tr>
<tr>
<td>2°C target</td>
<td>2306.64</td>
<td>-1.14</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>2308.13</td>
<td>0.35</td>
</tr>
<tr>
<td>Deforestation</td>
<td>2307.98</td>
<td>0.20</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>2300.38</td>
<td>-7.40</td>
</tr>
<tr>
<td>2°C target</td>
<td>2304.30</td>
<td>-3.48</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>2307.41</td>
<td>-0.37</td>
</tr>
<tr>
<td>Afforestation</td>
<td>2308.13</td>
<td>0.44</td>
</tr>
<tr>
<td>1.75°C target</td>
<td>2303.87</td>
<td>-3.91</td>
</tr>
<tr>
<td>2°C target</td>
<td>2306.07</td>
<td>-1.71</td>
</tr>
<tr>
<td>2.5°C target</td>
<td>2307.86</td>
<td>0.08</td>
</tr>
</tbody>
</table>

The results presented above depend on several parameter values and functional forms for which there is considerable uncertainty. It is well-known that the results of integrated assessment models such as RICE are highly dependent on assumptions regarding, for example, the climate damage function and the discount rate. Besides uncertainties associated with the original model assumptions, the extensions in the FRICE add additional assumptions coupled with uncertainties. Among these, the key assumptions are those related to the cost of afforestation and avoided deforestation, the potential of forest carbon sequestration, and the level of baseline deforestation. As shown in Appendix E, while the levels of the forest tools may vary as expected, the main conclusions of the paper remain robust.
4 Conclusions

This paper provides a multi-regional integrated assessment model to estimate the potential role, and spatial allocation, of two forest climate tools, namely, afforestation and avoided deforestation. To do this, I develop the FRICE, which is an extension of the RICE-2010 model by Nordhaus (2010). The climate benefits of avoided deforestation come from direct reductions of the baseline emissions from land of the RICE-2010. The climate benefits of afforestation come from regional sequestration curves. The costs associated with avoided deforestation are taken from the literature, while the regional costs of afforestation are estimated using symbolic regression and geospatial land data.

My main finding is that global climate policy can be considerably enhanced by taking advantage of cost-effective forest climate tools. Afforestation and avoided deforestation are complementary tools. Avoided deforestation initially provides the largest benefits while afforestation is most effective in the medium to long run. My results also highlight that in scenarios with stringent temperature targets emission reductions from avoided deforestation will be quickly exhausted, thereby increasing the importance of emission reductions from afforestation. At the regional level, the results clearly indicate that the largest potential gains lie in the tropical forests of Africa, Asia, and Latin America.

Like the RICE model, one of the main limitations of the FRICE stems from the highly aggregated approach and the simple model setup. This setup, nevertheless, allows for a transparent analysis that illustrates the potential role that regional afforestation and avoided deforestation efforts can have in global climate policy. The insights of FRICE should be viewed as complementary to those of more complex models. Irrespective of its simple structure, FRICE allows me to draw three policy conclusions. First, accounting for regional forest carbon in global climate policy is important because it allows us to reduce climate change at a lower cost. Practically, this implies that forest carbon should be given
a price. Second, given the limited capacity of avoided deforestation, especially under stringent climate targets, both avoided deforestation and afforestation efforts should be undertaken. Third, global climate policy would benefit considerably from achieving the regional afforestation and avoided deforestation targets derived for tropical regions, and in particular for Africa.
References


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Appendix A: Translating the RICE Excel Model into GAMS

To this date, the RICE-2010 model is only publicly available as an Excel model at Nordhaus webpage. The latest GAMS model is the RICE-99 version. Due to the unreliability of the Excel solver for large problems, and to construct the FRICE model, I first code the original RICE-2010 spreadsheet model in the GAMS modeling system. The model is stated as a non-linear optimization problem solved with the CONOPT solver in GAMS. The ending period of the model is 60 with a time step of ten years. Translating the Excel model into the GAMS programming language will not exactly reproduce the model. Some changes and simplifications from the original spreadsheet model are done. I do not recalculate the Negishi welfare weights but use the same time varying weights as in the spreadsheet version. The shadow price of capital between regions are acceptably close. It is preferred for the CONOPT algorithm to use smooth functions. In the sea-level rise (SLR) module of the RICE-2010 model, the melting point for the West Antarctic Ice Sheet is set at 3°C. The melt rate is negatively contributing to the SLR under a 3°C temperature increase, and contributing positively to the SLR at higher temperatures. Specifically, the melt rate function is linearly decreasing in temperature until the melting point. At the melting point, the melt rate jumps and the relationship becomes linearly increasing in temperature. I reformulate this melt rate function and smooth the function around this conjectural point. Figure 10 compares some of the results of the original RICE-2010 to the results from the GAMS model. The differences between the models are minimal in the short to medium run for the emissions, temperature, and energy abatement. In the longer run, however, the GAMS model produce slightly higher energy abatement under optimal control for some regions and lower global emissions. The difference in emissions have minimal effect on the global temperature increase. The baseline emissions are roughly equivalent between models.
Figure 10: Comparison between RICE-2010 and GAMS solutions

Appendix B: Cost of Avoiding Deforestation and Afforestation

The marginal cost of avoiding deforestation

Figure 11 shows the estimated marginal cost curves for Latin America (LA), Africa, and Other Non-OECD Asia (ASIA). These functions are derived from the marginal cost curves of avoiding emissions from deforestation in Central and South America, Africa, and Southeast Asia in Kindermann et al. (2008).
The Marginal Cost of Afforestation

I use the Global Agro-Ecological Zones (GAEZ v3.0) (Fischer et al., 2012) study developed by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems Analysis (IIASA) to estimate the cost of afforestation. Specifically, I use their 5 arc-minute resolution (≈ 9 by 9 km grids at the equator) map data of year 2000 crop production value in GK$ per ha. On this data, I also overlay data on forest cover and livestock. I exclude cropland with more than 20% forest cover and a ruminant livestock larger than 50 TLU/km² from the estimates of land area suitable for afforestation. The former because including agroforestry in the set of possible sites for afforestation will not give an accurate accounting of the gains in carbon by planting forest. The latter because including sites with high-density livestock might underestimate the production value of the land as values from livestock are not directly included in the crop production value. I extract the raster data with Arc GIS and convert the value to year 2005.
US$ using the Consumer Price Index from the U.S. Bureau of Labor Statistics. Then, for each region, the cumulative amount of hectares at each production value gives me an approximation of the opportunity cost of land for afforestation. The marginal cost curves of land eligible for afforestation in each region are estimated by using the symbolic regression software Eureqa. The marginal costs functions are shown in Figure 12 for regions with high afforestation potential, and in Figure 13 for regions with low afforestation potential. In addition to the marginal cost, afforestation also requires a one-time cost for tree plantation. I adopt a plantation cost of $800 per hectare in all regions, same as the reference cost one used in Benítez et al. (2007).

Figure 12: Cost of afforestation, US$ per ha
Figure 13: Cost of afforestation, US$ per ha

Appendix C: Regional Afforestation Parameters

Table 4: Regional parameters

<table>
<thead>
<tr>
<th>Regions</th>
<th>Average rotation length (year)(^1)</th>
<th>Average carbon carrying capacity (tC/ha)(^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFRICA</td>
<td>30</td>
<td>96.2</td>
</tr>
<tr>
<td>ASIA</td>
<td>30</td>
<td>107.9</td>
</tr>
<tr>
<td>CHINA</td>
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<td>31.7</td>
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<tr>
<td>EU</td>
<td>50</td>
<td>56.3</td>
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<tr>
<td>EURASIA</td>
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<td>62.6</td>
</tr>
<tr>
<td>INDIA</td>
<td>30</td>
<td>40.1</td>
</tr>
<tr>
<td>LA</td>
<td>20</td>
<td>116.2</td>
</tr>
<tr>
<td>ME</td>
<td>30</td>
<td>22.6</td>
</tr>
<tr>
<td>OHI(^4)</td>
<td>30</td>
<td>69.9</td>
</tr>
<tr>
<td>USA</td>
<td>45</td>
<td>55.9</td>
</tr>
</tbody>
</table>

1. The average rotation periods are approximations of the time it takes for forests to reach their average carbon carrying capacity. These rotation lengths are roughly

2. The regional average carbon carrying capacity is derived from country-level data on carbon stock in living forest biomass and forest area for the year 2010. The source is FAO (2015).

3. Afforestation in Russia, Canada, and Japan is excluded from the main analysis. The total effect of afforestation on the climate will depend not only on sequestration but, also on other factors, such as evaporation and surface albedo. Surface albedo is a measure of the amount of sunlight that gets absorbed. Because forests have lower surface albedo than agricultural land, increasing forest land can lead to higher local temperatures. The difference in albedo between forest and agricultural land is especially large during snow cover (Bonan, 2008). Moreover, Betts (2000) shows that the decrease of albedo followed by afforestation in many high-latitude forest areas can offset the effect of carbon sequestration and even lead to increased climate change. To the best of my knowledge, geophysical equations to describe, at a global level, the effect of albedo on the climate have not yet been derived. Accordingly, I take the most conservative approach and exclude from the analysis areas where the albedo effect is expected to offset the sequestration effect. Specifically, I exclude Russia and Canada as otherwise the analysis might overestimate the benefits of afforestation. Japan is excluded because while economically important, it has a very small afforestation potential.

4. Compared to the other regions, countries within the OHI region are geographically dispersed. Afforestation in OHI represents Australia and New Zealand. As described above, afforestation in Canada is excluded.
Appendix D: Supplementary Figures

Figure 14: Optimal scenario sequestration from afforestation, GtC per year
Figure 15: Optimal scenario reduction of emissions through avoided deforestation, GtC per year

Figure 16: Energy abatement as fraction of uncontrolled industrial emissions under Optimal and No Forest Tools scenario
Figure 17: Energy abatement as fraction of uncontrolled industrial emissions under Optimal and No Forest Tools scenario

Appendix E: Sensitivity Analysis

Cost of afforestation and avoided deforestation

Figure 18 displays the avoided deforestation, and Figure 19 and Figure 20 displays the afforestation, for three different cost levels. The low cost is 20% lower, and the high cost is 20% higher, than the benchmark integrated marginal cost function of both afforestation and avoided deforestation in Section 3. The result is as expected: lower cost leads to higher levels of avoided deforestation and afforestation, and vice versa.
Figure 18: Optimal scenario avoided deforestation as share of baseline deforestation: benchmark cost, high-cost, and low-cost

Figure 19: Optimal scenario cumulative afforestation in millions of hectares: benchmark cost, high-cost, and low-cost
Further simulations also show that the level of afforestation is not sensitive to changes in the cost of avoiding deforestation, and vice versa. These figures are available upon request.

**Carbon sequestration capacity of forest land**

The carbon sequestration capacity of forest land represents the maximal amount of carbon that can be sequestrated on a hectare of forest land. Figure 21 and Figure 22 display the afforestation for three capacities. The low capacity is 20% lower, and the high capacity is 20% higher, than the benchmark average carbon carrying capacities shown in Table 4.
Figure 21: Optimal scenario cumulative afforestation in millions of hectares: benchmark, high, and low sequestration capacity

Figure 22: Optimal scenario cumulative afforestation in millions of hectares: benchmark, high, and low sequestration capacity
A higher sequestration capacity corresponds to a higher efficiency of afforestation as a climate tool. Hence, a larger afforestation is optimal under a high capacity scenario. In absolute terms, the difference between the high and the low capacity scenario is greatest for regions with relatively large afforestation. Moreover, while the sequestration capacity changes the optimal level of sequestration from afforestation, I find no effect on the optimal levels of avoided emissions from deforestation. The optimal sequestration and reduction of emissions from deforestation under the high and the low sequestration potential are shown in Figure 23.

![Figure 23: Optimal scenario sequestration from afforestation and reduction of emissions through avoided deforestation in GtC per year: benchmark, high, and low sequestration capacity](image)

**Baseline deforestation**

Figure 24 displays the avoided deforestation as the share of baseline deforestation for three levels of baseline deforestation. The low baseline is 20% lower, and the high baseline is 20% higher, than the benchmark baseline deforestation of the FRICE. It is optimal to have a higher
avoided deforestation control rate when the baseline deforestation is lower, and vice versa.

![Graph showing deforestation control rate and year]  

Figure 24: Optimal scenario avoided deforestation as share of baseline deforestation: benchmark, high, and low baseline deforestation

The optimal sequestration from afforestation and reduction of emissions from deforestation under the high and the low baseline deforestation are shown in Figure 25. A higher baseline deforestation leads to a higher optimal amount of avoided emissions from deforestation and a slightly higher sequestration from afforestation in the long run.
Figure 25: Optimal scenario sequestration from afforestation and reduction of emissions through avoided deforestation in GtC per year: benchmark, high, and low baseline deforestation
When Not in the Best of Worlds: Uncertainty and Forest Carbon Sequestration

Mathilda Eriksson*† and Anders Vesterberg†‡

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 assess 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 de-
scribes 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. Be-
yond this midpoint, the growth of biomass decreases as the stock further
approaches its carrying capacity. Besides the natural growth of the for-
est, 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 de-
crease in forest area due to climate change, reduces the growth potential
through a decreased carrying capacity and decreased forest biomass. Ac-
ccordingly, avoided deforestation will have a larger short-run benefit than
afforestation.

Deforestation

Deforestation is mainly caused by the conversion of forest to agricul-
tural 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 GIS and perform symbolic regression to derive the afforestation cost equations.\(^3\) Appendix C contains detailed information regarding the

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\(^1\)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.

\(^3\)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.
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 \( \text{CO}_2 \) 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 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. 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. This simplification implies that the competition for biomass for energy and carbon storage will increase over time, with harvest to wood products being predominant.

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.

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 

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4The 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.

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

6Data 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).
bioenergy harvest, from industrial roundwood harvest, and from loss of forest area through deforestation or climate change.\textsuperscript{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.\textsuperscript{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. In order to model uncertainty, the integrated assessment literature has primarily relied on stochastic optimization or the Monte Carlo approach. In this paper, we focus on a third method: the state-contingent approach.

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)\textsuperscript{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).

\textsuperscript{8} The reader is referred to Nordhaus (2008) for the geophysical equations of the DICE-2007 model.
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. 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. 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:

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

where \( s = \{1, ... S\} \) is the state index and \( W_s \) is the welfare in one state,

---

9In 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.

10Because of the complexity of the problem, a solution can only be obtained numerically.
described by Equation 29 in Appendix A. The control variables are: investment $I_t$, carbon control rate $\mu_t$, and a set of forest control variables $\nu_t$ (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. 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 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>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Distribution</th>
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<tr>
<td>$\psi_{tro,t=1}$</td>
<td>Initial intrinsic growth rate</td>
<td>$TN[0.1989, 0.022, 0, 1]$</td>
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<tr>
<td>$\psi_{tem,t=1}$</td>
<td>Initial intrinsic growth rate</td>
<td>$TN[0.3726, 0.022, 0, 1]$</td>
</tr>
<tr>
<td>$\psi_{bor,t=1}$</td>
<td>Initial intrinsic growth rate</td>
<td>$TN[0.1128, 0.022, 0, 1]$</td>
</tr>
<tr>
<td>$\phi_{tro}$</td>
<td>Temperature-growth parameter</td>
<td>$TN[-0.04, 0.02, -10, 10]$</td>
</tr>
<tr>
<td>$\phi_{tem}$</td>
<td>Temperature-growth parameter</td>
<td>$TN[-0.03, 0.015, -10, 10]$</td>
</tr>
<tr>
<td>$\phi_{bor}$</td>
<td>Temperature-growth parameter</td>
<td>$TN[0.79, 0.027, 0, 10]$</td>
</tr>
<tr>
<td>$\kappa_{tro}$</td>
<td>Temperature-forest cover parameter</td>
<td>$TN[-20, 10, -\infty, 0]$</td>
</tr>
<tr>
<td>$\kappa_{tem}$</td>
<td>Temperature-forest cover parameter</td>
<td>$N[0, 2]$</td>
</tr>
<tr>
<td>$\kappa_{bor}$</td>
<td>Temperature-forest cover parameter</td>
<td>$TN[20, 10, -\infty, 0]$</td>
</tr>
</tbody>
</table>

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.
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.\textsuperscript{12} We take this direct forest growth uncertainty into account by assuming that the initial intrinsic growth rate, $\tilde{\psi}_{n,t=1}$, 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, the net impact of atmospheric CO\textsubscript{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.

\textsuperscript{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.
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:

\[ TI_{n,t} = \tilde{\phi}_1n \Delta T_t^2 \]  

(2)

and for the boreal forest is written as:

\[ TI_{bor,t} = \tilde{\phi}_{1bor} \Delta T_t^2 + \phi_{2bor} \Delta T_t^3 + \phi_{3bor} \Delta T_t^4 + \phi_{4bor} \Delta T_t \]  

(3)

\( \Delta T_t \) is the increase in the global mean temperature from the first time period. \( \phi_{2n}, \phi_{3n}, \) and \( \phi_{4n} \) are deterministic temperature-growth parameters. The temperature-growth parameter for each type of forest, \( \tilde{\phi}_{1n} \), 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:

$$TF_{n,t} = \tilde{\kappa}_{1n} \Delta T_t^2 \quad (4)$$

where $\tilde{\kappa}_{1n}$ is an uncertain temperature-land parameter and $\Delta T_t$ is the increase in the global mean temperature. The uncertain temperature-forest-area parameter, $\tilde{\kappa}_{1n}$, 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

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>NFC</td>
<td>No forest control and no uncertainty</td>
</tr>
<tr>
<td>FC</td>
<td>Optimal forest control and no uncertainty</td>
</tr>
<tr>
<td>UncNFC</td>
<td>No forest control under forest uncertainty</td>
</tr>
<tr>
<td>UncFC</td>
<td>Optimal forest control under forest uncertainty</td>
</tr>
</tbody>
</table>

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 m³ per decade](image)

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](image)

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](image)

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.
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.
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

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>NFC</th>
<th>FC</th>
<th>UncNFC</th>
<th>UncFC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective value</td>
<td>150</td>
<td>411</td>
<td>150</td>
<td>445</td>
</tr>
<tr>
<td></td>
<td>150</td>
<td>210</td>
<td>150</td>
<td>442</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>2015</th>
<th>2035</th>
<th>2055</th>
<th>2075</th>
</tr>
</thead>
<tbody>
<tr>
<td>NFC</td>
<td>41.6</td>
<td>66.3</td>
<td>98.0</td>
<td>137.7</td>
</tr>
<tr>
<td>FC</td>
<td>41.4</td>
<td>66.0</td>
<td>97.6</td>
<td>137.5</td>
</tr>
<tr>
<td>UncNFC</td>
<td>57.0</td>
<td>102.9</td>
<td>179.2</td>
<td>309.0</td>
</tr>
<tr>
<td>UncFC</td>
<td>41.5</td>
<td>66.2</td>
<td>97.9</td>
<td>138.0</td>
</tr>
</tbody>
</table>

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 Conclusions

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


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.


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:

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

(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:

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

(6)

The fraction $\frac{F_{MAX}^{n,t}}{F_{n,t}}$ 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, \( \theta_{tro} \).

The total tropical biomass deforestation in any time period is given by:

\[
D_{tro,t} = \frac{\Gamma_{tro,t}}{\theta_{tro}} (1 - RD_t),
\]

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:

\[
RE_t = \Gamma_{tro,t} RD_t.
\]

The marginal cost of avoiding deforestation is written as:

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

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 requires land with higher opportunity cost.

The total cost of avoiding deforestation is written as:

\[
CD_{t+1} = CD_t + \int_0^{RE_{t+1}} MD_{t+1}(x) dx,
\]

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:

\[ A_{n,t} = \xi_n H A_{n,t}, \]  

(11)

which is the hectares of land afforested, \( H A_{n,t} \) times the biomass carrying capacity per hectare, \( \xi_n \). The afforestation plantation cost,

\[ P A_{n,t} = \tau_n H A_{n,t}, \]  

(12)

is the per hectare cost of planting forest, \( \tau_n \), times the amount of of land being afforested, \( H A_{n,t} \). The marginal rental cost of land, \( M A_{n,t} \), is derived from the agricultural production value of land. The rental cost of afforestation in each time period,

\[ R A_{n,t} = \int_0^{H C_{n,t}} M A_{n,t}(x)dx, \]  

(13)

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

\[ C A_{n,t} = R A_{n,t} + P A_{n,t}. \]  

(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:

$$\psi_{n,t} = \tilde{\psi}_{n,t=1}(1 + TI_{n,t}),$$  \hspace{1cm} (15)

where $\tilde{\psi}_{n,t=1}$ 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:

$$TI_{n,t} = \tilde{\phi}_{1n} \Delta T^2_t$$  \hspace{1cm} (16)

and for the boreal forest is written as:

$$TI_{bor,t} = \tilde{\phi}_{1bor} \Delta T^2_t + \phi_{2bor} \Delta T^3_t + \phi_{3bor} \Delta T^4_t + \phi_{4bor} \Delta T_t$$  \hspace{1cm} (17)

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

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

$$G_{n,t} = \xi_n TF_{n,t}.$$  \hspace{1cm} (18)

$TF_{n,t}$ is the change in forest cover in hectares and $\xi_n$ 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:

\[ B_{n,t} = \varepsilon_n T F_{n,t} \]  

(19)

which is the average biomass per hectare, \( \varepsilon_n \) times the loss of forest area, \( T F_{n,t} \). The change in forest area induced by climate change is written as:

\[ T F_{t r o, t} = \tilde{\kappa}_{1n} \Delta T_t^2 \]  

(20)

where \( \tilde{\kappa}_{1n} \) is an uncertain temperature-land parameter.

**Harvest**

Total harvest of each type of biomass:

\[ H_{n,t} = H B_{n,t} + H S_{n,t}, \]  

(21)

is the sum of harvest dedicated to bioenergy production, \( H B_{n,t} \), and industrial roundwood harvest, \( H S_{n,t} \). The total industrial roundwood harvest is:

\[ H S_{t+1} = \sum_n \chi_n H S_t \left( \frac{L_{t+1}}{L_t} \right), \]  

(22)

which is the sum of the various forest biomass harvests, \( H S_{n,t} \), where \( \chi_n \) 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:

$$\Xi_t = Y_t \sigma_t (1 - \mu_t).$$

(23)

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

$$\Xi_t = \zeta H B_{trot}^{\beta_{trot}} H B_{bor}^{\beta_{bor}} H B_{tem}^{\beta_{tem}} F O_t^{1 - \beta_{trot} - \beta_{bor} - \beta_{tem}},$$

(24)

where $\zeta$ is a scale parameter, $H B_{n,t}$ is biomass harvest intended for energy production, and $F O_t$ is fossil fuel carbon. $(1 - \beta_{trot} - \beta_{bor} - \beta_{tem})$ is the elasticity of fossil fuel carbon and $\beta_{trot}$, $\beta_{bor}$ and $\beta_{tem}$ are the bioenergy elasticities for tropical, boreal, and temperate biomass harvest.\footnote{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,

$$E_t = F O_t - \sum_n E F_{n,t},$$

(25)

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

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

is the change in biomass multiplied by a forest carbon intensity parameter, $\theta_n$. 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:

$$Q_t = \frac{(1 - \Lambda_t)Y_t}{(1 + \pi_1T_t^{\pi_2})} - CD_t - \sum_n CA_{n,t},$$  \hspace{1cm} (27)

where $\Lambda_t$ 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, $\pi_1$ and $\pi_2$ 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,

$$c_t = \frac{Q_t - I_t}{L_t}.$$  \hspace{1cm} (28)
Optimization

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

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

(29)

where \( \alpha \) is the constant elasticity of the marginal utility of per capita consumption, \( \rho \) 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:

\[ \max_{I_t, \mu_t, RD_{n,t}, HA_{n,t}, HB_{n,t}} \frac{1}{S} \sum_{s=1}^{S} W_s. \]  

(30)
### Appendix B: Parameters and Variables of the Model

Table 5: Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Boreal</th>
<th>Temperate</th>
<th>Tropical</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \zeta )</td>
<td>Energy parameter</td>
<td>65.6297</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \delta )</td>
<td>Decline of the decarbonization rate</td>
<td>0.003</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \pi_1 )</td>
<td>Damage parameter</td>
<td>0.0028388</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \pi_2 )</td>
<td>Damage exponent</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \gamma )</td>
<td>Elasticity of production of capital</td>
<td>0.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \alpha )</td>
<td>Elasticity of marginal utility of consumption</td>
<td>2.0</td>
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</tr>
<tr>
<td>( \rho )</td>
<td>Pure rate of social time preference</td>
<td>0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \theta_n )</td>
<td>Carbon intensity in forest biomass (tc/m(^3))</td>
<td>0.406084</td>
<td>0.456057</td>
<td>0.637926</td>
</tr>
<tr>
<td>( \xi_n )</td>
<td>Carrying capacity (m(^3)/ha)</td>
<td>203</td>
<td>248</td>
<td>288</td>
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<tr>
<td>( \chi_n )</td>
<td>Share of total industrial roundwood harvest</td>
<td>0.277</td>
<td>0.535</td>
<td>0.188</td>
</tr>
<tr>
<td>( \tau_n )</td>
<td>Plantation cost ($/ha)</td>
<td>800</td>
<td>800</td>
<td>800</td>
</tr>
<tr>
<td>( \beta_n )</td>
<td>Energy elasticity of bioenergy harvest</td>
<td>0.0017</td>
<td>0.0223</td>
<td>0.0394</td>
</tr>
<tr>
<td>( o_1 )</td>
<td>Cost parameter of avoided deforestation</td>
<td>14.46</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( o_2 )</td>
<td>Cost parameter of avoided deforestation</td>
<td>0.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( o_3 )</td>
<td>Cost parameter of avoided deforestation</td>
<td>1.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( o_4 )</td>
<td>Cost parameter of avoided deforestation</td>
<td>0.03</td>
<td></td>
<td></td>
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<td>( o_5 )</td>
<td>Cost parameter of avoided deforestation</td>
<td>20</td>
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<td></td>
</tr>
<tr>
<td>( \lambda_1 )</td>
<td>First decade deforestation emissions (tc)</td>
<td>11.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \lambda_2 )</td>
<td>Deforestation decrease parameter</td>
<td>0.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \psi_{n,t=1} )</td>
<td>Initial intrinsic growth rate</td>
<td>0.1128</td>
<td>0.3726</td>
<td>0.1981</td>
</tr>
<tr>
<td>( \xi_n )</td>
<td>Forest biomass (m(^3)/ha)</td>
<td>101</td>
<td>124</td>
<td>144</td>
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<tr>
<td>( \phi_{1n} )</td>
<td>Temperature-forest growth parameter</td>
<td>-0.79</td>
<td>-0.04</td>
<td>-0.03</td>
</tr>
<tr>
<td>( \phi_{2n} )</td>
<td>Temperature-forest growth parameter</td>
<td>0.24</td>
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<td></td>
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<td>( \phi_{3n} )</td>
<td>Temperature-forest growth parameter</td>
<td>-0.026</td>
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</tr>
<tr>
<td>( \phi_{4n} )</td>
<td>Temperature-forest growth parameter</td>
<td>0.78</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \kappa_{1n} )</td>
<td>Temperature-forest cover parameter</td>
<td>20</td>
<td>0</td>
<td>-20</td>
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</tbody>
</table>
Table 6: Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{n,t}$</td>
<td>Forest biomass afforestation in carrying capacity (m$^3$)</td>
</tr>
<tr>
<td>$B_{n,t}$</td>
<td>Biomass reduction due to climate change (m$^3$)</td>
</tr>
<tr>
<td>$c_t$</td>
<td>Per capita consumption ($)</td>
</tr>
<tr>
<td>$CA_{n,t}$</td>
<td>Total cost of afforestation ($)</td>
</tr>
<tr>
<td>$CD_t$</td>
<td>Total cost of reduced emissions through deforestation ($)</td>
</tr>
<tr>
<td>$D_{n,t}$</td>
<td>Forest biomass deforestation (m$^3$)</td>
</tr>
<tr>
<td>$E_t$</td>
<td>Total emissions (tc)</td>
</tr>
<tr>
<td>$F_{n,t}$</td>
<td>Forest biomass (m$^3$)</td>
</tr>
<tr>
<td>$F_{MAX}^n$</td>
<td>Forest biomass carrying capacity (m$^3$)</td>
</tr>
<tr>
<td>$FO_t$</td>
<td>Fossil fuel carbon (tc)</td>
</tr>
<tr>
<td>$G_{n,t}$</td>
<td>Forest cover change due to climate change in carrying capacity (m$^3$)</td>
</tr>
<tr>
<td>$H_{n,t}$</td>
<td>Total forest biomass harvest (m$^3$)</td>
</tr>
<tr>
<td>$HA_{n,t}$</td>
<td>Land area afforested (ha)</td>
</tr>
<tr>
<td>$HB_{n,t}$</td>
<td>Forest biomass harvest for bioenergy (m$^3$)</td>
</tr>
<tr>
<td>$HC_{n,t}$</td>
<td>Cumulative land area afforested (ha)</td>
</tr>
<tr>
<td>$HS_{n,t}$</td>
<td>Forest biomass roundwood harvest (m$^3$)</td>
</tr>
<tr>
<td>$I_t$</td>
<td>Investment ($)</td>
</tr>
<tr>
<td>$L_t$</td>
<td>Labor</td>
</tr>
<tr>
<td>$MA_{n,t}$</td>
<td>Marginal cost of afforestation ($)</td>
</tr>
<tr>
<td>$MD_t$</td>
<td>Marginal cost of reduced emissions through deforestation ($)</td>
</tr>
<tr>
<td>$PA_{n,t}$</td>
<td>Plantation cost of afforestation ($)</td>
</tr>
<tr>
<td>$Q_t$</td>
<td>Output net of abatement and damages ($)</td>
</tr>
<tr>
<td>$RA_{n,t}$</td>
<td>Rental cost of afforestation ($)</td>
</tr>
<tr>
<td>$RD_{n,t}$</td>
<td>Deforestation control rate (fraction of uncontrolled deforestation)</td>
</tr>
<tr>
<td>$RE_t$</td>
<td>Reduced carbon emissions through deforestation control (tc)</td>
</tr>
<tr>
<td>$T_t$</td>
<td>Global mean surface temperature (°C increase from year 1900)</td>
</tr>
<tr>
<td>$TF_{n,t}$</td>
<td>Temperature-forest cover function (%)</td>
</tr>
<tr>
<td>$TI_{n,t}$</td>
<td>Temperature-intrinsic growth rate function (%)</td>
</tr>
<tr>
<td>$Y_t$</td>
<td>Gross output ($)</td>
</tr>
<tr>
<td>$\Xi_t$</td>
<td>Carbon-based energy function</td>
</tr>
<tr>
<td>$\Gamma_{tro,t}$</td>
<td>Baseline carbon emissions from land (tc)</td>
</tr>
<tr>
<td>$\Lambda_t$</td>
<td>Abatement cost function (fraction of world output)</td>
</tr>
<tr>
<td>$\mu_t$</td>
<td>Carbon control rate (fraction of uncontrolled emissions)</td>
</tr>
<tr>
<td>$\Pi_t$</td>
<td>Emissions from production (tc)</td>
</tr>
<tr>
<td>$\psi_{n,t}$</td>
<td>Intrinsic growth rate of forest biomass</td>
</tr>
<tr>
<td>$\sigma_t$</td>
<td>Emissions-output ratio (tc)</td>
</tr>
<tr>
<td>$\Omega_t$</td>
<td>Climate damages (fraction of world output)</td>
</tr>
</tbody>
</table>
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 than 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](image)

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

$$MA_{tro,t} = 13.5 + 0.783HC_{tro,t} + 3.08(10^{-36})HC_{tro,t}^{12.6} \tag{31}$$
\[ MA_{\text{tem},t} = 30.1 + 0.165HC_{\text{tem},t}^{1.29} \]  

(32)

where \( HC_{n,t} \) is the cumulative hectares afforested.

**Appendix D: A 2\textdegree C Temperature Limit**

Meeting the goal of limiting global warming to 2\textdegree 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\textdegree 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](image_url)

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
Table 8 shows the expected value of carbon price for different scenarios under a $2^\circ$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 $2^\circ$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 $2^\circ$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 $2^\circ$C temperature limit, 2005 U.S. dollar per tC

<table>
<thead>
<tr>
<th></th>
<th>2015</th>
<th>2035</th>
<th>2055</th>
<th>2075</th>
</tr>
</thead>
<tbody>
<tr>
<td>NFC $2^\circ$C limit</td>
<td>64.0</td>
<td>125.7</td>
<td>251.2</td>
<td>506.9</td>
</tr>
<tr>
<td>FC $2^\circ$C limit</td>
<td>55.2</td>
<td>102.7</td>
<td>192.9</td>
<td>369.3</td>
</tr>
<tr>
<td>UncNFC $2^\circ$C limit</td>
<td>68.8</td>
<td>138.2</td>
<td>282.6</td>
<td>587.1</td>
</tr>
<tr>
<td>UncFC $2^\circ$C limit</td>
<td>58.3</td>
<td>110.8</td>
<td>213.8</td>
<td>417.8</td>
</tr>
</tbody>
</table>
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 m³ 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
Pricing Forest Carbon: Implications of Asymmetry in Climate Policy

Mathilda Eriksson*, Runar Brännlund†, and Tommy Lundgren†

Abstract

In this paper, we use an integrated assessment model to examine the implications of not recognizing, and partially recognizing forest carbon in climate policy. Specifically, we investigate the impact of an asymmetric carbon policy that recognizes emissions from fossil fuels while ignoring emissions from forests. We additionally investigate the relative importance of not recognizing positive emissions from a reduction in the stock of forest biomass, or of not recognizing negative emissions from the growth of forest biomass. We show that asymmetric carbon policies lead to lower levels of welfare, as well as higher emissions and carbon prices. This occurs because the forest resource will be allocated inefficiently under these carbon policies. Broadly, we find that when the social planner does not account for neither positive or negative forest emissions, the planner will set bioenergy levels that are too high and afforestation and avoided deforestation levels that are too low. Our results further reveal that not recognizing forest emissions leads to larger welfare losses than not recognizing sequestration.

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1 Introduction

This paper uses an integrated assessment model, that accounts for the dynamics of the forest, to investigate the effectiveness of climate policy when positive and negative (sequestration) emissions of forest carbon are not recognized or only partially recognized by policy makers. Specifically, we will consider two asymmetric carbon policy regimes. In the first regime, which resembles the current state of climate policy, policy makers will take into account carbon emissions from fossil fuel but will not take into account either emissions or sequestration from forests. In the second regime, we will establish the relative importance of not recognizing forest emissions in relation to not recognizing carbon sequestration from forests.

Recently, policy makers have begun to coalesce around the idea of pricing carbon. In theory, a dynamic Pigouvian tax, which amounts to the marginal cost of carbon in the optimal emissions path, could fully internalize the adverse effects of carbon emissions. As all sources of carbon emissions are equal in terms of climate impact, the carbon price should be universal. However, a global carbon price covering all emissions is far from reality.

In practice, policy makers have favored levying taxes on fossil energy, while taxation of other emissions, such as those from bioenergy production, have been to a large extent disregarded. As shown by Lundgren et al. (2008) in a theoretical setting, this asymmetry in carbon policy leads to a distortion of the price differential between fossil energy and bioenergy which results in too high levels of bioenergy being produced. At the heart of this debate is the question of whether bioenergy production is carbon neutral. Previous literature has shown that treating bioenergy as carbon neutral will underestimate the negative climate impact of bioenergy production (e.g., Searchinger et al. (2009); Cherubini et al. (2011)). This occurs because bioenergy production is not carbon neutral in the short run. The release of carbon from bioenergy production is instantaneous, while sequestration via biomass growth occurs over
time. Lundgren and Marklund (2013) show that policies that rely on the carbon neutrality assumption are misleading and can lead to a reduction in welfare.

Lundgren et al. (2008) also highlight that pricing carbon requires not only taxing all emissions including those from bioenergy but also subsidizing at the same rate negative emissions from forest growth. From the bioenergy policy debate, it is thus clear that policies that aim to price carbon, risk falling short in two respects. First, by limiting the scope of sources of emissions. Second, by encouraging efforts to reduce emissions, while not valuing efforts to increase carbon sequestration.

Under the assumption that policymakers fully recognize forest carbon, the forest can play a key role in climate policy both through fossil-fuel substitution and carbon sequestration in biomass. In a review of sequestration cost studies, Richards and Stokes (2004) conclude that different forestry practices to increase carbon sequestration can significantly and cost-effectively reduce atmospheric carbon. However, as highlighted by another strand of the literature, there are various synergies and trade-offs between policies that incentivize the use of biomass for fossil-fuel substitution and those to increase the stock of biomass for carbon sequestration (e.g., Lecocq et al. (2011); Kallio et al. (2013)). It is therefore of particular importance to analyze the role of the forest and asymmetric policy regimes, in a framework that accounts for these trade-offs as well as the interactions between the various climate policies.

In this paper, we use such a framework to further develop the intuition of the bioenergy literature as discussed by Lundgren et al. (2008). Specifically, we extend the discussion in two ways. First, we use an integrated assessment model that accounts for the dynamics of the forest. This framework allows us to provide estimates of the price of carbon under optimal and asymmetric policy regimes. Second, we take the discussion of asymmetric carbon policy to a broader category of forest controls, which besides bioenergy harvest also includes avoided deforestation and afforestation. These controls are especially important as the amount of
forest land is directly related to the potential to increase forest biomass and thus bioenergy harvest. More broadly, including this controls, allows us to increase the scope of the analysis, as we are now able to study the dynamics and the interactions between various controls capable of altering the stock of forest biomass.

Using an extended version of the FOR-DICE (Eriksson, 2015), we investigate the impact of two types of asymmetric carbon policy regimes. In this model, the social planner maximizes welfare by choosing the level of forest controls in addition to savings and energy abatement. In the first asymmetric policy regime, the social planner does not account for positive or negative forest carbon emissions when choosing the level of the forest controls. In the second regime, we investigate two variations: in the first variation, the planner accounts for negative emissions from forests but not for positive emissions. In the second variation, the planner accounts for positive emissions from forests but not for negative emissions. These regimes are compared against the optimal case where the social planner fully recognizes all sources and types of emissions considered in the model.

The model provides three key findings: First, asymmetric carbon policy regimes lead to considerable distortions in the allocation of forest resources. Specifically, not accounting for emissions or sequestration from forests will lead to levels of bioenergy harvest that are too high, and to levels of afforestation and avoided deforestation that are too low. This inefficient allocation leads to the lowest level of welfare, the highest emissions, and the highest carbon prices. Second, while it is always preferable to account for both positive and negative forest emissions in carbon policy, we can avoid the largest welfare losses, and achieve close to optimal levels of total emissions, by just accounting for forest emissions. Third, our back of the envelope calculation, on the optimal forest tax and subsidy scheme, indicates that the cost of the subsidy would outpace the revenue from taxing forest emissions. However, this subsidy could be financed by a broader tax policy that also include revenues from taxing
fossil fuels.

The paper is organized as follows: Section 2 presents briefly the integrated assessment model that is used. Section 3 presents the main findings from the analyzed scenarios, as well as a discussion. Finally, Section 4 offers some concluding comments and direction for future research.

2 The Integrated Assessment Model

This paper uses a version of the FOR-DICE model by Eriksson (2015). The FOR-DICE model is an extension of the DICE-2007 (Nordhaus, 2008). FOR-DICE key extensions include the modeling of the global forest biomass and the introduction of forest controls. In this section, we briefly describe the main features of the framework and the channels of forest carbon emissions. The reader is referred to Eriksson (2015) for further details on the model.

FOR-DICE is a global neoclassical economic growth model where carbon emissions, via the global mean temperature, affects the economic output through a damage function. Total carbon emissions come from fossil carbon and forest carbon net of sequestration. The objective function of the FOR-DICE is the present value sum of all future utility of consumption. A social planner maximizes the objective function by choosing the levels of investment, abatement, bioenergy harvest, and avoided deforestation. In this paper, we additionally extend the controls of the FOR-DICE model by including afforestation.

Energy in the FOR-DICE is a perfect complement to the Cobb-Douglas production function of capital and labor. Total energy consists of non-carbon based energy and carbon-based energy. Non-carbon energy is represented by abatement and corresponds to all types of energy that are not based on carbon sources. Carbon energy consists of fossil energy and forest bioenergy. Specifically, carbon energy is produced by a

\[ \text{Energy} = \text{Non-carbon energy} + \text{Carbon energy} \]

\[ \text{Non-carbon energy} = \text{Abatement} \]

\[ \text{Carbon energy} = \text{Fossil energy} + \text{Forest bioenergy} \]
constant return to scale Cobb-Douglas function of fossil fuel carbon and of bioenergy harvest from each of the types of forest.\(^2\)

The model has three types of forest stocks: tropical forest, temperate forest, and boreal forest. The dynamics of each of these stocks of biomass follows a logistic growth function formulation. The growth rate of the forest biomass is close to its intrinsic growth rate when the stock is small and decreases as the stock approaches its carrying capacity. Accordingly, while removing forest biomass will decrease the size of the stock, it will have a positive impact on the growth rate. In this model, total removals consist of harvest for goods and services and harvest for bioenergy.\(^3\)

Besides harvest, forest stocks are also affected by changes in forest area.\(^4\) Ongoing deforestation is reducing the forest area and the stock of forest biomass in the tropics. In the FOR-DICE, baseline deforestation is exogenous and declining over time, following the path of emissions from land in the DICE-2007 model. This baseline deforestation can be reduced by the deforestation control variable.\(^5\) The cost of the deforestation control in FOR-DICE is derived from estimates by Kindermann et al. (2008). This cost can be seen as a payment to land owners necessary in each period to prevent the conversion of forest land.

The global forest area can also change through afforestation.\(^6\) In this paper, afforestation in the temperate and tropical zone are control variables.\(^7\) The costs of afforestation follow the ones derived in Eriksson

\(^2\)The Cobb-Douglas function implies an imperfect substitution between bioenergy harvest and fossil fuel carbon which requires each of these inputs to be strictly positive, as long as the global economy remains dependent on carbon energy. While this assumption is limiting, it avoids the unrealistic case of perfect substitution between these inputs.

\(^3\)Harvest to produce goods and services other than energy in the FOR-DICE is exogenous and grows linearly with labor. This simplification implies that the demand of biomass for energy and climate purposes are subordinate.

\(^4\)FOR-DICE disregards any potential climate effects on forest growth or forest cover.

\(^5\)The model does not consider leakages, namely, deforestation avoided in one location cannot be reallocated to another location.

\(^6\)Afforestation refers both to the establishment of forests where there has not previously been any forests, and reestablishment of previously forested area.

\(^7\)We exclude afforestation in the boreal zone due to the ambiguous climate benefits
and Vesterberg (2016). The marginal costs of afforestation in Eriksson and Vesterberg (2016) are estimated from total agricultural production value per hectares from the Global Agro-Ecological Zones (GAEZ v3.0) geospatial dataset (Fischer et al., 2012). The marginal cost curves of afforestation, like avoided deforestation, are upwards sloping due to the opportunity cost of land. In addition to this cost of land, the total afforestation cost also includes a plantation cost.\(^8\)

Forest carbon emissions are directly linked to the change in the growing forest biomass. Specifically, the forests release carbon through the loss of forest biomass from deforestation and harvest. Conversely, the forests sequester carbon through the gain of forest biomass from growth.\(^9\) As previously mentioned, harvest decreases the stock of forest biomass but at the same time increases growth the rate of the stock. Deforestation, on the other hand, both decreases the size of the stock and the carrying capacity such that the dynamics of remaining biomass is unchanged. Afforestation increases the growth of forest biomass through an increased carrying capacity. Since bioenergy harvest and deforestation actions lead to an instantaneous increase of emissions from loss of biomass, in the short run, the climate benefits of reducing these actions will be larger than those of increasing afforestation.

### 3 Results

This section presents the key results for four scenarios: optimal (OPT), no forest policy (NF), forest sequestration policy (FS), and forest emissions policy (FE). The optimal control scenario represents utility maximization when all control variables are determined optimally. These

\(^8\) As in Eriksson and Vesterberg (2016), the plantation cost is taken from Nabuurs and Masera (2007).

\(^9\) All carbon in biomass lost through harvest and deforestation is assumed to be released within one decade. This simplification disregards the fact that some of the carbon in wood from deforestation and harvest will be stored in long-lived wood products for a considerable amount of time.
control variables include capital investment, abatement, and the forest controls (bioenergy harvest, afforestation, and avoided deforestation).

To examine the implications of asymmetric forest carbon pricing, we explore two types of asymmetric policy regimes: The first regime, focuses on an asymmetry between fossil carbon and forest carbon. This asymmetry is explored in the no forest policy scenario (NF) where the forest controls are set without consideration of the role of the forest carbon in the climate cycle. The second regime refers to an asymmetry within the pricing of forest carbon, specifically, between carbon emissions and sequestration by forests. This type of asymmetric carbon policy regime is investigated in the forest emissions policy scenario (FE) and the forest sequestration policy scenario (FS). In these scenarios, the social planner recognizes only forest emissions, or only sequestration, when setting the controls. Table 1 summarizes the main scenarios.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OPT</strong></td>
<td><em>Optimal scenario with full climate policy.</em> Controls are set when fully recognizing both fossil carbon and forest carbon in global emissions.</td>
</tr>
<tr>
<td><strong>NF</strong></td>
<td><em>No forest carbon are included in climate policy.</em> Controls are set without recognizing the role of forest emissions and sequestration in global emissions.</td>
</tr>
<tr>
<td><strong>FE</strong></td>
<td><em>Forest carbon emissions are included in climate policy.</em> Controls are set without recognizing the role of sequestration in global emissions.</td>
</tr>
<tr>
<td><strong>FS</strong></td>
<td><em>Forest carbon sequestration is included in climate policy.</em> Controls are set without recognizing the role of forest emissions in global emissions.</td>
</tr>
</tbody>
</table>

The results concerning global carbon emissions from the different scenarios are presented in Figure 1. The figure illustrates clearly that forest
carbon plays an important role in the total global emissions. The figure plots the total emissions from fossil fuel and forest carbon over the next 100 years for four scenarios. Figure 1 reveals that recognizing forest carbon in climate policy leads to lower emissions. Furthermore, it is revealed that while the lowest emissions are achieved by recognizing both the sequestration and forest carbon emissions, the largest reductions are the result of taking into account the emissions from loss of forest biomass.

![Figure 1: Total global carbon emissions, GtC per year](image)

Figure 2 shows the path of total forest carbon emissions net of sequestration. Consistent with the previous figure, emissions are lowest when both sequestration and forest carbon emissions are recognized. As before, accounting for forest carbon emissions play the largest role. This figure additionally reveals that just recognizing forest carbon sequestration is not enough to offset the release of carbon from not taking emissions from the forest into account. On the other hand, just recognizing the emissions from forests in carbon policy leads to a negative emissions path, in other words, under this scenario the forest acts as a net carbon sink.
Forests differ substantially in their biological characteristics, baseline forest cover, and bioenergy efficiency. For these reasons, the model predicts a clear ranking of the forest types in terms of the potential to reduce emissions through forest controls. Figure 3 plots for each type of forest, the carbon emissions net of sequestration under the two most extreme scenarios shown in the previous figure, that is, optimal and no forest policy scenario. The figure illustrates that the largest potential carbon reduction lies in the tropical forest. The tropical forest is a large source of carbon emissions in the no forest policy scenario due to high bioenergy harvest and deforestation. However, under optimal forest climate policy, the tropical forest acts as a net carbon sink. Moreover, the temperate and boreal forest are also sources of carbon emissions in the no forest policy scenario while roughly being carbon neutral in the optimal scenario. In accordance with previous literature, these results suggest that forest policy efforts should be focused in countries with tropical forests.
Figure 3: Forest carbon emissions net of sequestration, GtC per year

The paths of forest carbon emissions and sequestration depends on the change of forest biomass. In the model, forest biomass depends on the levels of forest controls. In what follows, we discuss how different policy scenarios affect the choice of forest controls, that is, avoided deforestation, afforestation, and bioenergy harvest.

As previously mentioned, deforestation is a large source of carbon emissions in the tropical forest. Avoiding deforestation decreases the emissions from the tropical forest through both a direct reduction of the baseline carbon released at deforestation and an increase in current and future sequestration. Figure 4 shows the avoided deforestation as a fraction of baseline deforestation. The optimal scenario displays the highest rate of avoided deforestation. Furthermore, not including forest carbon emissions in the carbon policy lead to a lower avoided deforestation than not including the benefit of sequestration. Interestingly, when both forest carbon sequestration and emissions are excluded in the carbon policy, the avoided deforestation is not zero. This avoided deforestation in the
medium to long run occurs to meet the demand for biomass to produce bioenergy. Note, however, that the baseline deforestation is declining over time.

Figure 4: Avoided deforestation, share of baseline deforestation

Figure 5 and 6 shows the cumulative afforestation in the tropical and temperate region, respectively. The highest cumulative afforestation occurs in the optimal scenario. Because the climate benefit of increasing forest land comes through sequestration, the lowest level of afforestation occurs when sequestration is not included in carbon policy. The level of afforestation, while low, is not zero because there is demand for biomass to produce bioenergy, especially in the long run.

The scenario that only takes into account sequestration leads to a level of afforestation that is different from the level in the optimal scenario. To see why this is the case, note that in this scenario emissions from forests are not being taken into account. This implies two things: First, that overall emissions will be misleadingly low, thereby reducing the incentives to undertake sequestration efforts. Second, that the true cost
of using bioenergy will not be observed, thereby increasing the incentives to increase the forest biomass. The combination of this two counteracting demands leads to different effects on the level of afforestation for the two forest types. For the tropical forest, the level of afforestation in the scenario that only takes into account sequestration is lower than the optimal scenario. For the temperate forest, the level of afforestation in the scenario that only takes into account sequestration is higher in the short run, but lower in the long run.

![Cumulative tropical afforestation, million hectares](image)

Figure 5: Cumulative tropical afforestation, million hectares
Figure 7, 8, and 9 shows the level of bioenergy harvest in the tropical, temperate, and boreal forest, respectively. Not recognizing the forest carbon in carbon policy gives remarkably high harvest levels. This harvest is especially high in the early time periods, but decline over time as the stocks of forest biomass decreases. Figure 10, 11, and 12 in Appendix A shows the evolution of forest biomass stocks under the different scenarios. Furthermore, not including the cost of release of carbon from forests also leads to higher bioenergy harvest than optimal for all types of forests. Not including the benefits from sequestration, on the other hand, leads to a lower bioenergy harvest than optimal for the tropical and temperate forest. This result follows from the logistic growth function formulation of the forest biomass where harvest increases the relative growth rate of the forest biomass and, hence, the rate of sequestration. The effect on the boreal forest is insignificant as the intrinsic growth rate of the boreal forest is low.
Figure 7: Tropical bioenergy harvest, billion m$^3$ per decade

Figure 8: Temperate bioenergy harvest, billion m$^3$ per decade
Figure 9: Boreal bioenergy harvest, billion m$^3$ per decade

The overall effect of the various scenarios can be expressed in terms of the price of carbon, which reflects the Pigouvian tax that should be introduced to internalize the negative externalities of carbon emissions. Table 2 shows the carbon price for the different scenarios. The optimal scenario leads to the lowest carbon prices. Ignoring all types forest carbon in climate policy leads to the highest carbon prices. Moreover, in line with our previous results, not recognizing forest carbon emissions leads to higher carbon prices than not recognizing forest carbon sequestration.

<table>
<thead>
<tr>
<th>Year</th>
<th>OPT</th>
<th>NF</th>
<th>FE</th>
<th>FS</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>41.25</td>
<td>42.51</td>
<td>41.35</td>
<td>42.17</td>
</tr>
<tr>
<td>2035</td>
<td>65.31</td>
<td>67.10</td>
<td>65.47</td>
<td>66.64</td>
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<tr>
<td>2055</td>
<td>96.01</td>
<td>98.15</td>
<td>96.24</td>
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<tr>
<td>2075</td>
<td>134.73</td>
<td>136.89</td>
<td>135.03</td>
<td>136.43</td>
</tr>
<tr>
<td>2115</td>
<td>242.9</td>
<td>244.6</td>
<td>243.4</td>
<td>244.3</td>
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</table>

Consistent with the carbon price results, we find that the social welfare
for the scenarios has the following ranking, from high to low: OPT, FE, FS, and NF. On the whole, scenarios that recognize forest carbon emissions lead to the lowest carbon prices and the highest level of welfare. Note that while the difference in carbon prices between scenarios may seem small, these results are conditional on the damage function of the DICE model. The DICE model projects relatively small damages from climate change and the optimal temperatures will reach above 3°C in all scenarios. For example, in the optimal scenario, the temperature increase exceeds 2°C in 2075 and continues to increase until it peaks at 3.2°C by 2185. Table 4 in Appendix A shows the temperature increase in the different scenarios.

In optimal climate policy instruments should include both taxing emissions and subsidizing sequestration. Table 3 provides a back of the envelope calculation on the optimal taxation of fossil and forest carbon over the next decades. The total tax and subsidy of forest carbon are also displayed by forest type. The table reveals that the subsidy will exceed the tax revenue from forest emissions. The tropical forest accounts for the bulk of this imbalance between tax and subsidy. To get a better a sense of the magnitudes consider that world GDP amounts to approximately $58.2 trillion, in 2015 this implies that the tax from forest emissions amounts to 0.15% of world GDP while the subsidy amounts to 0.18%. Notice, however, that the sequestration subsidy can be fully financed when tax revenue also includes taxes from fossil fuels, which amount to 0.53% of world GDP.\footnote{The magnitudes are calculated using the 2014 World GDP in constant 2005 US dollars, as calculated by the World Bank. http://data.worldbank.org/indicator/NY.GDP.MKTP.KD}
Table 3: Optimal total tax and subsidy payments, billion 2005 U.S. dollar per year

<table>
<thead>
<tr>
<th>Forest Carbon Tax</th>
<th>2015</th>
<th>2025</th>
<th>2035</th>
<th>2045</th>
<th>2055</th>
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<tr>
<td>Tropical</td>
<td>48.5</td>
<td>58.5</td>
<td>68.8</td>
<td>80.3</td>
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<td>Temperate</td>
<td>27.6</td>
<td>37.6</td>
<td>49.0</td>
<td>61.8</td>
<td>76.1</td>
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<tr>
<td>Boreal</td>
<td>9.5</td>
<td>12.9</td>
<td>16.7</td>
<td>21.0</td>
<td>25.8</td>
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<tr>
<td>Total</td>
<td>85.6</td>
<td>109.0</td>
<td>134.5</td>
<td>163.1</td>
<td>195.0</td>
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<table>
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<tr>
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<td>Tropical</td>
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<td>77.9</td>
<td>94.4</td>
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<tr>
<td>Temperate</td>
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<td>40.4</td>
<td>49.9</td>
<td>60.8</td>
<td>73.1</td>
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<tr>
<td>Boreal</td>
<td>11.2</td>
<td>14.2</td>
<td>17.7</td>
<td>21.6</td>
<td>26.0</td>
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<tr>
<td>Total</td>
<td>105.5</td>
<td>132.5</td>
<td>162.0</td>
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<table>
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<tr>
<td>Total</td>
<td>306.9</td>
<td>431.6</td>
<td>580.2</td>
<td>754.1</td>
<td>954.8</td>
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4 Conclusions and Policy Implications

This paper uses an extended version of FOR-DICE (2015) to investigate the effectiveness of climate policy under two asymmetric carbon policy regimes. In the first regime, policymakers account for carbon emissions from fossil fuels but do not account for positive or negative emissions from forests. In the second regime, policymakers do not account for either positive emissions, or negative emissions, from forests.

These regimes are represented by three scenarios which are compared against and optimal benchmark scenario. The model quantifies, by forest type, the level of forest controls that should be pursued in each scenario. These controls include avoided deforestation, afforestation, and bioenergy harvest. While it is not the aim of the paper to provide definitive policy targets for these controls, our results clearly highlight that asymmetric carbon policies have a large impact on the forest controls. In addition to the climate effects of the forest controls, these results are also important because they imply, apart from an overall welfare effect,
distributional effects, both between regions and over time.

Our results from the first policy regime indicate that not recognizing positive and negative emissions from forests in carbon policy leads to the highest levels of total emissions, the highest carbon prices, and the lowest welfare. The intuition behind these results is that the forest resource will be allocated inefficiently if carbon values associated with the forest are not included in the decision-making process. Specifically, the relative value between using forest carbon and fossil fuel carbon will be distorted. These results are consistent with those of the bioenergy literature, where the price differentials between bioenergy and other energy will be distorted when we do not fully account for the total negative and positive impact of using forest biomass. Moreover, without any consideration of the climate impact from forests, afforestation and avoided deforestation will only be driven by the need to supply biomass for harvest to bioenergy and timber. In general, not accounting for emissions or sequestration from forests will lead to the highest levels of bioenergy harvest, and the lowest levels of afforestation and avoided deforestation. These effects on the forest controls are particularly strong for the tropical forest.

In the second policy regime, the social planner separately accounts for either positive emissions, or negative emissions, from forests. While both of these scenarios lead to lower levels of welfare that the optimal scenario, our results indicate that not recognizing positive emissions from forests leads to higher total emissions, higher carbon prices, and lower welfare, than not recognizing negative emissions. The intuition behind these results, as in the previous case, is that the failure to recognize either positive or negative emissions leads to a distortion in the cost and benefits of the forest controls. Broadly, we find that not recognizing forest emissions leads to the largest diversion from the optimal path for bioenergy harvest and avoided deforestation. While not recognizing sequestration leads to the largest diversion for afforestation.

The simple framework presented in this paper could be further devel-
oped to account for factors that could alter the impact of asymmetric carbon policy. One interesting extension would be to explicitly include the technological development of the use of biomass for energy. This is especially important since, for example, the development of bioenergy production with carbon capture and storage could in practice lead to energy production with net negative emissions. Another potentially important extension is to account for the risk of carbon leakage associated with the long-term storage of carbon in forests.

Despite its simple structure, the model allows us to draw three important policy conclusions. First, our results clearly indicate that the forest resource will be allocated inefficiently if forest carbon is not correctly priced. Correct pricing implies both taxing forest emissions as well as subsidizing carbon sequestration. Second, our results highlight that confronted with the choice between pricing forest emissions or pricing forest sequestration, it is relatively more important to price forest emissions. Accordingly, policy makers are encouraged to fully price forest carbon, or given implementation constraints to prioritize the pricing of forest emissions. Third, our back of the envelope calculation indicates that the overall subsidy for forest sequestration will be larger than the overall tax revenue from forest emissions, with this imbalance being largest for the tropical forests. Our calculation, however, also indicates that the sequestration subsidy can be fully financed in the context of a broader climate policy where revenue is derived from both taxing fossil fuels and forest emissions.
References


Figure 10: Growing tropical forest stock, billion m$^3$
Figure 11: Growing temperate forest stock, billion m$^3$

Figure 12: Growing boreal forest stock, billion m$^3$
Figure 13: Forest carbon emissions, GtC per year

Table 4: Temperature increase, °C from 1900

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<tr>
<td>OPT</td>
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<td>3.1</td>
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<td>1.8</td>
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