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Mitigating Climate Change with Forest Climate Tools

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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 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

[1] The 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)).

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 an 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:

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

where n denotes the region, α is the elasticity of the marginal utility of per capita consumption, $c_{n,t}$, $\omega_{n,t}$ is the Negishi weight, ρ 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 redistribution 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 approximations of baseline deforestation.[5] The RICE-2010 model baseline carbon emissions from land are given by:

$$BD_{n,t} = \lambda 1_n \lambda 2_n^t, \tag{2}$$

[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`).

[5]The 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).

where the parameter $\lambda 1_n$ represents the first-period carbon emissions and the parameter $\lambda 2_n$ 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.

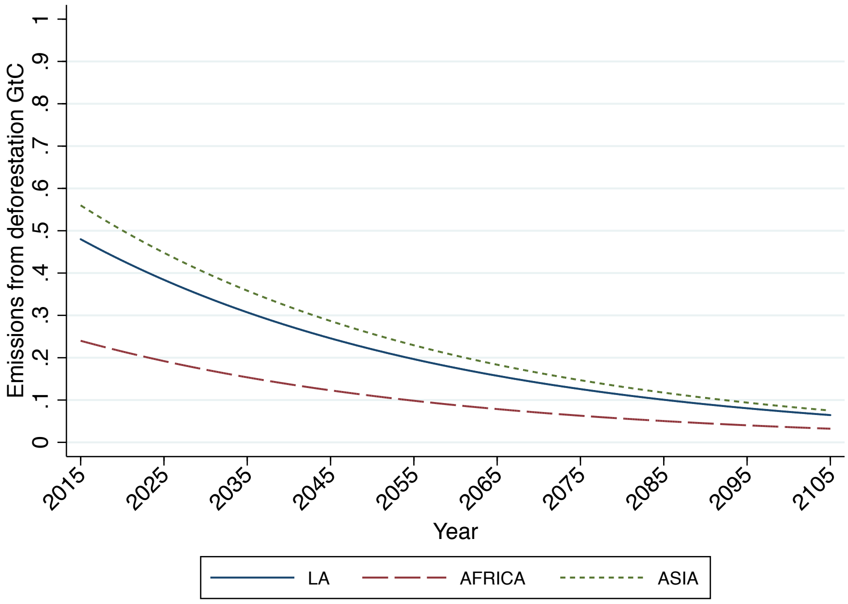

Figure 1: Baseline emissions from deforestation, GtC per year

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 from deforestation. Specifically, the deforestation control rate reduces the release of carbon stored in forest biomass.[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.

[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).

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 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:

$$S_{t,n} = \frac{1}{1 + e^{-(t-m_n)}}, \tag{3}$$

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]

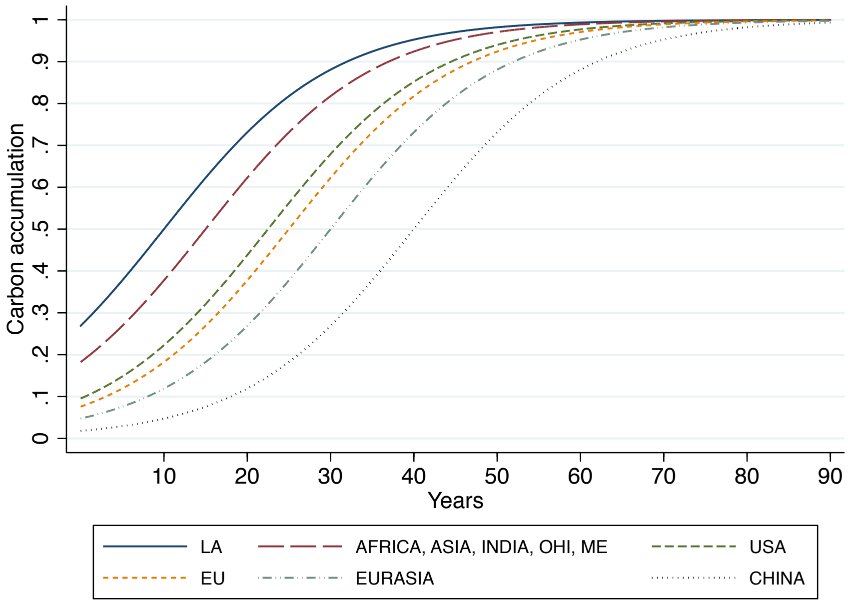

Figure 2: Sigmoidal function carbon accumulation

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

[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 on 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 theses 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.

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 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.[9] 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.

[9]The 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

Scenario	Controls
Optimal	All controls
Deforestation	Saving, energy abatement, and deforestation control rate
Afforestation	Saving, energy abatement, and afforestation
No Forest Tools	Saving and energy abatement

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 used of the forest tools leads to the lowest emissions in the short and the medium run.

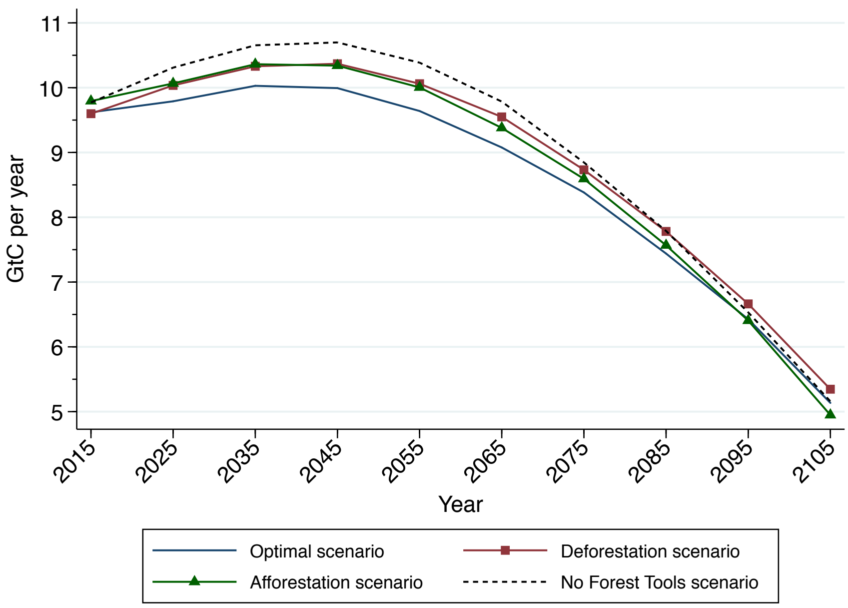

Figure 3: Total global emissions under different scenarios, GtC per year

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)).

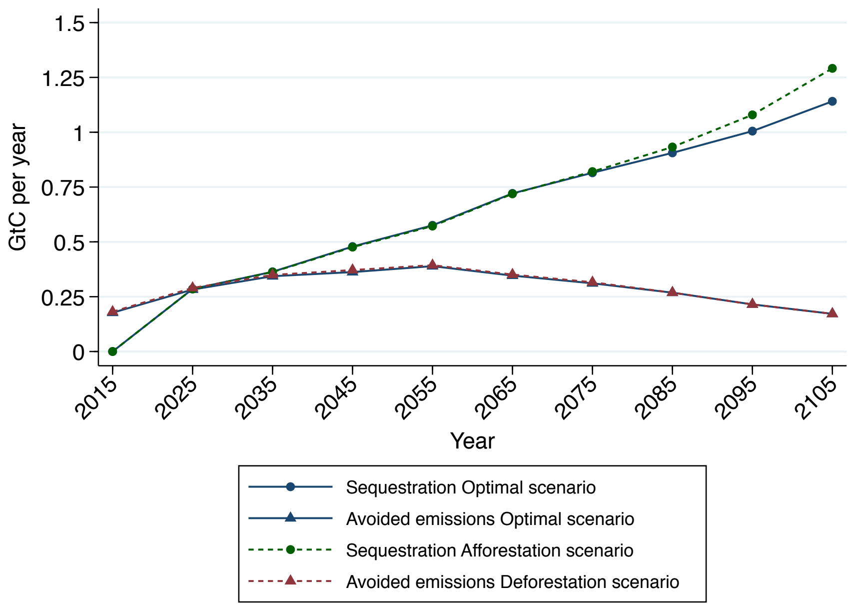

Figure 4: Sequestration from afforestation and reduction of emissions through avoided deforestation under different scenarios, GtC per year

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 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.

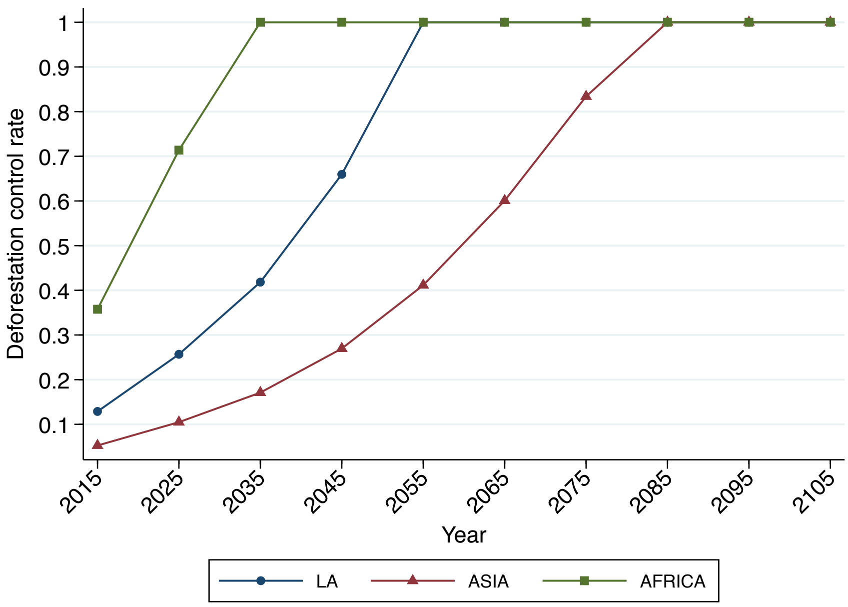

Figure 5: Optimal scenario avoided deforestation, share of baseline deforestation

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)).

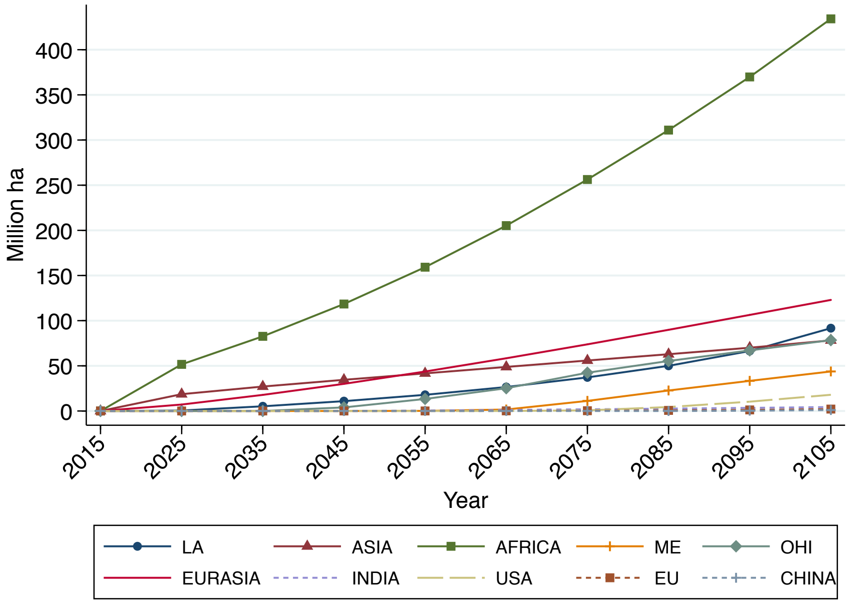

Figure 6: Optimal scenario cumulative afforestation, million hectares

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.[10]

[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 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.

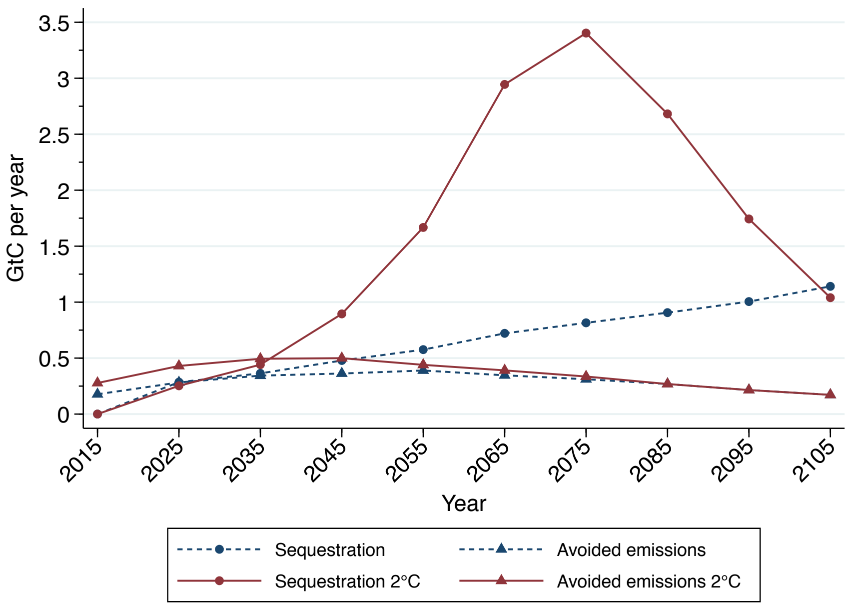

Figure 7: Optimal scenario sequestration from afforestation and reduction of emissions through avoided deforestation with and without a 2°C target, GtC per year

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.

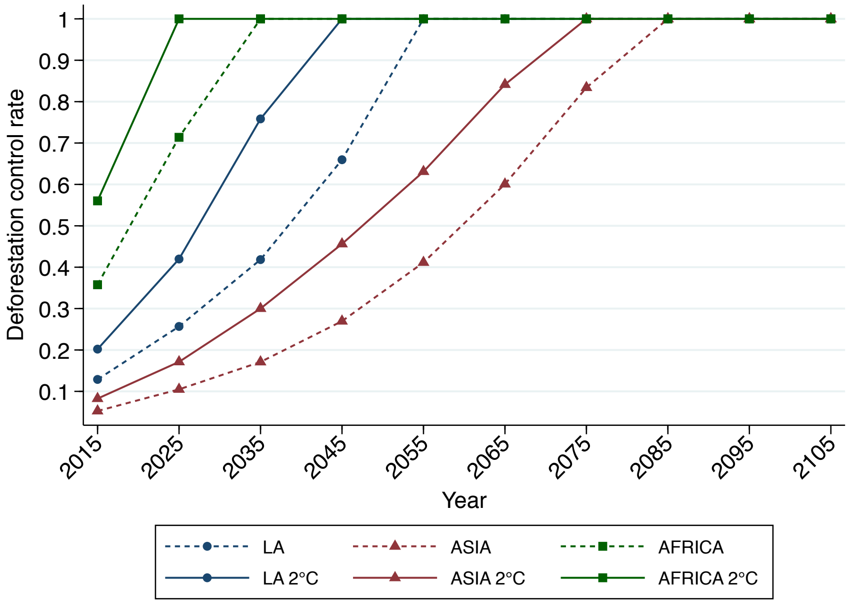

Figure 8: Optimal scenario avoided deforestation with and without a 2°C target, share of baseline deforestation

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.

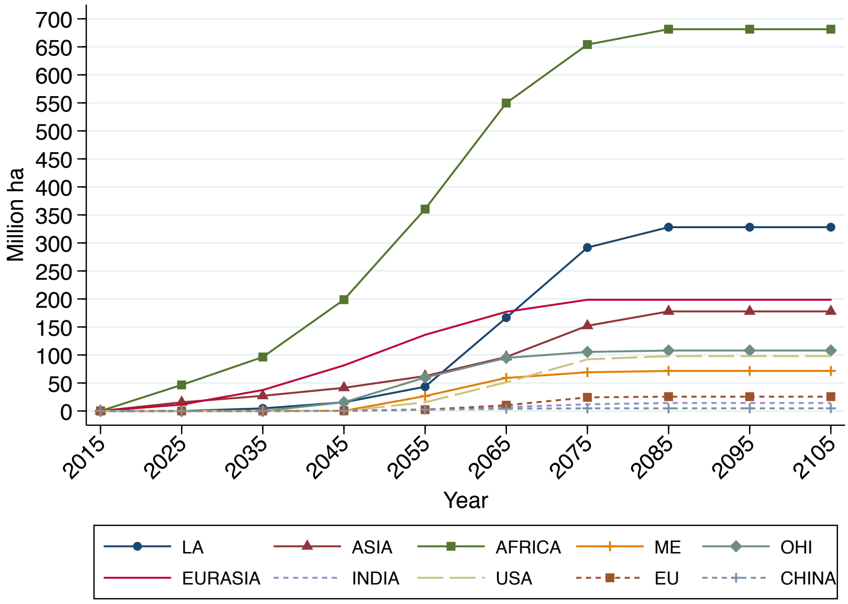

Figure 9: Optimal scenario cumulative afforestation with a 2°C target, million hectares

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

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

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

	PV utility	Difference from No Forest Tools	Climate change year 2115
Scenarios	Trillions of 2005 U.S. $		°C from 1900
No Forest Tools	2307.78		2.89
1.75°C target	2298.00	-9.78	1.75
2°C target	2303.18	-4.60	2
2.5°C target	2307.04	-0.74	2.5
Optimal	2308.31	0.53	2.81
1.75°C target	2304.77	-3.01	1.75
2°C target	2306.64	-1.14	2
2.5°C target	2308.13	0.35	2.5
Deforestation	2307.98	0.20	2.86
1.75°C target	2300.38	-7.40	1.75
2°C target	2304.30	-3.48	2
2.5°C target	2307.41	-0.37	2.5
Afforestation	2308.13	0.44	2.85
1.75°C target	2303.87	-3.91	1.75
2°C target	2306.07	-1.71	2
2.5°C target	2307.86	0.08	2.5

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.

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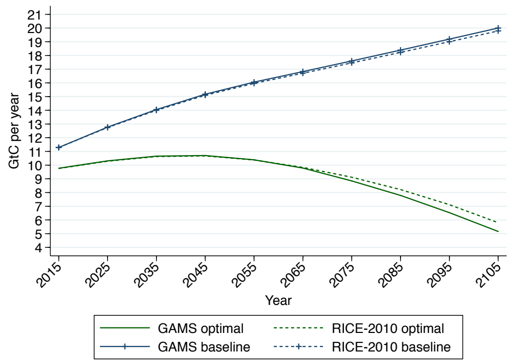
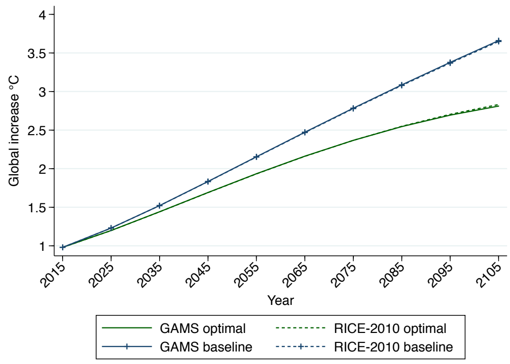
Appendix A: Translating the RICE Excel Model into GAMS

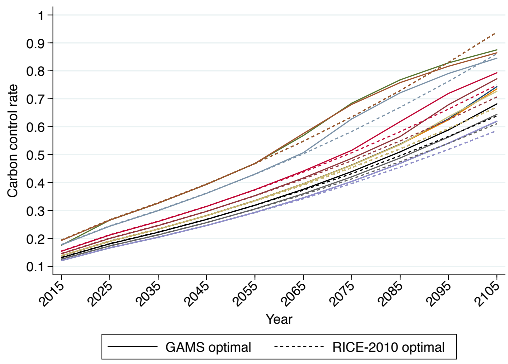
To this date, the RICE-2010 model is only publicly available as an Excel model at Nordhaus webpage. The latest GAMS model is the RICE-99 version. Due to the unreliability of the Excel solver for large problems, and to construct the FRICE model, I first code the original RICE-2010 spreadsheet model in 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.



(a) Global emissions, GtC per year



(b) Global temperature increase, °C



(c) Regional energy abatement, fraction of uncontrolled industrial emissions

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).

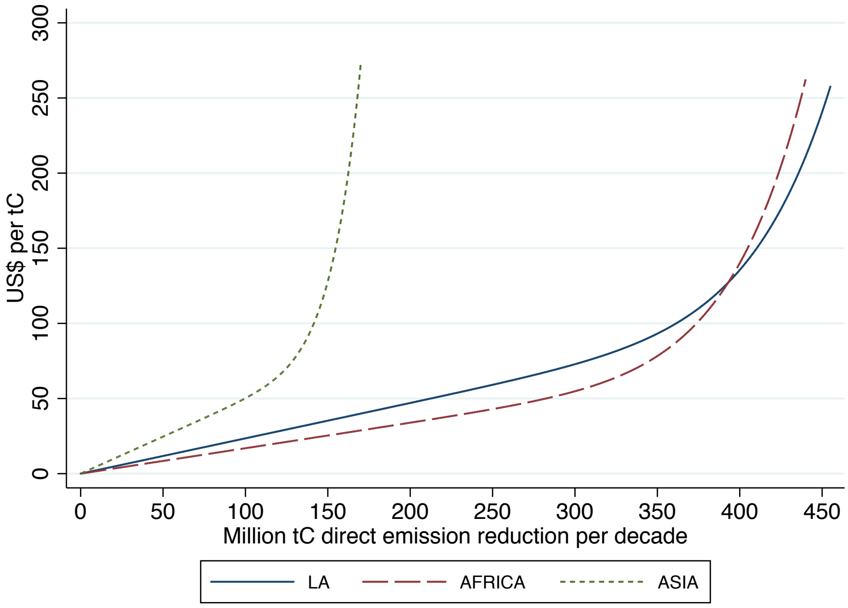


Figure 11: Cost of avoiding deforestation, US$ per tC

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 ($\approx$ 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/km^2 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).

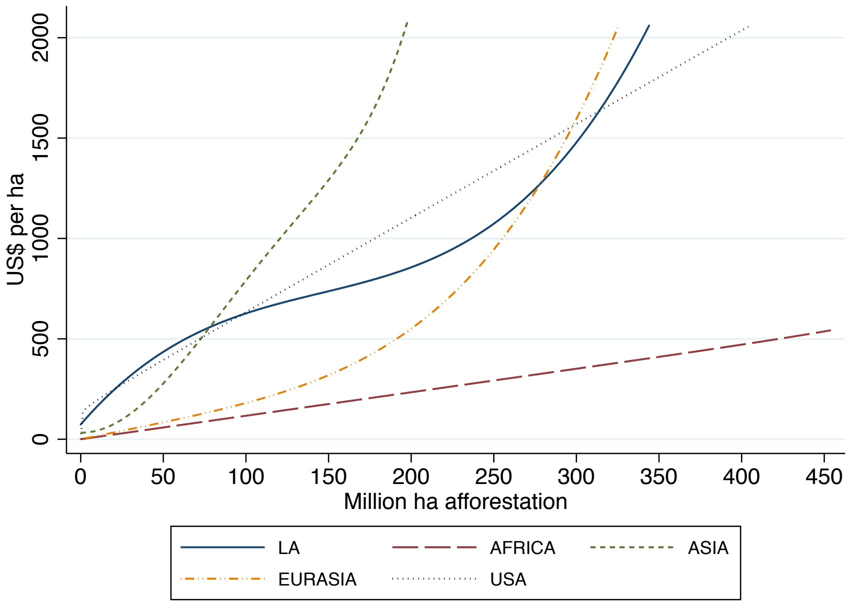


Figure 12: Cost of afforestation, US$ per ha

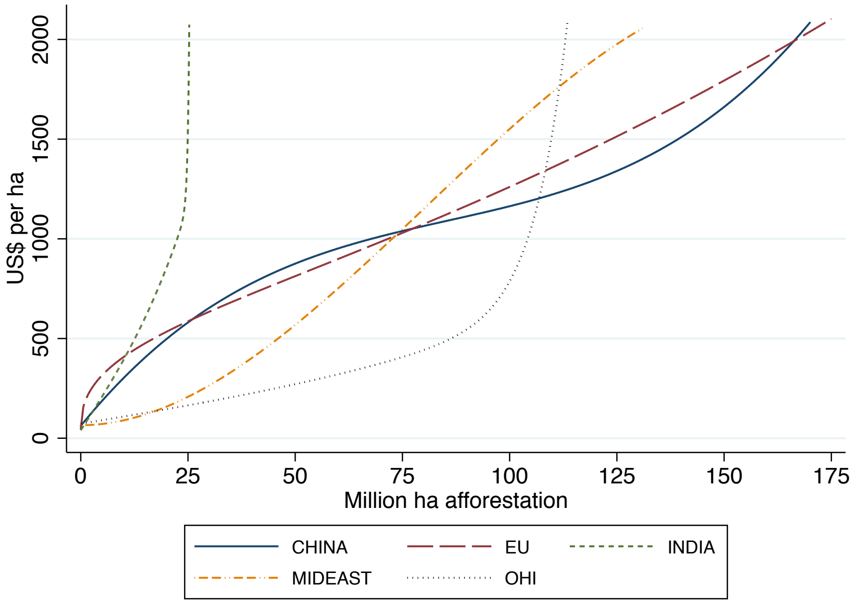


Figure 13: Cost of afforestation, US$ per ha

Appendix C: Regional Afforestation Parameters

Table 4: Regional parameters

Regions[3]	Average rotation length (year)[1]	Average carbon carrying capacity (tC/ha)[2]
AFRICA	30	96.2
ASIA	30	107.9
CHINA	80	31.7
EU	50	56.3
EURASIA	60	62.6
INDIA	30	40.1
LA	20	116.2
ME	30	22.6
OHI[4]	30	69.9
USA	45	55.9

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 based on the rotation periods in Nilsson and Schopfhauser (1995).

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

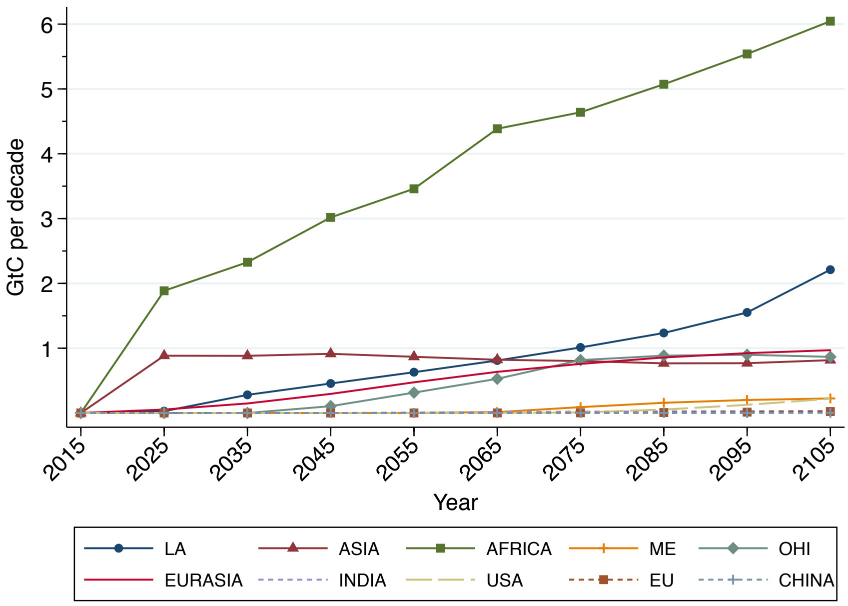


Figure 14: Optimal scenario sequestration from afforestation, GtC per year

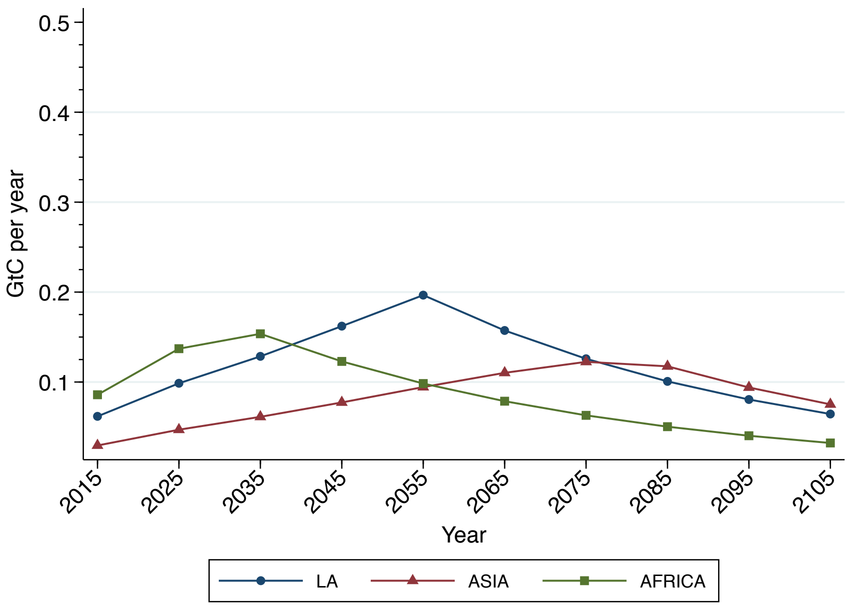


Figure 15: Optimal scenario reduction of emissions through avoided deforestation, GtC per year

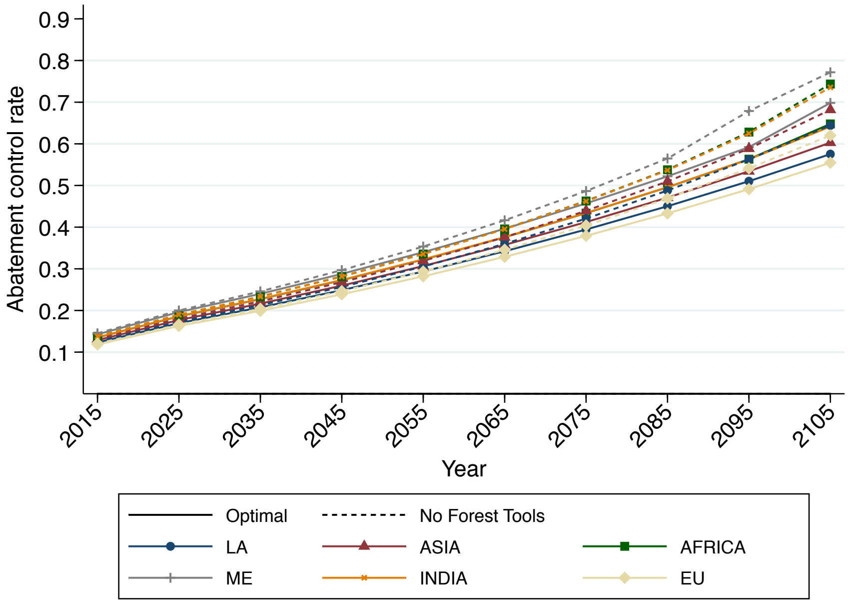


Figure 16: Energy abatement as fraction of uncontrolled industrial emissions under Optimal and No Forest Tools scenario

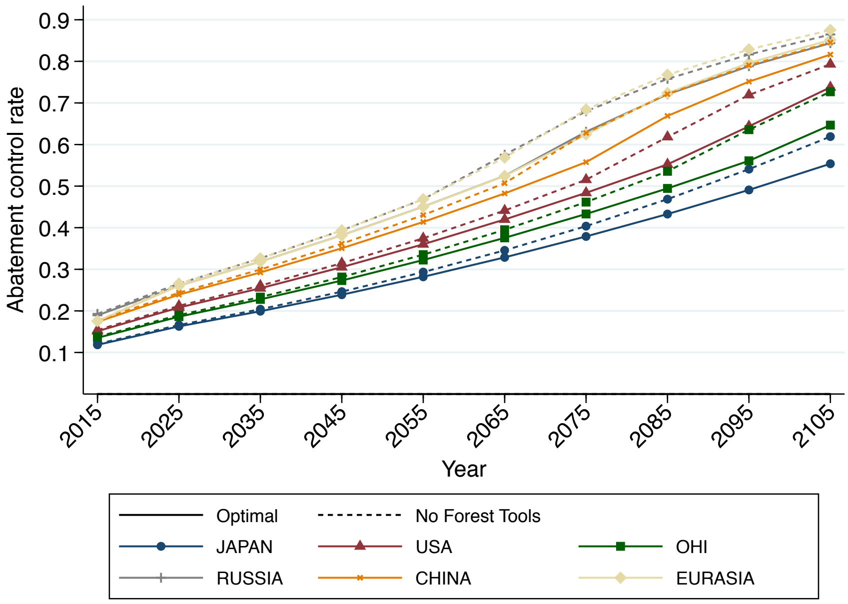


Figure 17: Energy abatement as fraction of uncontrolled industrial emissions under Optimal and No Forest Tools scenario

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.

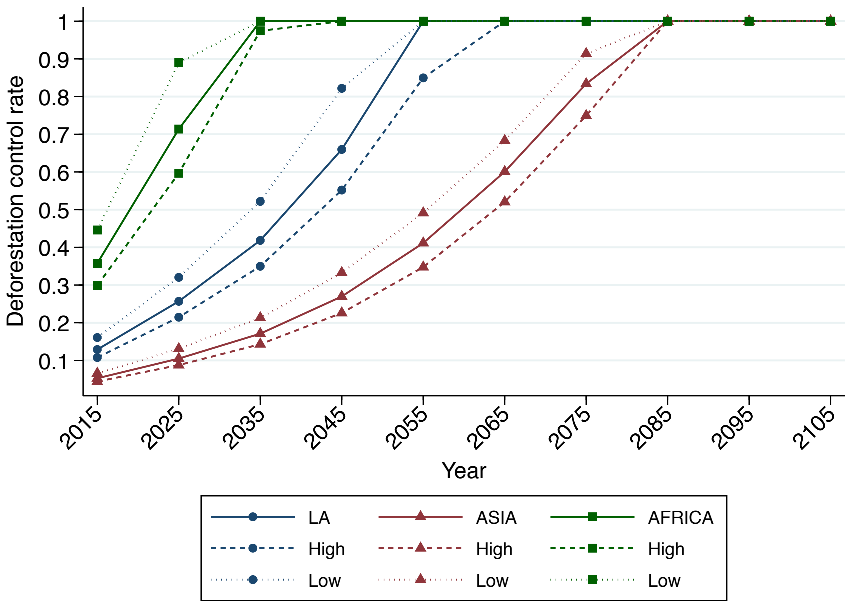


Figure 18: Optimal scenario avoided deforestation as share of baseline deforestation: benchmark cost, high-cost, and low-cost

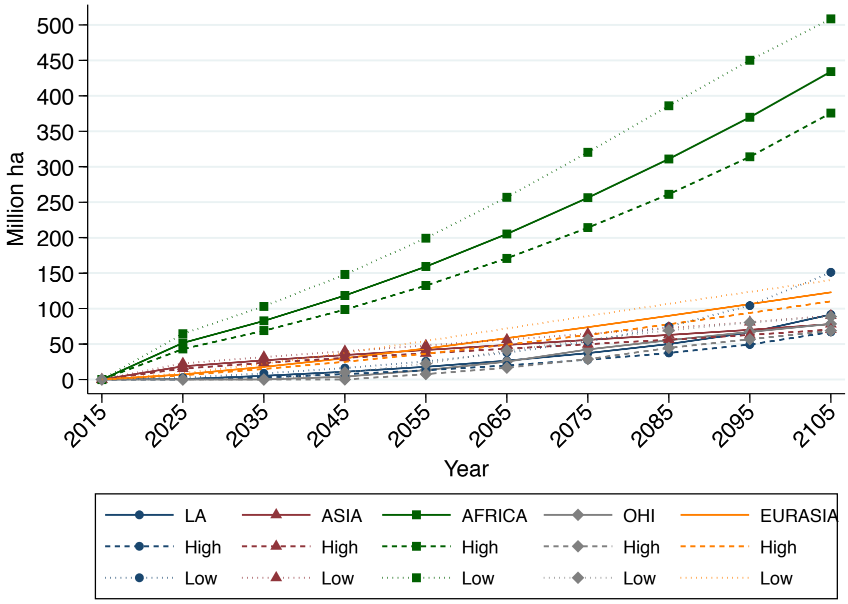


Figure 19: Optimal scenario cumulative afforestation in millions of hectares: benchmark cost, high-cost, and low-cost

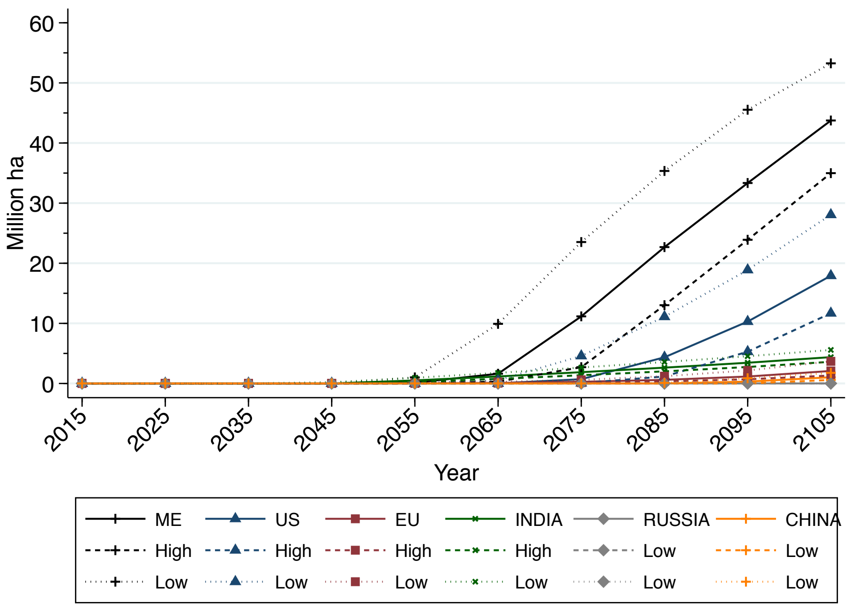


Figure 20: Optimal scenario cumulative afforestation in millions of hectares: benchmark cost, high-cost, and low-cost

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 avarage carbon carrying capacities shown in Table 4.

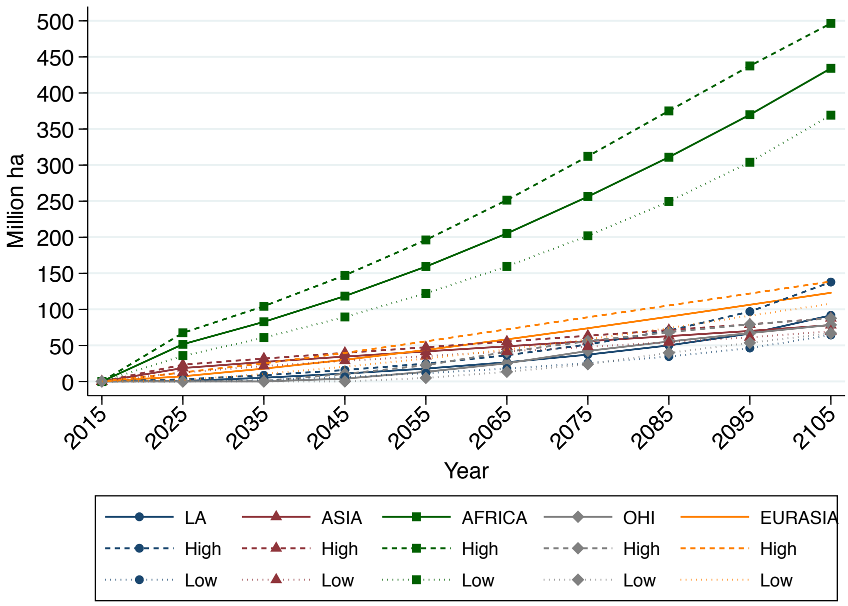


Figure 21: Optimal scenario cumulative afforestation in millions of hectares: benchmark, high, and low sequestration capacity

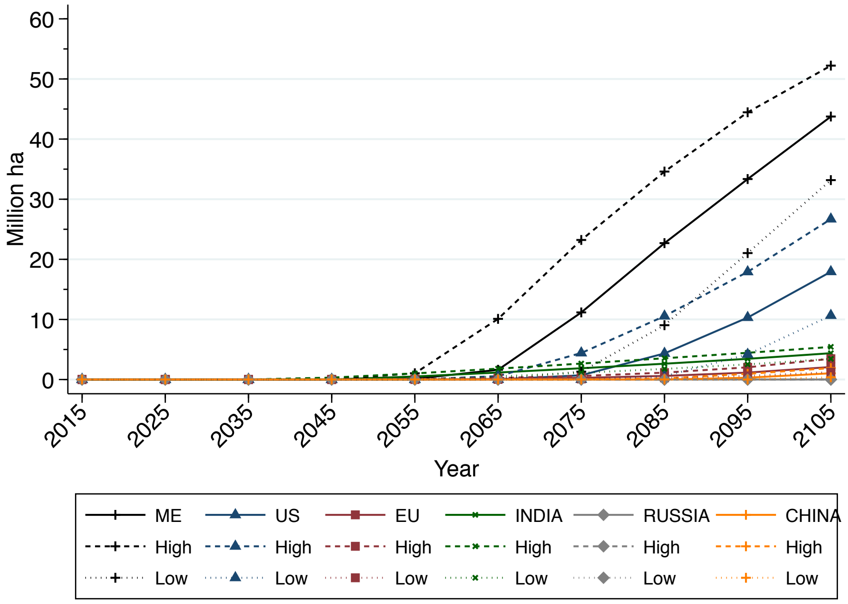


Figure 22: Optimal scenario cumulative afforestation in millions of hectares: benchmark, high, and low sequestration capacity

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.

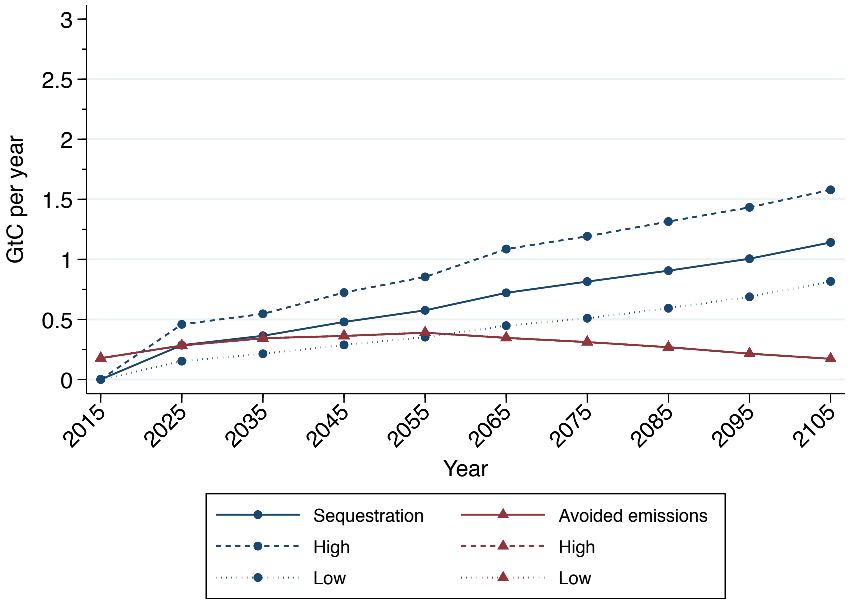


Figure 23: Optimal scenario sequestration from afforestation and reduction of emissions through avoided deforestation in GtC per year: benchmark, high, and low sequestration capacity

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.

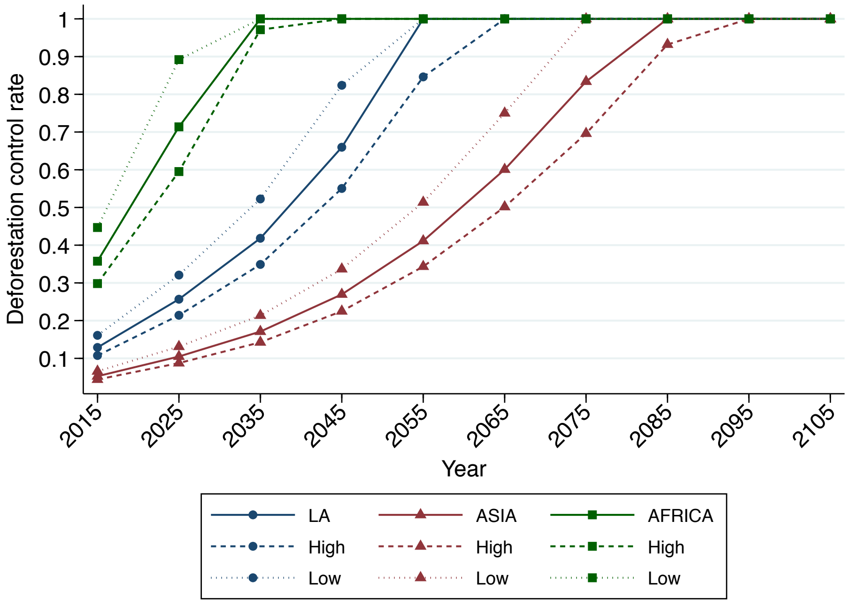


Figure 24: Optimal scenario avoided deforestation as share of baseline deforestation: benchmark, high, and low baseline deforestation

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.

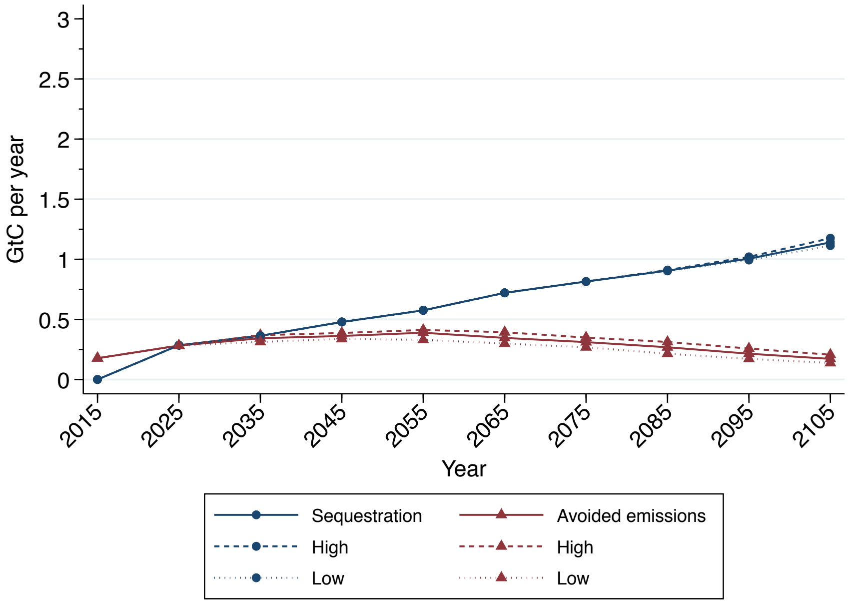


Figure 25: Optimal scenario sequestration from afforestation and reduction of emissions through avoided deforestation in GtC per year: benchmark, high, and low baseline deforestation