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# A SUPPLY CURVE FOR FOREST-BASED CO2 REMOVAL

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**ABSTRACT**

Forestation is viewed as an important means of removing $CO_2$ from the atmosphere and thereby reducing net $CO_2$ emissions. But how much $CO_2$ can be removed, and at what cost? Focusing on forested and forestable areas in South America, and using spatially disaggregated data, we estimate a supply curve for forest-based atmospheric $CO_2$ removal. The supply curve traces out the marginal cost of removing a metric ton of $CO_2$ as a function of total annual $CO_2$ removal. Each point on the curve corresponds to a specific location, and accounts for land opportunity costs as well as costs of tree planting and maintenance. We show that over a billion tons of $CO_2$ can be removed annually via forestation at a cost below $45 per ton, and about 2.5 billion tons can be removed at a cost below $90 per ton. The supply curve applies to only South America, but with sufficient data could be extended to the entire world.

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# 1 Introduction

Global $CO_2$ emissions continue to rise. That may eventually change, but even with a substantial decline in emissions, the atmospheric $CO_2$ concentration will keep growing and remain high for many years. That is why policy objectives have focused on *net* emissions, and the need to remove $CO_2$ from the atmosphere. But how? Planting trees (afforestation and reforestation) might be seen as an obvious solution, but where and at what cost? Here we focus on forested and forestable land in South America, and use spatially disaggregated data to estimate a supply curve for forest-based atmospheric $CO_2$ removal. The supply curve traces out the marginal cost of removing a metric ton of $CO_2$ as a function of total annual $CO_2$ removal. Each point on the curve corresponds to a specific location, so our analysis tells us where and how many trees can be planted, and at what cost.[1]

Before we explain our methodology, here are some very rough numbers to help set the stage for our work:

1. Estimates vary depending on climate, the age and type of tree, and the local tree density, but on average a mature (about 10 to 20 years old) hardwood tree will absorb about 20 kg of $CO_2$ per year.

2. Again, the numbers vary considerably depending on climate and type of tree, but on average at least 500 trees can be grown and maintained on one hectare of land.[2]

3. How much land could potentially be forested? Using satellite data, a recent study puts the global number of hectares that could be forested at about 1 billion. If we take this number at face value, full forestation of all available land could remove about $1 \times 10^9 \times 500 \times .02 = 10$ Gt (billion tons) of $CO_2$ per year from the atmosphere.[3]

4. Global $CO_2$ emissions are currently around 40 Gt per year. Thus, we could potentially reduce net emissions by about 25% by foresting all 1 billion hectares. That won't bring the world to net zero, but 25% is a good start.

[1] There is considerable ongoing R&D focused on carbon removal and sequestration (CRS) technologies, but those technologies are currently too expensive for practical use. See Pindyck (2022) and references therein. Other land- and water-based plants, such as mangroves and kelp, can also absorb $CO_2$, but compared to trees, their potential for $CO_2$ absorption is quite limited.

[2] 1 hectare = .01 square kilometers ≈ 2.47 acres.

[3] This estimate of 1 billion hectares is by Bastin et al. (2019). Also see references in Pindyck (2022).

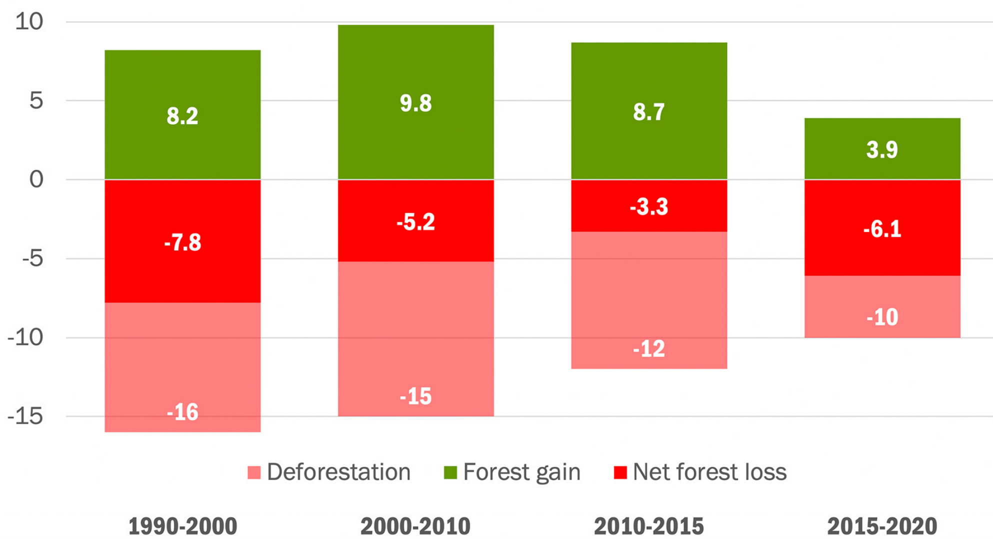



Figure 1: Net Annual Forest Loss. For each period the figure shows estimates of annual global deforestation, annual global gains in forest areas, and the net loss, all in millions of hectares. During 2015–2020 annual deforestation was about 10 million hectares, but this was partially offset by 3.9 million hectares of forest gain, for a net annual loss of 6.1 million hectares. Source: United Nations' Food and Agriculture Organization (2020*b*) and https://rainforests.mongabay.com/deforestation/.

So why don't we start planting large numbers of trees? Yes, it would take time, but after 10 years or so, net emissions could be substantially reduced.

We are indeed planting some trees, but cutting down many more. As shown in Figure 1, during the period 2015 to 2020, there were about 10 million hectares per year of deforestation, which was partly offset by about 4 million hectares per year of forest gain, for an annual net forest loss of about 6 million hectares. The rate of net forest loss has been changing over time; as Figure 1 shows, it was greatest during the 1990s, declined through 2015, but increased again during 2015–2020, largely because of a reduction in forest gain.

Deforestation occurs because land is valuable, and can be used for agriculture, cattle grazing, mining, and other economic activities.[4] And that is one of the main reasons why we are not planting trees in sufficient number to have a significant impact on net $CO_2$ emissions. Planting and maintaining trees requires valuable land, which can make it costly. The nature and extent of these and other costs will be explored in this paper.

Suppose deforestation at recent rates continues. What impact would an ongoing loss of, say, 6 million hectares per year have for $CO_2$ emissions? Each year $CO_2$ absorption is

[4]For a detailed discussion of deforestation in different parts of the world, and recent research to better understand the causes and effects of deforestation, see Balboni et al. (2023).

reduced (i.e., net emissions are increased) by $6 \times 10^6 \times 500 \times .02 = .06$ Gt per year, or about 1 Gt after 17 years. But net emissions actually increase by much more, because a tree contains about 200 kg of carbon, which releases around $200 \times 3.67 \approx 700$ kg of $CO_2$ when the fallen tree decays or (more often) is burned. This in turn implies that an ongoing loss of 6 million hectares per year would increase net $CO_2$ emissions by 0.27 Gt per year, or about 1 Gt after four years.[5]

Deforestation is a serious problem, but our focus is on *forestation*. How many hectares can potentially be forested, and at what cost? There are estimates based on satellite data, such as the 1-billion hectare estimate from Bastin et al. (2019) that we used above. These macro-level estimates attempt to account for the land that is potentially forestable, but tell us very little about forestation costs, which vary considerably across regions. The variation is due to sharp regional differences in the current use of the land, and in rainfall and other climatic factors that affect forest growth.

We address this problem at the micro level and develop a supply curve for forest-based $CO_2$ removal. The supply curve traces out the marginal cost of removing 1 ton of $CO_2$ from the atmosphere as a function of total annual $CO_2$ removal, all by planting trees. Given data limitations, we focus on forested and forestable areas in South America, which include the Amazon rainforest (accounting for 13 percent of the world's total forest area), the Atlantic forest, the Gran Chaco region, and areas of savanna and grassland. Although our study is limited to South America, with sufficient data our methodology can be applied to other regions, so that a complete global supply curve could be constructed.

We consider planting trees in areas that during the past 50 years were once densely forested but have experienced forest loss, as well as areas that were never forested and may instead have existed as savanna or grassland. However, some recent studies have suggested that the forestation of areas that have never existed as forests can have negative environmental repercussions, and thus some have argued should be avoided.[6] Flora and fauna that can

[5] 1 kg of carbon is equivalent to 3.67 kg of $CO_2$ because of the two oxygen atoms connected to each carbon atom. Tropical moist forests contain about 130 tons of carbon per hectare above ground (Figure 6 in ForestPlots.net et al. (2021)). To add the belowground biomass, multiply the aboveground carbon stock by 1.26 (Mokany, Raison and Prokushkin, 2006). Tree density is in the range 550-650 trees/ha (ForestPlots.net et al., 2021; Crowther et al., 2015). That leads to the average of 270 kg of carbon per tree. For temperate deciduous and coniferous forests the carbon content is lower, so 200 kg is a conservative average number. See Ramankutty et al. (2007). That $CO_2$ enters the atmosphere fairly quickly, but to measure its impact on temperature, we can "amortize" it over 10 years, so it is roughly equivalent to additional $CO_2$ emissions of $700/10 = 70$ kg of $CO_2$ per year. See Amazon Fund (2010) and Franklin and Pindyck (2018). Adding that to the 20 kg of lost absorption yields 90 kg of $CO_2$ per year for each tree cut down, and with an average of 500 trees per hectare this implies an increase in net emissions of $6 \times 10^6 \times 500 \times .09 = .27$ Gt per year.

[6] See, for example, Pörtner et al. (2021) and Holl and Brancalion (2020).

survive in a savanna, for example, might not be able to survive in a dense forest, so turning a savanna into a forest could reduce biodiversity. We do not take a stand on this issue, but for purposes of comparison, we also develop a supply curve that restricts potentially forestable land to those areas that were previously forested.

Our analysis accounts for the three most important types of cost involved in forestation:

1. **Opportunity cost of land.** This varies greatly across locations, and is often the largest cost component for forestation. Deforestation occurs because land has economic value, and foresting a hectare of land means it cannot be used for other purposes.

2. **Planting and maintenance costs.** Planting a tree involves more than sticking an acorn in the ground. It begins with planting and growing seedlings, and then replanting those seedlings with fertilizer, water, and insect repellent. Later, the trees must be protected from insects and pruned as they mature, and sometimes must be replanted. Mature trees have ongoing maintenance costs, which includes continual addition of fertilizer and insect repellent, and depending on the area, water.

3. **Forest conservation costs.** Later, mature trees must be protected from illegal logging, which is a serious problem in much of the world. Monitoring and law enforcement efforts must be put in place in order to ensure forest conservation.

Based on these costs, we determine where and how many trees can feasibly be planted. We mentioned that water is a critical input; indeed forestation in areas with limited rainfall is usually prohibitively expensive, and most areas deemed suitable for forestation have considerable rainfall. In developing a supply curve for South America, we consider areas where precipitation patterns can potentially support forest growth.

As explained in more detail below, we begin by examining tree cover distributions and precipitation patterns in tropical and subtropical regions *worldwide*, using a $0.5° \times 0.5°$ resolution land grid. The objective is to determine where precipitation patterns make it economical to plant trees and the number of trees that should be planted on each land grid element. Turning to South America, we then estimate the land opportunity, tree planting and forest conservation costs for each $0.5° \times 0.5°$ resolution land grid element. Combining this with estimates of the $CO_2$ absorption rate per hectare and per tree, we compute the marginal cost of a one-ton reduction in net $CO_2$ emissions via forestation. Then, starting with the lowest-cost opportunities for $CO_2$ removal, we build up the supply curve.

Of course forestation can have different objectives, and much of it is done to produce timber and other wood products. Timber producers plant trees, cut them down at or before maturity, plant new ones, and so on, with the total number of trees roughly constant over time. Hence we ignore timber production and focus on forestation with the objective of removing atmospheric $CO_2$.

In the next section we briefly review the prior literature on the use of forestation to absorb $CO_2$. In Section 3 we provide an overview of the sources and coverage of our data. In Section 4 we show how the data are used to identify areas with high precipitation and potential for increased tree cover. In Section 5 we present our estimates of land opportunity, tree planting and forest conservation costs in different locations. In Section 6 we use these results to build a supply curve for forest-based $CO_2$ removal. We examine the sensitivity of our results to certain assumptions in Section 7, and discuss policy implications of our results, caveats, and suggestions for further work in Section 8.

# 2 Related Studies versus Our Approach

We are not the first to address the potential of forestation for atmospheric $CO_2$ removal, but other studies have typically been at a macro level using models that simulate the aggregate response of abatement suppliers to variable carbon prices. Some studies have used regression models to forecast global forest sector mitigation potential and costs (Busch et al. (2019)), or an optimal control model of the global timber market (Austin et al. (2020)), sometimes combined with an integrated assessment climate-economy model (Favero, Mendelsohn and Sohngen (2017)). Here we briefly summarize a few of the macro level studies of forestation that have appeared recently, and explain the need for a micro level study like ours.

Favero, Mendelsohn and Sohngen (2017) combined two large models, a "global dynamic forest model" and a "global mitigation model" (an integrated assessment model) to study whether to use forestland for biomass burning or for carbon storage given alternative carbon price paths. Their model explores the dynamics of woody biomass and forest carbon sequestration demand and supply over time, and determines an optimal amount of forestland in each carbon price scenario, the mix of managed versus natural forest, and how planting, rotation length, and management intensity should be adjusted on managed forestland. Their results generally support the potential of forestation for reducing net $CO_2$ emissions.

Busch et al. (2019) used a regression model to estimate how forestation responds to changes in agricultural prices, using data on spatially disaggregated forest cover gain over the two years 2000 and 2010. The dependent variable is the fraction of a cell area that undergoes a non-forest to forest transition, and the main independent variable is the 30-year present value of the maximum potential revenue stream were the land used for agriculture, which they treat as the land use opportunity cost. Assuming forestation occurs if the carbon price exceeds this opportunity cost, they replace the potential agricultural revenue by a carbon price incentive variable, and trace out marginal cost curves for forestation by projecting areas that would undergo forestation at varying carbon prices. They then simulate forestation (and resulting $CO_2$ removal) during 2020 to 2050 from alternative carbon prices.[7]

Austin et al. (2020) estimated forestation costs using an optimal control model of the global timber market to simulate how forests and forest management change over time because of both ecological and market forces. Higher timber prices incentivize more mitigation via rotation and other forest management activities. The authors considered forest regeneration costs and land rental costs, but their focus was on forest management, so theirs is a global model that is not specific to any biome or geography.

Two recent studies also support the view that the conservation and restoration of forests can contribute to carbon sequestration. Mo et al. (2023) and Walker et al. (2022), respectively, estimate that the total global carbon stock for living tree biomass (above and below ground) is currently 217 and 224 Gt of carbon below its full potential, of which 123 and 152 Gt can be attributed to tropical regions. Their estimates are based on the carbon stock that would exist under current climate conditions in the "hypothetical absence of human influence." The global carbon stock for living tree biomass takes into account overall carbon gains (e.g., forest growth) and losses (e.g., forest fires) over time. Averaging these two studies, tropical forests worldwide can store an additional 138 Gt C. If that 138 Gt C materializes over 50 years, global annual $CO_2$ removal from natural forest growth (absent "human influence") could reach $(138 \times 3.67)/50 = 10$ Gt $CO_2$.

These and related macro-level studies are useful in that they provide an overview of forestation potential and its relation to agricultural revenues and price incentives. But they lack the granular detail needed to show where forestation is best targeted, and at what cost. Land opportunity and tree planting costs vary considerably across regions, as does precipitation. Thus much can be gained by a more micro level approach to the use of forestation for $CO_2$ removal. To show why, Figure 2 presents one of our main results — a supply curve for forest-based atmospheric $CO_2$ removal in South America. The curve shows the marginal cost of removing (via forestation) one ton of $CO_2$ as a function of total forest-based annual $CO_2$ removal. Each point on the curve corresponds to a $0.5° \times 0.5°$ resolution land grid element.

Point A on the curve shows the lowest cost ($23 per ton) at which $CO_2$ can be removed

[7]Their land opportunity cost reflects agricultural revenues but ignores costs. Other variables in their model are site characteristics such as slope, elevation, distance from cities, and initial forest cover.

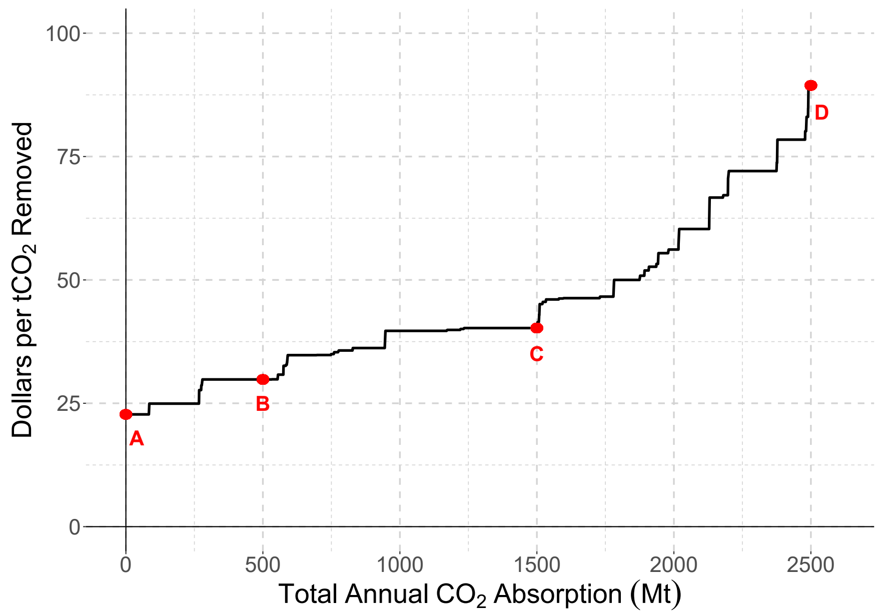



Figure 2: Supply curve for forest-based atmospheric $CO_2$ removal in South America. The curve shows the marginal cost (in 2020 US dollars) of removing one ton of $CO_2$ per year as a function of total forest-based $CO_2$ removal. Each point on the curve corresponds to a land grid element.

from the atmosphere by planting and maintaining trees in South America. It applies to a land grid element in the Amazon forest of Brazil, state of Pará, at location (-57.75° longitude, 1.25° latitude). This is the lowest-cost location in part because of plentiful rainfall, but also because of relatively low tree planting and land opportunity costs.[8]

Point B is also in the Amazon forest of Brazil, state of Pará, but now at location (-49.25°, -4.25°). As at Point A, here rainfall is plentiful, but tree planting costs are higher, so the cost of removing $CO_2$ is \$30 per ton. Point C is in the Amazon forest of Brazil, state of Mato Grosso, at location (-53.75°, -14.75°). Land opportunity costs are higher so the cost of removing $CO_2$ is \$40 per ton. Finally, Point D, at the top of the curve, is in the Brazilian Cerrado at location (-49.75°, -20.25°). This area is largely savanna, with lower forestation potential and higher land opportunity costs, so the cost of removing $CO_2$ is about \$90 per ton. (Details regarding points A, B, C and D are in the Appendix in Table A1.)

Figure 2 shows that regional variations in the marginal cost of forestation are large. The cost breakdown also varies regionally. Table A1 shows that the land opportunity cost accounts for about half of full marginal cost at Point A on the supply curve, but about 75%

[8]There are 160 land grid elements with the same \$23 per ton marginal cost spread across 8 Amazon countries. They are all on the short horizontal line that begins at Point A.

at Point D. That is why we work at the spatially disaggregated level of $0.5^\circ \times 0.5^\circ$ resolution land grid elements, and account for regional variations in rainfall, forestation costs, tree densities, and $CO_2$ absorption rates.

# 3 Data

Our supply curve applies to all forested and forestable areas in South America. To build the curve we must determine where it is economical to plant trees, how many trees can be planted (say, per hectare), and the full cost of planting and maintaining those trees. Table A2 shows summary statistics for some of the key variables, and Table A3 summarizes the input data and corresponding web-based data sources.

## 3.1 Climate, vegetation, and borders

Given the importance of water, we first examine tree cover distributions and rainfall patterns in tropical and subtropical regions around the world. The objective is to determine the relationship between tree cover and precipitation. Precipitation is described by a combined measure of average rainfall volume and average dry season intensity (the difference between precipitation and evapotranspiration). From the observed relationship, we determine the areas in South America where precipitation patterns can support forest growth.

Annual tree cover data were extracted from the publicly available website of Moderate Resolution Imaging Spectroradiometer/Vegetation Continuous Fields (MODIS/VCF), and monthly precipitation data were extracted from the publicly available website of Climatic Research Unit Gridded Time Series (CRU/TS).[9] Monthly precipitation data are available at $0.5^\circ$ resolution (approximately 50 km latitude and longitude, i.e., 2,500 km$^2$ = 250,000 ha), while the annual tree cover data from MODIS/VCF are available at a 250-meter resolution (0.0625 km$^2$ = 6.25 ha).[10] To ensure that the tree cover and precipitation data apply to the same time periods and land grid elements, annual values of rainfall volume and dry season

[9] MODIS is a satellite-based sensor used for earth and climate measurements, and MODIS/VCF contains annual tree cover data (with years beginning on day 65, i.e., from March through February). MODIS/VCF provides a global representation of surface vegetation cover at a 250-meter spatial resolution, and has three ground cover components: percent tree cover, percent non-tree cover, and percent non-vegetated (DiMiceli et al. (2020)). The CRU/TS product is a widely used climate dataset with a $0.5^\circ$ latitude by $0.5^\circ$ longitude grid over all land domains of the world except Antarctica, derived by the interpolation of monthly climate anomalies from extensive networks of weather station observations (Harris et al. (2020)).

[10] One degree latitude or longitude near the equator is equivalent to 111 km, so one degree in the tropics is approximately 100 km, and $0.5^\circ$ resolution is 50 km.

intensity were computed from March through February, and tree cover values were sampled at the centroid of each corresponding precipitation land grid element.

Using the tree cover data from MODIS/VCF, we also derive the relationships between percent tree cover, tree density (stems per hectare), and $CO_2$ absorption rates in the tropics. Estimates of tree densities were obtained from ForestPlots.net et al. (2021) and Crowther et al. (2015). Estimates of carbon gains and $CO_2$ absorption rates were obtained from ForestPlots.net et al. (2021), Busch et al. (2019) and Mokany, Raison and Prokushkin (2006). In particular, Figure 6 in ForestPlots.net et al. (2021) and Figure 1 in Crowther et al. (2015) show that the average tree density in tropical moist forests worldwide is about 600 trees per hectare. These estimates were used to determine the average $CO_2$ absorption rate per tree in South America's tropical and subtropical regions (Section 4.3).

To work at the spatially disaggregated level of land grid elements, we must delineate the borders of different biomes, and the borders of the countries (or states) where these biomes are located. The Amazon forest includes territory belonging to nine nations, with about 60% in Brazil, 13% in Peru, 10% in Colombia, and smaller amounts in six other countries. The Atlantic forest includes territory belonging to three nations, with 92% in Brazil, 6% in Paraguay, and 2% in Argentina. The Gran Chaco region is in three countries, with just above half in Argentina, a third in Paraguay, and the remainder in Bolivia. The borders of the Amazon rainforest were obtained from the Brazilian Institute for Space Research (INPE), the borders of the Atlantic forest and Gran Chaco region were obtained from the MapBiomas Project (http://mapbiomas.org), the borders of South American countries were obtained from the Global Administrative Database (GADM), and the borders of Brazilian states came from the Brazilian Institute of Geography and Statistics (IBGE).

## 3.2 Economic data

Land opportunity cost is particularly important. Most land that is not forested (or was deforested) is used to produce food products in three general ways: grow and harvest temporary crops (e.g., soy, corn and other grains, and vegetables); grow and harvest permanent crops (largely tree-growing crops such as apples, avocados, coffee and palm); and raise livestock for meat and milk. Farmers incur operating and overhead expenses, so land opportunity costs should not be confused with gross production values. If land is currently being used for agricultural purposes, its opportunity cost is just gross revenue minus total operating costs, where the latter excludes rents or other costs associated with the use of the land.

Land opportunity costs in Brazil for the most important temporary crops (soy and corn), permanent crops (coffee and oranges) and livestock (bovine meat and milk) were obtained by request from the Brazilian Confederation of Agriculture and Livestock (CNA).[11] The CNA collects data on agricultural production costs by conducting meetings with fatmers, input providers, and technical experts in Brazilian states and cities. From these meetings, the CNA derives information about agricultural production costs, including the opportunity cost of land, for agricultural activities in different regions. The land opportunity costs that we use here were derived by the CNA through the consensus reached among meeting participants (most often based on rental contracts through which farmers rented land) during 2018-2020.

Brazil has 26 states and one federal district, which are grouped into five major regions with different natural, economic and social characteristics, as shown in Figure 3.[12] We do not have data on land opportunity costs in all Brazilian states, but only for several states in each region. Using that data, we estimated the land opportunity costs for each Brazilian state as the average rental value for each agricultural activity in the corresponding region. Some regions are more attractive for agriculture than others, due to differences in climate, terrain, and proximity to markets. For South American countries other than Brazil, we use the average land opportunity costs in the Brazilian regions closest to their frontiers. Table A4 shows land opportunity costs for each agricultural activity in each Brazilian region and in other South American countries in 2018-2020. We use these numbers to derive land opportunity costs for each land grid element, as explained in Section 5.1.

Land opportunity costs have grown steadily over the past few decades, and we assume they will continue to grow over the next 50 years at a rate equal to the Brazilian gross agricultural production value growth rate over 2010 to 2020. Gross production values for temporary and permanent crops in each Brazilian state were obtained from the Brazilian Institute of Geography and Statistics (IBGE), and gross production values of livestock (bovine meat and milk) in each state were obtained from the Brazilian Ministry of Agriculture and Livestock (MAPA). The average growth rate for both was 4% per year.

Tree planting and maintenance costs depend on the choice of forest recovery technique,

[11] These products are respectively responsible for 62%, 50% and 60% of the gross production values of all temporary crops, permanent crops and livestock in Brazil.

[12] The North (N) covers more than 40% of Brazilian territory, including the largest portion of Amazon rainforest, but accounts for a small proportion of the nation's population and economic output. The Northeast (NE) is the driest and hottest, and accounts for nearly 20% of Brazil's land area and more than 25% of the population. The Central-West (CW) region covers roughly 25% of Brazil's land area, including forested valleys, semiarid highlands, and vast wetlands, and accounts for a small proportion of the population. The Southeast (SE) covers 10% of Brazil's territory, but has 40% of its population and the greatest concentration of industrial and agricultural production. The South (S) is the smallest region, and its diversified economy includes manufacturing, agriculture and services.

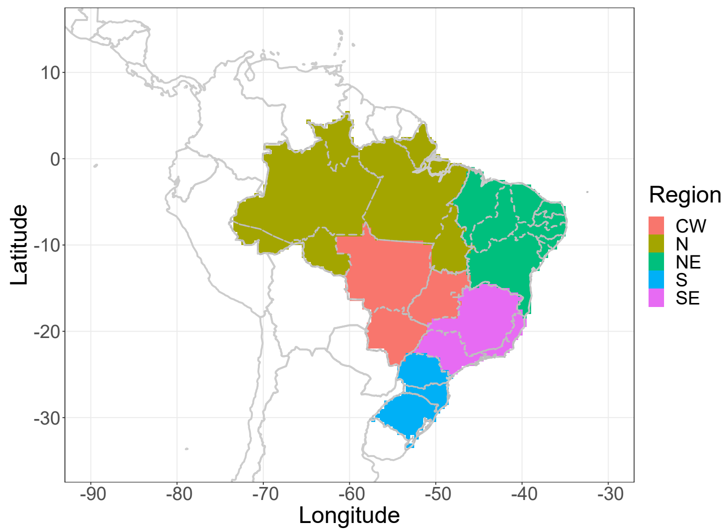



Figure 3: The Brazilian territory, 26 states and one federal district, grouped into five regions: North (N); Northeast (NE); Central-West (CW); Southeast (SE); and South (S).

which in turn depends on such factors as soil degradation, work scale, possibility of mechanization, and, most importantly, tree cover. Kishinami and Watanabe Jr. (2016) and Benini and Adeodato (2017) provide estimates of tree planting and maintenance costs for the most widely used forest recovery techniques. As explained in Section 5.2, we use these estimates to determine planting and maintenance costs for each land grid element.

Forest conservation costs depend on governments' conservation policies and budgets. Cunha et al. (2016) and Assunção, Gandour and Rocha (2023) provide estimates for the forest conservation costs incurred by Brazil from 2000 to 2014. As explained in Section 5.3, we use these estimates to derive the forest conservation cost numbers used in our model.

The land areas used for growing temporary and permanent crops in each Brazilian state were obtained from the Brazilian Institute of Geography and Statistics (IBGE), and the land areas used for raising livestock were obtained from the MapBiomas Project (see http://mapbiomas.org). The land areas used for growing temporary and permanent crops and raising livestock in each South American country were obtained from the United Nations' Food and Agriculture Organization. (In Section 6, we discuss the planted and pasture areas in different Brazilian states and South American countries.)

# 4 Forestation Targets

Tree growth requires large amounts of water, which in many parts of the world is expensive, making forestation uneconomical. Thus, we need to determine the areas where precipitation patterns make it economical to plant new trees, and the number of trees that could be planted in each 0.5° resolution land grid element.

## 4.1 Where to plant trees

Given the importance of water, we look for areas where precipitation patterns support forest growth. We start by investigating the relationship between tree cover and precipitation patterns in tropical and subtropical regions around the world, in order to draw insights that help define the economically efficient forestation target zone in South America.

Several studies have examined the relationship between tree cover and precipitation patterns, with the latter described by a measure of rainfall volume (the mean annual precipitation, MAP) and dry season intensity (the mean maximum cumulative water deficit MMCWD).[13] Hirota et al. (2011) found that the relationship between mean annual precipitation (MAP) and tree cover is highly nonlinear; tree cover does not increase steadily with rainfall, but instead is constrained to ranges that could be identified as treeless (0 to 5% tree cover), savanna (around 20%) or tropical forest (around 80%). It is rare for tree cover to remain between 40 and 60% over a sustained period, consistent with the view that feedback loops (including fire spread feedbacks) tend to move the ecosystem closer to either the forest or savanna state.[14] Zemp et al. (2017) examined how MAP and MMCWD affect tree cover, and found two tree-cover states in the tropics, an intermediate state (5 to 55%) comprising deciduous forests, shrubs and herbaceous plants, and a high tree cover state (above 55%) corresponding to evergreen forests. Suppl. Figure 1 in Zemp et al. (2017) illustrates how tropical forests can be found in areas where MAP $>$ 1,000 mm/yr *or* dry season intensity MMCWD $<$ 400 (mm/yr). Our results are consistent with these earlier studies.

We use tree cover data from MODIS/VCF to estimate probability distributions of tree cover in tropical and subtropical regions of South America (SAM), Africa (AFR) and Asia and Oceania (AOC). We then use precipitation data from CRU/TS to investigate the relationships between tree cover and rainfall volume, and between tree cover and dry season intensity, both worldwide. For each 0.5° resolution land grid element with latitudes in $[-35, +15]$, we collected time series of yearly tree cover (from 2001 to 2018) and monthly

[13]The maximum cumulative water deficit (MCWD) is the maximum value of the monthly accumulated water deficit (i.e., difference between precipitation and evapotranspiration) reached on a given piece of land in a given year. The details of the MCWD calculation is described in Aragão et al. (2007). The annual precipitation (AP) and maximum cumulative water deficit (MCWD) are calculated for several years and averaged to yield the means (MAP and MMCWD).

[14]Fire spread depends on a continuous grass layer, so that the higher the tree cover is, the lower the fire spread is (i.e., the more fire-resilient the forest is), and vice-versa (Staver, Archibald and Levin (2011)).

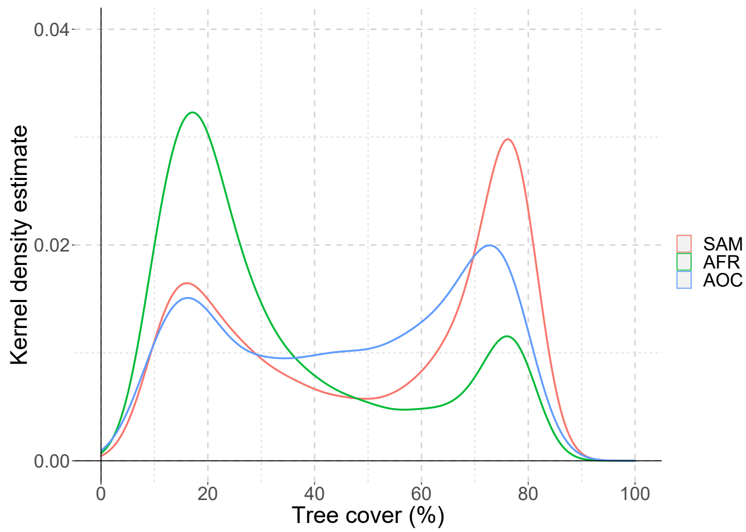


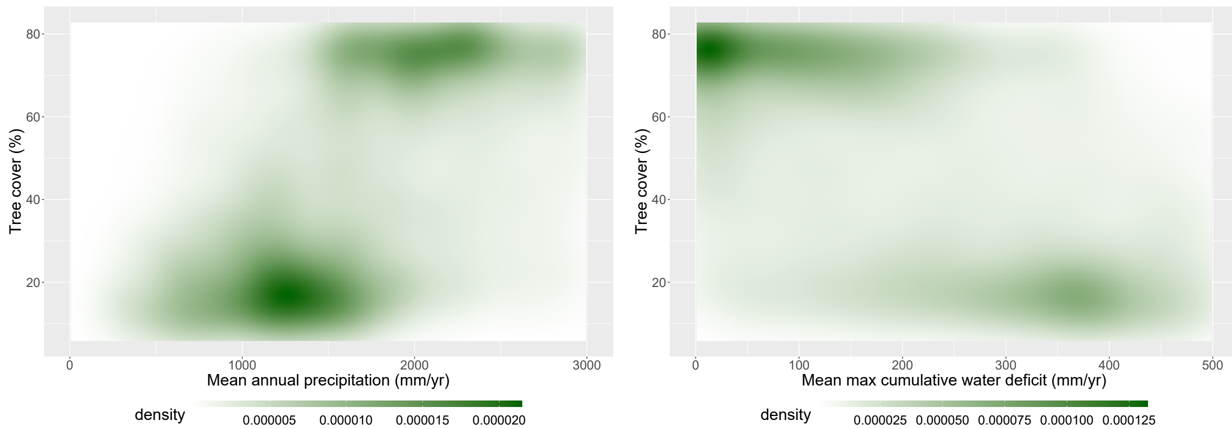

Figure 4: Probability distributions of the average tree cover from 2001 to 2018 in tropical and subtropical regions of South America (SAM), Africa (AFR), and Asia and Oceania (AOC). Note the peaks at low (10 to 30%) and high (70 to 80%) tree cover, corresponding to savanna and fully forested, respectively.

rainfall (from March 2001 to February 2019), and calculated the mean annual precipitation (MAP), mean maximum cumulative water deficit (MMCWD) and average tree cover (ATC) over 2001–2018. There are 8009 land grid elements over these latitudes worldwide, giving us 8009 samples of MAP, MMCWD and ATC. From these samples, we obtained kernel density estimates of tree cover distributions for these three continents, and joint probability distributions of ATC, MAP, and MMCWD worldwide.[15]

Figure 4 shows the probability distributions of average tree cover (ATC) in SAM, AFR, and AOC. The distributions differ across these three continents, but they all have peaks at the characteristic tree cover of forest (around 75%) or savanna (around 20%). This is consistent with models of forest evolution that show how low and high tree cover are stable equilibria.[16] Figures 5a and 5b show kernel density estimates of the joint probability distributions for ATC and MAP, and for ATC and MMCWD, again using worldwide data, but now combining SAM, AFR, and AOC. In these two-dimensional graphs, the magnitude of the probability density is shown by the darkness of the shading. As with Figure 4, this graph

[15]Silverman (1986) shows that for a Gaussian kernel and most unimodal and bimodal underlying distributions, the optimal window width is $h = 0.9 \times A \times n^{-1/5}$, where $A = \min$ (standard deviation, interquartile range/1.34), and $n$ is the sample size. We used two kernel smoothing functions in R, geom_density and stat_density2d, with the normal kernel functions and bandwidth suggested by Silverman (1986). Land grids in the treeless state (0-5%) were removed to avoid distortions caused by human activity and habitation.

[16]See, e.g., Hirota et al. (2011), Zemp et al. (2017), Staal et al. (2018) and Franklin and Pindyck (2018).




(a) Tree cover and annual precipitation. (b) Tree cover and max. cumulative water deficit.

Figure 5: Bivariate probability distributions among the 18-year averages of tree cover, annual precipitation and maximum cumulative water deficit (2001-2018). The magnitude of the probability density is shown by the darkness of the shading.

show that the characteristic tree cover of forest and savanna dominate. But the graph also shows that high tree cover can be found in areas where MAP $>$ 1,000 mm/yr *or* MMCWD $<$ 400 (mm/yr). Likewise, low tree cover is found in areas with low annual precipitation and/or high maximum water deficits. Thus, these precipitation conditions are necessary for the development and sustainability of dense tropical forests.

We therefore take the forestation target zone in South America to be those areas with mean annual precipitation at or above 1,000 mm/yr and mean maximum cumulative water deficit at or below 400 mm/yr. The forestation target zone is shown in Figure 6.

## 4.2 Target tree cover and forestation potential

We now estimate the forestation potential for each land grid candidate for forestation in the target zone. We base the forestation potential on the characteristic tree cover of the biome that previously existed in each land grid element. Thus, for land grids that during the past 50 years were once densely forested but have experienced forest loss, including areas of the Amazon rainforest, Atlantic forest and Gran Chaco region, we use the tree cover target of 75%, which is the characteristic tree cover of forest, and we assume this target can be reached and maintained over the long run. In areas that were never densely forested, going from a low tree cover (e.g., 20%) to 75% may not be feasible over the long run. Figure 4 shows that the tree cover rarely remains between 40 and 60% over a sustained period. Thus, for land grids that are in the target zone but existed as savanna (e.g., Cerrado) or grassland (e.g.,

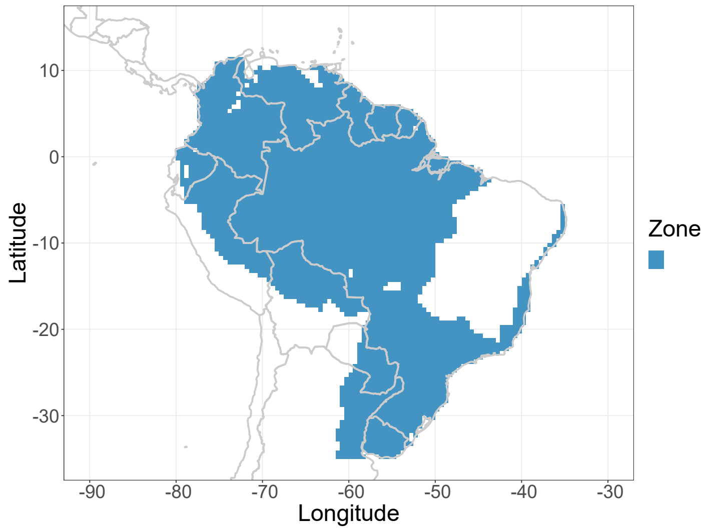



Figure 6: Forestation target zone in South America: The areas where precipitation patterns support forest growth (i.e., MAP $\geq$ 1,000 and MMCWD $\leq$ 400 mm/yr) are in blue.

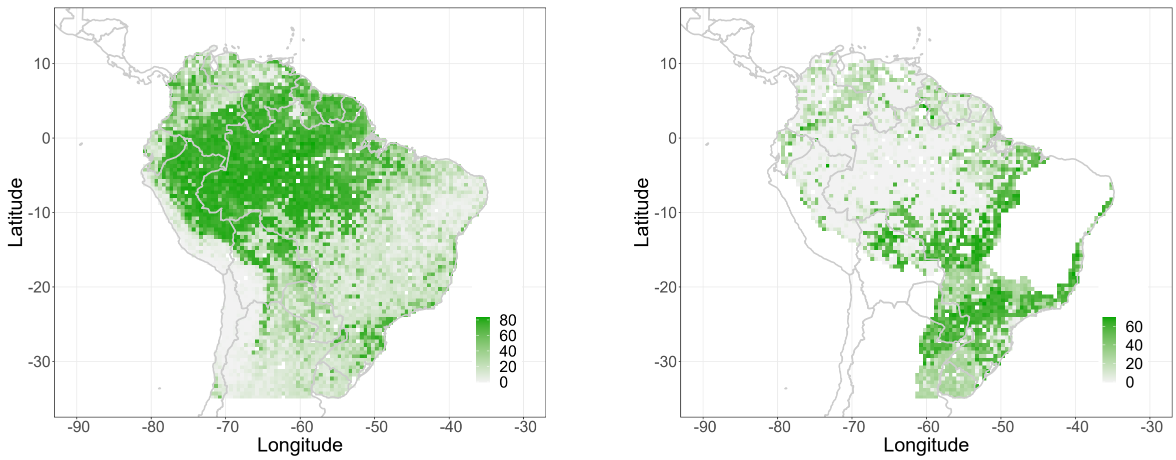
Pampas), we use a tree cover target of 40%. This is higher than the characteristic tree cover of savanna, but below the unstable range of 40-60%.[17]

The forestation potential for each land grid candidate for forestation is just the difference between the target tree cover (either 75% or 40%) and the current tree cover. Figure 7 shows the average tree cover observed from remote sensing (MODIS/ VCF) in 2016-2018, and the forestation potential calculated for each land grid candidate for forestation. We treat a land area with 75% tree cover as "fully forested."

## 4.3 Tree density, $CO_2$ absorption rate, and forestable area

A single tree can absorb 10 to 40 kg of $CO_2$ per year, depending on climate and the age and type of tree, so to estimate the average $CO_2$ absorption rate for a land grid element, we must account for the variety of trees it contains. Organic carbon accumulates in above and below ground biomass. Patterns of above ground biomass (stems, bark, branches) are reasonably well understood, whereas knowledge of below ground biomass (roots) is limited, mostly because it is difficult to observe and measure root biomass. Most often, the below ground biomass is expressed as a fraction of the above ground biomass using "root-to-shoot" ratios. A root-to-shoot ratio is the amount of plant tissue with supportive functions (root

[17]The 40% target might be reached by foresting part of a land grid above 40% (e.g., by creating forest parks with 75% tree cover) and part below, averaging 40%.




(a) Current tree cover (%).

(b) Forestation potential (%).

Figure 7: Current tree cover (2016-2018) and forestation potential over the forestation target zone. Each pixel represents a 0.5° resolution land grid element.

biomass) divided by the amount of plant tissue with growth function (shoot biomass).[18]

To estimate the $CO_2$ absorption rate per tree, we start with the above ground biomass (AGB). For 20-30 year old trees in tropical moist forests, the average carbon stock accumulation above ground is about 2.4 tons of carbon per hectare per year.[19] For the below ground biomass (BGB), we use the root-shoot ratio of 0.26.[20] Multiplying the above ground biomass by 1.26, we find the total carbon stock accumulation (above and below ground) is 3.0 tons of carbon per hectare per year, or $3.0 \times 3.67 = 11$ tons of $CO_2$. Given an average tree density of 600 trees per hectare (Section 3.1), we estimate the average $CO_2$ absorption rate to be $11,000/600 = 18.333$ kg $CO_2$ per tree per year. These estimates apply to trees in tropical moist forests; we use them here because our forestation target zone consists of areas in South America where precipitation patterns are similar to those in tropical forests.

For the characteristic tree cover of forest (75%) and 600 trees per hectare, a one percentage point increase in tree cover means going from, say, 40% to 41% tree cover, with an upper limit of 75%. A fully forested hectare has 600 trees, so a 1 percentage point increase means planting $600/75 = 8$ new trees. We assume that these 8 trees are planted so as to allow the effective combination of agriculture and trees, while occupying an area of $8/600 = 1/75 =$

[18] Root and shoot biomass are estimated via sampling methods, as discussed in Mokany, Raison and Prokushkin (2006), who also provide a review of the root-shoot ratios for major terrestrial biomes.

[19] See, e.g., ForestPlots.net et al. (2021) and Busch et al. (2019).

[20] Here we follow Harris et al. (2012) and Busch and Engelmann (2015). This estimate is based on a regression model of root biomass ($y$) as a function of shoot biomass ($x$), using data from forests and woodlands, which resulted in $y = 0.26\,x$, with $R^2 = 0.78$. See Figure 3 in Mokany, Raison and Prokushkin (2006).

0.01333 hectare.[21] This is the agricultural area that will be lost for forest growth. Then, for a land grid with 250,000 hectares, a 1 percentage point increase in tree cover means planting $8 \times 250,000 = 2$ million trees over an area of $0.01333 \times 250,000 =$ 3,333 hectares, and will increase the $CO_2$ absorption rate by $2,000,000 \times 18.333 =$ 36,667 tons of $CO_2$ per year.

The potentially forestable area in a geographic unit is the sum of the forestable areas in all land grids inside the unit's borders. Take, for example, two land grids, X and Y, where X has 55% tree cover so its forestation potential is $75\% - 55\% = 20\%$, and Y has 30% tree cover so its forestation potential is 45%. The forestation potential of these two land grids combined is $20+45 = 65$ percentage points. Multiplying that sum by the increase in forested area from a 1 percentage point increase in tree cover (3,333 hectares) yields a potentially forestable area of $65 \times 3,333 =$ 216,645 hectares. Multiplying that area by the average tree density of 600 trees per hectare, the number of trees that can be added to these two land grids is $216,645 \times 600 = 130$ million trees.

Summing the forestation potential over all land grid elements inside the forestation target zone (see Figure 7b) yields 68,400 percentage points. Multiplying that sum by the increase in forested area from a 1 percentage point increase in tree cover (3,333 hectares), we find the potentially forestable area in South America's tropical and subtropical regions is $68,400 \times 3,333 = 228$ million hectares. With 600 trees per hectare, the total number of trees that can potentially be added to the forestation target zone is 228 million $\times 600 = 137$ billion trees.

The potentially forestable area in each Brazilian state or South American country may be higher or lower than the sum of the areas used for temporary crops, permanent crops and livestock. It will be higher, for example, if a large area has been deforested for wood as opposed to any agricultural activity. It will be lower if the area is not completely inside the target zone.

# 5 Forestation Costs

In this section we estimate the land opportunity, tree planting and forest conservation costs for each land grid element in the forestation target zone. These costs vary over the life cycle of the forest. Land opportunity costs grow as food demand grows, and tree planting costs are concentrated during the first few years of forestation when new trees are planted, and

[21] This assumes an agroforestry system where trees or shrubs are grown around or among crops or pasture-land. The target tree density of 600 trees per hectare implies on a tree spacing of $(0.01)^{0.5}/(600^{0.5}) = 4.082$ meters, so each tree occupies $4.082^2 = 16.663\ \text{m}^2$, and 8 trees occupy $8 \times 16.663 = 133.3\ \text{m}^2 = 0.01333$ hectare. For more information on agroforestry systems, see https://www.fao.org/forestry/agroforestry/80338/en/. For the potential use of agroforestry in Brazil, see Gusson et al. (2023).

then become smaller. However, we treat the $CO_2$ absorption rate as constant, so to estimate the marginal cost of absorbing a ton of $CO_2$ we want to smooth out these costs over time.

Using a 50-year time horizon, we smooth out these costs by first calculating the 50-year present value of each flow of cost, and then converting these present values into 50-year annualized costs. In what follows we do this using an annual discount rate of 5%, which is approximately the average long term real interest rate on Brazilian government bonds over the last 20 years. For comparison, we also develop a supply curve using a discount rate of 2.5%, based on survey results in Pindyck (2019).

### 5.1 Land opportunity costs

Land is used to grow temporary crops, grow permanent crops, or raise livestock, so there are three possible values for the land opportunity cost. We estimate the land opportunity cost for each agricultural activity in each Brazilian region and in other South American countries.

As explained earlier, Brazil has five regions, some of which are more attractive for agriculture than others. Of these regions, the North has the lowest land opportunity costs for all three agricultural activities, and the South has the highest costs for temporary crops and livestock (3.6 and 2.5 times as large as in the North, respectively). Land opportunity cost data are unavailable for other South American countries, so we use the average cost in the Brazilian regions closest to their frontiers. (Brazil accounts for 67% of the entire potentially forestable area of South America.) We assume that land opportunity costs will continue to grow over the next 50 years at the 4% growth rate of the Brazilian gross value of agricultural production from 2010 to 2020.

From the data for 2018-2020 (Table A4), we calculate the 50-year present values for the land opportunity cost for each agricultural activity in the Brazilian regions and South American countries covered by the forestation target zone, and convert these present values into 50-year annualized costs. Table 1 shows the annual land opportunity cost for each agricultural activity in the forestation target zone.[22]

To illustrate, consider a land grid element with 55% tree cover in the North region of Brazil's Amazon forest, which is partially used for raising livestock, so its land opportunity cost is \$131 per hectare per year (Table 1). What is the land opportunity cost of increasing the tree cover to its potential of 75%? A land grid element comprises 250,000 hectares, so a 1

[22]The 50-year present value of an annuity of \$1, discounted at 5%, is $(1-(1+5\%)^{-50})/5\% = 18.25593$. The 50-year present value of a growing annuity that begins at \$1 but increases at a 4% annual rate, discounted at 5%, is $(1-(1+4\%)^{50} \times (1+5\%)^{-50})/(5\%-4\%) = 38.02707$. Thus, Table 1 was derived by multiplying each entry of Table A4 by $38.02707/18.25593 = 2.083$.

Table 1: Annual land opportunity costs for temporary crops, permanent crops and livestock in the Brazilian regions and South American countries covered by the forestation target zone (2020 US dollars per hectare).

| **Geographic unit** | **Temporary crops (US$/(ha yr))** | **Permanent crops (US$/(ha yr))** | **Livestock: bovine (US$/(ha yr))** |
|---|---|---|---|
| Brazilian region: | | | |
| South (S) | 596 | 614 | 467 |
| Southeast (SE) | 246 | 717 | 312 |
| Central-West (CW) | 246 | 717 | 240 |
| Northeast (NE) | 362 | 935 | 196 |
| North (N) | 242 | 304 | 131 |
| Argentina | 596 | 614 | 467 |
| Bolivia | 244 | 510 | 185 |
| Colombia | 242 | 304 | 131 |
| Ecuador | 242 | 304 | 131 |
| French Guiana | 242 | 304 | 131 |
| Guyana | 242 | 304 | 131 |
| Paraguay | 421 | 666 | 353 |
| Peru | 242 | 304 | 131 |
| Suriname | 242 | 304 | 131 |
| Uruguay | 596 | 614 | 467 |
| Venezuela | 242 | 304 | 131 |

percentage point increase in tree cover requires $8 \times 250,000 = 2$ million new trees, occupying 1.33% of 250,000 = 3,333 hectares, which can no longer be used for agriculture. The 20% increase in tree cover requires $20 \times 2,000,000 = 40$ million trees over an area of $20 \times 3,333 =$ 66,660 hectares, so the land opportunity cost is $131 \times 66,660 = \$8.7$ million per year.

## 5.2 Tree planting and maintenance costs

The costs of planting and maintaining trees depend on the choice of forest recovery technique, which in turn depends on such factors as soil degradation, work scale, possibility of mechanization, access, and – most importantly – current tree cover. Different forest recovery techniques imply different activities and inputs, and thus different costs. These activities and inputs may also vary for the same forest recovery technique, depending on existing conditions (e.g., degraded soil, problematic access, etc.).

Benini and Adeodato (2017) and Kishinami and Watanabe Jr. (2016) provide cost estimates for the three most widely used forest recovery techniques, based on the range of activities and input requirements. The techniques are: (i) “facilitating natural regeneration,” which involves controlling land degradation, enabling the spontaneous restoration of native species, and increasing species richness; (ii) “enhancing tree density and enrichening,” which involves planting a large number of trees so as to increase tree density and improve species diversity; and (iii) “total planting,” the most expensive technique, which consists of direct planting of seeds and seedlings.

“Facilitating natural regeneration” is most economical for land grids with high tree cover (55-65%), “enhancing tree density and enrichening” is frequently used for land grids with medium tree cover (30-55%), typically on the margins of remnant forest areas and in large clearings, and “total planting” is usually most appropriate for land grids with low tree cover (5-30%). Economies of scale make it uneconomical to plant small numbers of trees, so we only consider areas where the forestation potential is at least 10%. Land grid elements where the current tree cover is below 5% are too difficult or expensive to forest (e.g., in urban and industrial areas, or in areas of lakes, rivers, and degraded and rocky soil), and are ignored. Because we work at the spatially disaggregated level of land grid elements, we assume forest recovery takes place in contiguous areas of 250,000 hectares.[23]

From the present value estimates in Benini and Adeodato (2017), we calculate the average tree planting cost per hectare for each forest recovery technique in the Amazon and Atlantic forests. Tree planting costs depend on the number of trees planted, so we estimate the average cost per tree by dividing the per hectare cost by the average number of trees added to each hectare, which in turn is 8 times the difference between the target tree cover (either 75% or 40%) and its midrange tree cover.[24] We convert these present values (per tree) into 50-year annualized costs. Table 2 shows the tree planting cost present values and 50-year annualized costs for different forest recover techniques and biomes.

Let’s return to our example of a land grid element in the northern of Brazil, with 55% tree

[23]According to Kishinami and Watanabe Jr. (2016), the forest recovery technique “facilitating natural regeneration” requires a high density of regenerative trees (mainly of pioneering species), and is recommended for areas with canopy cover of 50 to 80%, and the forest recovery technique “enhancing tree density and enrichening” is recommended for areas with a moderate density of natural regeneration, with canopies varying between 30 to 60%. Other factors also affect the choice of forest recovery technique (e.g., soil degradation, possibility of mechanization, etc.). In the absence of field specific data, we use the tree cover intervals of 55-65% for facilitating natural regeneration, 30-55% for enhancing tree density and enrichening, and 5-30% for total planting. Forest areas with tree cover greater than 65% are left for (passive) natural regeneration.

[24]The midrange tree cover for the forest recovery techniques of facilitating natural regeneration, enhancing tree density and enrichening, and total planting are, respectively, $(55\% + 65\%)/2 = 60\%$, $(30\% + 55\%)/2 = 42.5\%$, and $(5\% + 30\%)/2 = 17.5\%$. Recall that each 1 percentage point increase in tree cover requires 8 trees per hectare (and $8 \times 250,000 = 2$ million trees per land grid element). Note that the number of trees actually planted may exceed the number added because some trees die and must be replanted.

Table 2: Tree planting cost present values and 50-year annualized costs for different forest recovery techniques and biomes (2020 US dollars).

| Biome and forest recovery technique | Present values | | Annualized costs |
|---|---|---|---|
| | (US$/ha (*)) | (US$/tree) | (US$/(tree yr)) |
| **Amazon rainforest, Atlantic forest, Gran Chaco region:** | | | |
| Facilitating natural regeneration | 420 | 3.50 | 0.192 |
| Enhancing tree density/enrichening | 1,100 | 4.23 | 0.232 |
| Total planting (seeds and seedlings) | 2,700 | 5.87 | 0.322 |
| **Savannas and grasslands:** | | | |
| Total planting (seeds and seedlings) | 1,440 | 8.00 | 0.438 |

(*) Average tree planting costs per hectare in the Amazon and Atlantic forests were obtained from Benini and Adeodato (2017). For areas of savanna and grassland, where the tree cover target is 40%, we take the tree planting cost per hectare as (40/75) of the value for areas of forest, where the target is 75%.

cover. The forest recovery technique for that land grid is "facilitating natural regeneration," for which the annualized tree planting cost is \$0.192 per tree per year (Table 2). The 20% increase in tree cover requires planting $20 \times 2,000,000 = 40$ million trees, so the tree planting cost is $40,000,000 \times 0.192 = \$7.7$ million per year.

## 5.3 Forest conservation costs

We utilize data from the Brazilian government's budgeted forest conservation policies from 2000 to 2014. Those data show that Brazil's substantial reduction in annual forest loss after 2004 was accompanied by an increase in forest conservation expenditures. From 2005 to 2014, Brazil spent on average \$1.1 billion per year on forest conservation at the federal level (44% more than it spent from 2001 to 2004),[25] while the annual forest loss dropped by about 40% (Cunha et al., 2016). Taking all forested areas in the Brazilian Amazon and Atlantic forests (340 million hectares), the annual forest conservation cost was about $(1.1 \times 10^9)/(340 \times 10^6) = \$3.20$ per hectare per year over 2005-2014.

To be conservative, we assume that successful forest conservation requires \$4.00 per hectare per year. Thus, the conservation of existing forest areas in the Amazon rainforest, Atlantic forest, and Gran Chaco region (about 550 million hectares) requires an expenditure of \$2.2 billion per year. Adding the potentially forestable area of 228 million hectares (Section 4.3), successful forest conservation will require \$3.1 billion per year. Returning to

[25] Amazon monitoring and law enforcement efforts alone have amounted to about \$620 million per year over that period (Assunção, Gandour and Rocha (2023)).

our example of a land grid element in the northern of Brazil, with 55% tree cover, livestock as the agricultural activity, and where a 20% increase in tree cover requires $20 \times 2,000,000 = 40$ million trees, which will occupy $20 \times 3,333 =$ 66,660 hectares, the increase in forest conservation cost will be $4 \times 66,660 =$ \$0.3 million per year.

To summarize this example, the total annualized forestation cost to reach and maintain a target tree cover of 75% is the sum of \$8.7 million (land opportunity cost), \$7.7 million (tree planting cost) and \$0.3 million (forest conservation cost), which comes to \$16.7 million. The resulting increase in annual $CO_2$ absorption is $20 \times 36,667 = 0.73$ Mt $CO_2$. Thus, the cost per ton of $CO_2$ removed is $16.7/0.73 =$ \$23, which corresponds to Point A in Figure 2.

# 6 A Supply Curve for Forest-Based $CO_2$ Removal

For every land grid element in the forestation target zone, we consider increasing its current tree cover up to its target level (75% or 40%). We have data on the current tree cover (through remote sensing), target tree cover, forestation potential and $CO_2$ absorption rate (Section 4), and land opportunity, tree planting and forest conservation costs (Section 5), but to determine the land opportunity cost for each land grid element we need to know which agricultural activity is performed in that element.

Planted and pasture areas in the forestation target zone are not georeferenced, so we do not know which activity is performed in each land grid element. However, we do know the planted and pasture areas in each Brazilian state and South American country,from which we calculate the percentages currently used for temporary crops, permanent crops and livestock. We use these percentages to estimate the potentially forestable area for each agricultural activity, as shown in Table A5, and the land opportunity cost for each land grid element. (For example, from the last row of Table A5, we estimate that for Venezuela the potentially forestable area from livestock is $6,840,000 \times 87\% =$ 5,950,800 hectares.)

## 6.1 Land use

For each geographic unit (Brazilian state or South America country), we estimate the area that can be forested from each agricultural activity by multiplying the potentially forestable area by the percentage of area currently used for each activity. For example, from the first row of Table A5, we estimate that for Brazil, state of Paraná (Brazil-PR), the potentially forestable areas from temporary crops, permanent crops and livestock are respectively 8.714

(= $0.80 \times 10.892$), 0.109 (= $0.01 \times 10.892$), and 2.069 (= $0.19 \times 10.892$) million hectares.[26]

Starting with all 0.5° resolution land grid elements inside the target zone with current tree cover above 5% (i.e., not in areas of lakes, rivers, and degraded and rocky soil), we remove those with forestation potential below 10% to account for economies of scale. (Later, for comparison, we also estimate a supply curve that includes all land grid elements with any forestation potential.) We assume each land grid element is being used for the agricultural activity with lowest land opportunity cost (Table 1), and pick the element with the lowest *total* forestation cost per ton of $CO_2$ removed. We call this the proposed land use conversion. It turns out that the land grid element with minimum total forestation cost per ton of $CO_2$ removed is in the Amazon forest of Brazil, state of Pará (Brazil-PA), with 55% tree cover, where the activity with lowest land opportunity cost is livestock. This is point A in Figure 2.[27]

We calculate the increase in forested area from the proposed land use conversion, and check whether it is less than the available area (in a state or country) for the lowest land opportunity cost agricultural activity. If it is, we perform the land use conversion and update the potentially forestable area. If it is not, we convert only the area that is available, and shift the geographic unit's agricultural activity to the next lowest cost activity. For example, for Point A (land grid element with 55% tree cover in the Amazon forest of Brazil-PA), the increase in forested area from the proposed conversion is $(75 - 55) \times 3,333 = 0.067$ million hectares, the lowest land opportunity cost activity is livestock (Table 1), and the potentially forestable area from livestock is $0.91 \times 19.569 = 17.808$ million hectares (Table A5). Because the potentially forestable area from livestock exceeds the increase in forested area from the proposed land use conversion ($17.808 > 0.067$), we perform the conversion, and update the potentially forestable area (to $17.808 - 0.067 = 17.741$ million hectares). Later, as we move along the supply curve, when Brazil-PA's potentially forestable area for the livestock activity has been depleted, we shift its remaining land grid elements to the next lowest cost activity, temporary crops, for which the potentially forestable area is $0.06 \times 19.569 = 1.174$ million hectares (Table A5).[28]

[26]Recall that the potentially forestable area in a geographic unit may be higher or lower than the sum of the areas currently used for temporary crops, permanent crops and livestock (Section 4.3). The potentially forestable area in Brazil-PR is lower than the sum of these areas: $10.892 < 10.741 + 0.121 + 2.626 = 13.488$.

[27]There are 160 land grid elements with the same (minimum) total forestation cost per $tCO_2$ removed, all in countries with the lowest land opportunity costs (northern region of Brazil, Colombia, Ecuador, French Guiana, Guyana, Peru, Suriname and Venezuela), restored using the cheapest forest recovery technique (facilitating natural regeneration; for land grids with tree cover in the interval 55-65%).

[28]That happens at point (522 MM $tCO_2$, \$29.8/ $tCO_2$) of the supply curve (Figure 8), when the $451^{th}$ land grid element is selected for forestation ($156^{th}$ in Brazil-PA), which has 25% tree cover, and the increase in forested area from the proposed land use conversion is $(75 - 25) \times 3,333 = 0.167$ million hectares. After the

We then pick the next land grid element with lowest total forestation cost per ton of $CO_2$ removed, and repeat the above steps until all land grid elements in the target zone have been forested (from their current tree covers up to their target levels), and the remaining forestable area from each agricultural activity in each geographic unit is reduced to zero.

### 6.2 The supply curve

There are 3,662 land grid elements inside the forestation target zone, from which 3,545 have current tree cover between 5 and 100%. From these 3,545 land grid elements, 1,784 have forestation potential below 10% (either already fully forested or with low forestation potential). Thus, there are 3,545 – 1,784 = 1,761 land grids candidates for forestation. After going through the above steps for the entire forestation target zone, a total of 1,761 land grid elements were completely forested (either at 75% or 40% tree cover), and the total forested area reached 228 million hectares (equal to the potentially forestable area shown in Section 4.3). The number of new trees planted reached 137 billion.

Figure 8 shows the resulting supply curve for forest-based $CO_2$ removal. Each point on the curve shows the cost per ton of $CO_2$ removed for a land grid element in the forestation target zone as a function of total annual $CO_2$ removal. The figure shows that a carbon price at or below \$20/t$CO_2$ will have no impact on forest-based $CO_2$ sequestration, a carbon price of \$45/t$CO_2$ can induce the sequestration of 1.5 Gt of $CO_2$ per year, and a carbon price of \$90/t$CO_2$ can induce the sequestration of 2.5 Gt of $CO_2$ per year.

Figures 9a, 9b and 9c show the first 100, 880 and 1,761 land grid elements selected for forestation, and Figures 9d, 9e and 9f show the tree cover evolution after the forestation of these land grid elements. Reductions in agricultural land need not imply higher food prices. Different Brazilian regions and South American countries have different agricultural productivities, so reductions in agricultural areas can be compensated for by the adoption of best production practices.

## 7 Sensitivity of Results and Policy Implications

Our results show that in South America alone, about 1.5 Gt of $CO_2$ can be removed annually via forestation at a cost of \$45 per ton, and about 2.5 Gt can be removed at a cost of \$90

forestation of 155 land grid elements in Brazil-PA, the remaining forestable area from the livestock activity is just 0.072 million hectares, which is smaller than the increase in forested area from the proposed land use conversion, so we perform the conversion only for the area that is available (0.072 million hectares), and shift Brazil-PA's remaining land grid elements to the next lowest cost activity, temporary crops.

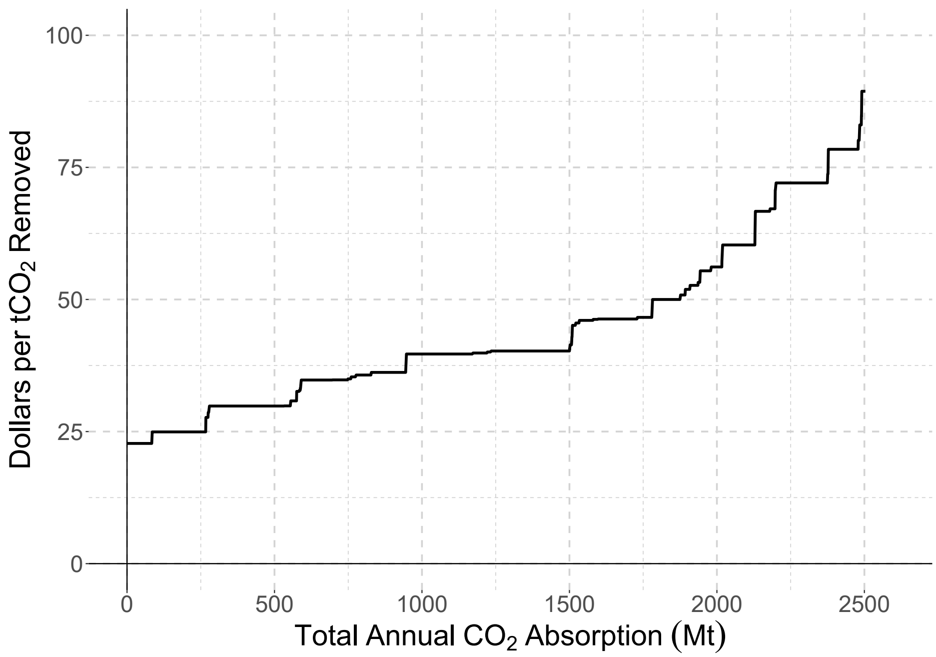
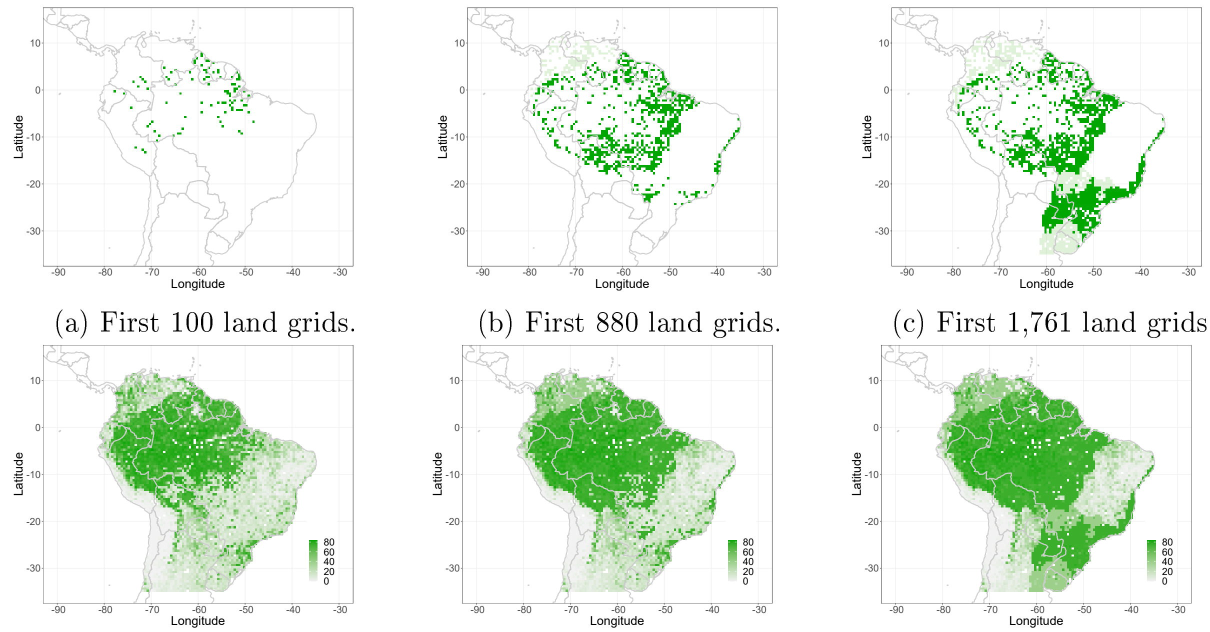



Figure 8: Supply curve for forest-based atmospheric $CO_2$ removal in South America. The curve shows the marginal cost of removing one ton of $CO_2$ as a function of total tree-based annual $CO_2$ removal. Each point corresponds to a land grid element in the target zone.

per ton. Given that global annual $CO_2$ emissions are about 40 Gt, removing 2.5 Gt would reduce net emissions by about 6 percent. But this reduction is not cheap. Removing 2.5 Gt at a cost of \$90 per ton implies an annual expenditure of \$225 billion. On the other hand, if payments are based on marginal cost (e.g., \$23 per ton for Point A), the total annual expenditure to remove 2.5 Gt, found by integrating the area under the supply curve from 0 to 2.5 Gt, would be \$110 billion.

That expenditure and resulting $CO_2$ absorption applies to South America. By how much could net $CO_2$ emissions be reduced worldwide, and at what cost? South America accounts for about 21% of the world's forested area (Food and Agriculture Organization (2020*a*)), and about 23% of the world's forestable area (228 million hectares divided by the 1 billion hectares from Bastin et al. (2019)). If we assume the distributions of tree cover, precipitation, and costs in the rest of the world are similar to those in South America and scale up the supply curve accordingly, we could remove about $4 \times 2.5 = 10$ Gt of $CO_2$ annually, which amounts to reducing net global emissions by 25 percent. That reduction would cost about $10 \times 90 =$ \$900 billion annually if payments were \$90 per ton, or $4 \times 110 =$ \$440 billion annually if payments were at marginal cost. The \$900 and \$440 billion values respectively amount to about 4 and 2 percent of US GDP, and about 0.9 and 0.5 percent of world GDP.




(a) First 100 land grids. (b) First 880 land grids. (c) First 1,761 land grids.

(d) After 100 land grids. (e) After 880 land grids. (f) After 1,761 land grids.

Figure 9: Land grid elements selected for forestation and the respective tree cover evolution. Each pixel represents a 0.5° resolution land grid element.

Alternatively, removing only 6 Gt of $CO_2$ annually worldwide (corresponding to 1.5 Gt in South America), would cost about $6 \times 45 = \$270$ billion annually at a cost of \$45 per ton, or $4 \times 51 = \$204$ billion annually if payments are at marginal cost. (The integral of the supply curve from 0 to 1.5 Gt is \$51 billion.) The \$270 and \$204 billion amount to about 0.3% and 0.2% of world GDP, respectively — still significant, but probably more feasible.

These numbers correspond to our "base case" supply curve, for which we made several assumptions. In particular, we used a discount rate of 5% to capitalize flows of expenditures; we assumed that all previously forested and unforested land could potentially be forested; and we excluded land grid elements with forestation potential below 10% (on the grounds that scale economies make foresting these locations uneconomical). Here we examine the sensitivity of our results to these assumptions by calculating three alternative supply curves.

The results are shown in Figure 10, where SC1 is the base case supply curve shown in Figure 8. SC2 is the supply curve that results when the discount rate is lowered from 5% to 2.5%, and is very close to the base case curve. The reason is that lowering the discount rate raises the present value of the flow of expenditures, but lowers the corresponding annualized costs, leaving the annual expenditures nearly unchanged.

To generate SC3, we assumed that only land that had been previously forested during the

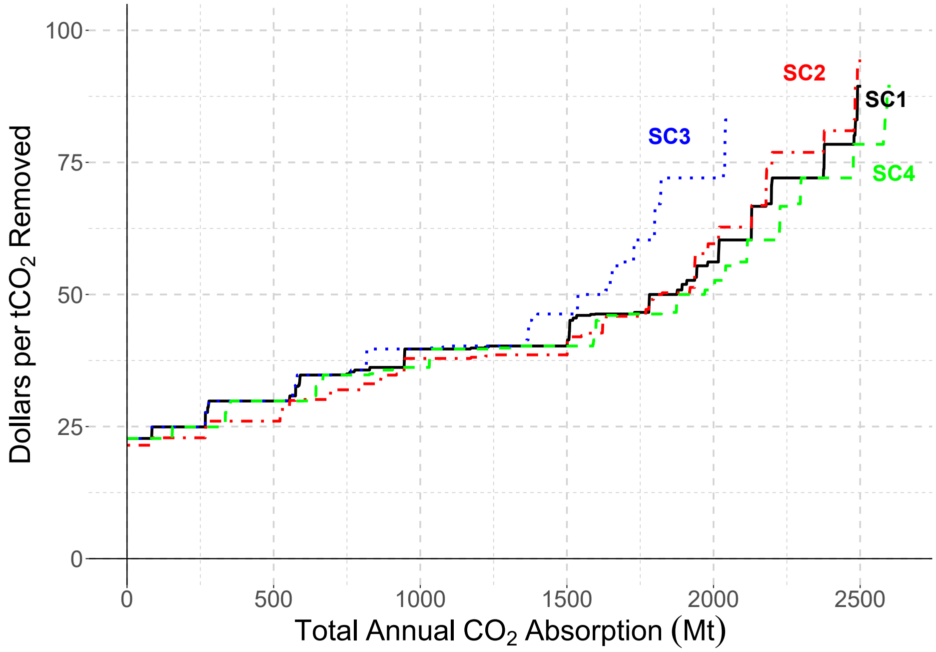



Figure 10: Supply curves for forest-based atmospheric $CO_2$ removal in South America. Each curve shows the marginal cost of removing one ton of $CO_2$ as a function of total tree-based annual $CO_2$ removal: SC1 (black) is the base case supply curve described above. SC2 is the supply curve for a 2.5% discount rate (instead of 5%). SC3 (blue) is the supply curve that only includes areas that were previously forested, and SC4 (green) is the curve that results if we include all land grids with any forestation potential (instead of only those with forestation potential above 10%).

past 50 years could be reforested now, and excluded land that was never forested but instead existed as savanna or grassland. (Some have argued that foresting areas that never existed as forests could have negative environmental repercussions, such as reducing biodiversity, and thus should be avoided.) As one would expect, SC3 is well above SC1, and in fact the maximum feasible $CO_2$ absorption is 2 Gt, at a cost of about \$85 per ton. It may indeed be the case that foresting land that had previously existed as savanna or grassland could reduce biodiversity (we take no stand on this), but excluding such land is expensive.

Finally, to generate SC4 we included *all* land grids with any forestation potential, instead of only including those with forestation potential above 10%. Including these additional land grids lowers the supply curve, but the difference is small, and is only noticeable when the total annual $CO_2$ absorption is above 1.7 Gt. (At a total of 2 Gt, for example, the difference in marginal cost is less than \$5 per ton.)

With the exception of excluding land that was never forested (SC3), our results are not very sensitive to these assumptions. But of course there are other assumptions and estimates that could be tested. Examples include the numbers that went into our calculation of the per-tree $CO_2$ absorption rate, the potential tree density per hectare, and our assumptions regarding land opportunity costs in countries other than Brazil. We leave this for further work, although we think it is unlikely that (reasonable) changes in these assumptions would have much impact on the supply curve.

# 8 Conclusions

Forestation is viewed as an important means of removing $CO_2$ from the atmosphere and thereby reducing net $CO_2$ emissions. But where should trees be planted, how many should be planted, and at what cost? Given a price of carbon, how much $CO_2$ can be removed? We addressed these questions by developing a supply curve for forest-based $CO_2$ removal in South America. Our supply curve traces out the marginal cost of removing a ton of $CO_2$ as a function of total annual $CO_2$ removal. We use data on tree cover and precipitation at the spatially disaggregated level of $0.5° \times 0.5°$ resolution land grid elements. Each point on the curve corresponds to a specific location (grid element), and accounts for land opportunity costs as well as costs of tree planting and maintenance. We show that over a billion tons of $CO_2$ can be removed annually via forestation at a cost below \$45 per ton, and about 2.5 billion tons can be removed at a cost below \$90 per ton.

The supply curve applies to only South America, but with sufficient data could be extended to the entire world. If the rest of the world looks like South America (in terms of its potential for forestation), and our supply curve were scaled up accordingly, a considerable amount of $CO_2$ could in principle be removed from the atmosphere via forestation. But doing so would be costly. For example, reducing net $CO_2$ emissions by 25% via forestation would cost something around \$1 trillion annually, which is about 1 percent of world GDP.

One could take issue with several aspects of our analysis. First, we have effectively assumed that trees last forever, which is clearly not the case. When trees die, the carbon they have sequestered will be released back into the atmosphere as $CO_2$. Thus, it might seem that planting trees cannot sequester $CO_2$ over the long run because those trees will eventually die. But the key is "eventually." Trees can live for a few hundred years, so trees planted now will sequester $CO_2$ for many years before those trees will have to be replanted. (Recall that our supply curve is based on a 50-year time horizon.)

We have ignored potential demand shifts and innovations in agriculture and in forestry that might occur over the next 50 years. If consumers' food preferences shift from meat to grains and vegetables, so that less land is used for livestock and more for temporary and permanent crops, land opportunity costs will change, and may not grow at the assumed rate of 4% per year. Likewise, innovation may lead to reductions in tree planting and maintenance costs. We have no way to predict such changes.

We have also ignored other benefits that forestation can provide, such as water recycling, erosion control, and short-term climate regulation. These benefits have external economic value, and from a public policy perspective should affect the supply curve by reducing the "full" marginal cost of $CO_2$ removal. Lastly, we have not addressed the cost of maintaining existing forest areas, so as to reduce $CO_2$ emissions from deforestation.

Because data limitations have limited our analysis to South America, this paper might be viewed as a "proof of concept." With sufficient data, however, our method can be extended to forests and forestation in other continents. Doing so requires identifying the climate and precipitation patterns adequate for other biomes, and defining the respective target zones, tree cover targets, quantities and types of trees, carbon gains and economic costs.

# References

**Amazon Fund.** 2010. “Amazon Fund Activity Report 2010.” Brazilian National Development Bank Report.

**Aragão, Luiz Eduardo O. C., Yadvinder Malhi, Rosa M. Roman-Cuesta, Sassan Saatchi, Liana O. Anderson, and Yosio E. Shimabukuro.** 2007. “Spatial patterns and fire response of recent Amazonian droughts.” *Geophysical Research Letters*, 34(7).

**Assunção, Juliano, Clarissa Gandour, and Romero Rocha.** 2023. “DETER-ing Deforestation in the Amazon: Environmental Monitoring and Law Enforcement.” *American Economic Journal: Applied Economics*, 15(2): 125–56.

**Austin, K.G., J.S. Baker, B.L. Sohngen, C.M. Wade, A. Daigneault, S.B. Ohrel, S. Ragnauth, and A. Bean.** 2020. “The Economic Costs of Planting, Preserving, and Managing the World’s Forests to Mitigate Climate Change.” *Nature Comm.*, 11(1): 1–9.

**Balboni, Clare A., Aaron Berman, Robin Burgess, and Benjamin A. Olken.** 2023. “The Economics of Tropical Deforestation.” National Bureau of Economic Research Working Paper 31410.

**Bastin, Jean-Francois, Yelena Finegold, Claude Garcia, Danilo Mollicone, Marcelo Rezende, Devin Routh, Constantin M. Zohner, and Thomas W. Crowther.** 2019. “The Global Tree Restoration Potential.” *Science*, 365(6448): 76–79.

**Benini, Rubens de Miranda, and Sergio Adeodato.** 2017. “Forest Restoration Economy.” The Nature Conservancy Brasil – TNC Brasil Report.

**Busch, Jonah, and Jens Engelmann.** 2015. “The Future of Forests: Emissions from Tropical Deforestation With and Without a Carbon Price, 2016-2050.” eSocialSciences Working Papers.

**Busch, Jonah, Jens Engelmann, Susan C. Cook-Patton, Bronson W. Griscom, Timm Kroeger, Hugh Possingham, and Priya Shyamsundar.** 2019. “Potential for Low-Cost Carbon Dioxide Removal through Tropical Reforestation.” *Nature Climate Change*, 9(6): 463–466.

**Crowther, Thomas W., Henry B. Glick, Kristofer R. Covey, Charlie Bettigole, Daniel S. Maynard, et al.** 2015. “Mapping Tree Density at a Global Scale.” *Nature*, 525(7568): 201–205.

**Cunha, Felipe Arias Fogliano de Souza, Jan Börner, Sven Wunder, Carlos Alberto Nunes Cosenza, and André F.P. Lucena.** 2016. “The implementation costs of forest conservation policies in Brazil.” *Ecological Economics*, 130: 209–220.

**DiMiceli, C. M., M. L. Carroll, R. A. Sohlberg, C. Huang, M. C. Hansen, and J. R. G. Townshend.** 2020. "Annual global automated MODIS vegetation continuous fields (MOD44B) at 250m spatial resolution for data years beginning day 65, 2000–2018, collection 6% tree cover, Ver. 1." University of Maryland, College Park, MD, USA.

**Favero, Alice, Robert Mendelsohn, and Brent Sohngen.** 2017. "Using Forests for Climate Mitigation: Sequester Carbon or Produce Woody Biomass?" *Climatic Change*, 144: 195–206.

**Food and Agriculture Organization.** 2020*a*. "Global Forest Resources Assessment 2020 - Main Report." United Nations Report.

**Food and Agriculture Organization.** 2020*b*. "State of the World's Forests." United Nations Report.

**ForestPlots.net, Cecilia Blundo, Julieta Carilla, Ricardo Grau, Agustina Malizia, Lucio Malizia, et al.** 2021. "Taking the pulse of Earth's tropical forests using networks of highly distributed plots." *Biological Conservation*, 260: 108849.

**Franklin, Sergio L., Jr., and Robert S. Pindyck.** 2018. "Tropical Forests, Tipping Points, and the Social Cost of Deforestation." *Ecological Economics*, 153: 161–171.

**Gusson, E., F.T. Souza e Miranda, G.C. Cunha, P. Pinheiro, S. Leitão, and V. Antonioli.** 2023. "Estratégias de Recuperação da Vegetação Nativa em Ampla Escala para o Brasil." Instituto Escolhas Relatório Técnico.

**Harris, I., T. J. Osborn, P. Jones, and D. Lister.** 2020. "Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset." *Scientific Data*, 7(109): 232–235.

**Harris, Nancy L, Sandra Brown, Stephen C Hagen, Sassan S Saatchi, Silvia Petrova, William Salas, Matthew C Hansen, Peter V Potapov, and Alexander Lotsch.** 2012. "Baseline map of carbon emissions from deforestation in tropical regions." *Science*, 336(6088): 1573–1576.

**Hirota, M., M. Holmgren, E. H. Van Nes, and M. Scheffer.** 2011. "Global Resilience of Tropical Forest and Savanna to Critical Transitions." *Science*, 334(6053): 232–235.

**Holl, Karen D., and Pedro H. S. Brancalion.** 2020. "Tree planting is not a simple solution." *Science*, 368(6491): 580–581.

**Kishinami, R., and S. Watanabe Jr.** 2016. "Quanto o Brasil precisa investir para recuperar 12 milhões de hectares de florestas?" Instituto Escolhas Report.

**Mokany, Karel, R. John Raison, and Anatoly S. Prokushkin.** 2006. “Critical analysis of root : shoot ratios in terrestrial biomes.” *Global Change Biology*, 12(1): 84–96.

**Mo, Lidong, Constantin M. Zohner, Peter B. Reich, Jingjing Liang, Sergio De Miguel, et al.** 2023. “Integrated global assessment of the natural forest carbon potential.” *Nature*, 1–10.

**Pindyck, Robert S.** 2019. “The Social Cost of Carbon Revisited.” *Journal of Environmental Economics and Management*, 94: 140–160.

**Pindyck, Robert S.** 2022. *Climate Future: Averting and Adapting to Climate Change.* New York:Oxford University Press.

**Pörtner, H.O., R.J. Scholes, J. Agard, E. Archer, A. Arneth, et al.** 2021. “Scientific outcome of the IPBES-IPCC co-sponsored workshop on biodiversity and climate change.” IPBES secretariat, Bonn, German Workshop report.

**Ramankutty, Navin, Holly K. Gibbs, Frédéric Achard, Ruth Defries, Jonathan A. Foley, and R.A. Houghton.** 2007. “Challenges to Estimating Carbon Emissions from Tropical Deforestation.” *Global Change Biology*, 13(1): 51–66.

**Silverman, B.W.** 1986. *Density Estimation.* Chapman and Hall/CRC, London.

**Staal, A., O. A. Tuinenburg, J. H. C. Bosmans, M. Holmgren, E. H. van Nes, M. Scheffer, D. C. Zemp, and S. C. Dekker.** 2018. “Forest-rainfall cascades buffer against drought across the Amazon.” *Nature Climate Change*, 8(6).

**Staver, A. C., S. Archibald, and S. Levin.** 2011. “The Global Extent and Determinants of Savanna and Forest as Alternative Biome States.” *Science*, 334(6053): 230–232.

**Walker, W.S., S.R. Gorelik, S.C. Cook-Patton, A. Baccini, M.K. Farina, K.K. Solvik, P.W. Ellis, J. Sanderman, R.A. Houghton, S.M. Leavitt, C.R. Schwalm, and B.W. Griscom.** 2022. “The global potential for increased storage of carbon on land.” *Proc Natl Acad Sci*, 119(23).

**Zemp, D. C., C-F. Schleussner, H. M. J. Barbosa, M. Hirota, V. Montade, G. Sampaio, A. Staal, L. Wang-Erlandsson, and A. Rammig.** 2017. “Self-amplified Amazon forest loss due to vegetation-atmosphere feedbacks.” *Nature Communications*, 8(14681).

Table A1: Details regarding Points A, B, C, and D on the supply curve in Figure 2.

| Point | Model outputs | Calculations |
|---|---|---|
| **A** | Location: Amazon forest of Brazil.<br>Coordinates: (-57.75° long, 1.25° lat).<br>Initial tree cover: 55.0%.<br>Forestation potential: 20.0%.<br>Agricultural activity: Livestock.<br>Land area converted to forest: 66,667 ha.<br>$\Delta CO_2$ absorption rate: 0.73 $MtCO_2$/yr.<br>Total forestation cost: US$ 16.7 MM/yr.<br>Cost per $tCO_2$ removed: US$ 23. | Trees planted = 20.0× 2 MM = 40.0 MM. Land area converted to forest = $20.0 \times 3,333.333$ = 66,667 ha. $\Delta CO_2$ absorption rate = $20.0 \times 36,667$ = 0.73 $MtCO_2$/yr (Section 4.3). Land opportunity cost = $131 \times 66,667$ = \$8.7 MM/yr (Table 1). Tree planting cost = $40,000,000 \times 0.192$ = \$7.7 MM/yr (Table 2). Forest conservation cost = $4 \times 66,667$ = \$0.3 MM/yr (Section 5.3). Total forestation cost = \$(8.7 + 7.7 + 0.3 = 16.7) MM/yr. Cost per $tCO_2$ removed = 16.7/0.73 = \$23. |
| **B** | Location: Amazon forest of Brazil.<br>Coordinates: (-49.25° long, -4.25° lat).<br>Initial tree cover: 23.667%.<br>Forestation potential: 51.333%.<br>Agricultural activity: Livestock.<br>Land area converted to forest: 171,111 ha.<br>$\Delta CO_2$ absorption rate: 1.88 $MtCO_2$/yr.<br>Total forestation cost: US$ 56.1 MM/yr.<br>Cost per $tCO_2$ removed: US$ 30. | Trees planted = 51.333× 2 MM = 102.666 MM. Land area converted to forest = $51.333 \times 3,333.333$ = 171,110 ha. $\Delta CO_2$ absorption rate = $51.333 \times 36,667$ = 1.88 $MtCO_2$/yr (Section 4.3). Land opportunity cost = $131 \times 171,110$ = \$22.4 MM/yr (Table 1). Tree planting cost = $102,666,000 \times 0.322$ = \$33.1 MM/yr (Table 2). Forest conservation cost = $4 \times 171,110$ = \$0.7 MM/yr (Section 5.3). Total forestation cost = \$(22.4 + 33.1 + 0.7 = 56.2) MM/yr. Cost per $tCO_2$ removed = 56.2/1.88 = \$30. |
| **C** | Location: : Amazon forest of Brazil.<br>Coordinates: (-53.75° long, -14.75° lat).<br>Initial tree cover: 29.333%.<br>Forestation potential: 45.667%.<br>Agricultural activity: Temporary crops.<br>Land area converted to forest: 152,222 ha.<br>$\Delta CO_2$ absorption rate: 1.67 $MtCO_2$/yr.<br>Total forestation cost: US$ 67.4 MM/yr.<br>Cost per $tCO_2$ removed: US$ 40. | Trees planted = 45.667× 2 MM = 91.334 MM. Land area converted to forest = $45.667 \times 3,333.333$ = 152,223 ha. $\Delta CO_2$ absorption rate = $45.667 \times 36,667$ = 1.67 $MtCO_2$/yr (Section 4.3). Land opportunity cost = $246 \times 152,223$ = \$37.4 MM/yr (Table 1). Tree planting cost = $91,334,000 \times 0.322$ = \$29.4 MM/yr (Table 2). Forest conservation cost = $4 \times 152,223$ = \$0.6 MM/yr (Section 5.3). Total forestation cost = \$(37.4 + 29.4 + 0.6 = 67.4) MM/yr. Cost per $tCO_2$ removed = 67.4/1.67 = \$40. |
| **D** | Location: Brazilian savanna (Cerrado).<br>Coordinates: (-49.75° long, -20.25° lat).<br>Initial tree cover: 18.0%.<br>Forestation potential: 22.0%.<br>Agricultural activity: Permanent crops.<br>Land area converted to forest: 73,333 ha.<br>$\Delta CO_2$ absorption rate: 0.81 $MtCO_2$/yr.<br>Total forestation cost: US$ 72.1 MM/yr.<br>Cost per $tCO_2$ removed: US$ 89. | Trees planted = 22.0× 2 MM = 44.0 MM. Land area converted to forest = $22.0 \times 3,333.333$ = 73,333 ha. $\Delta CO_2$ absorption rate = $22.0 \times 36,667$ = 0.81 $MtCO_2$/yr (Section 4.3). Land opportunity cost = $717 \times 73,333$ = \$52.6 MM/yr (Table 1). Tree planting cost = $44,000,000 \times 0.438$ = \$19.3 MM/yr (Table 2). Forest conservation cost = $4 \times 73,333$ = \$0.3 MM/yr (Section 5.3). Total forestation cost = \$(52.6 + 19.3 + 0.3 = 72.2) MM/yr. Cost per $tCO_2$ removed = 72.2/0.81 = \$89. |

Table A2: Summary statistics for key variables that affect the supply curve (*). Monetary values are in 2020 US dollars.

| **Variable** | **Minimum** | **Median** | **Mean** | **Maximum** | **Std Dev** |
|---|---|---|---|---|---|
| Mean annual precipitation (mm/yr) | 0 | 1620 | 1626 | 7435 | 848 |
| Mean maximum cumulative water deficit (mm/yr) | 0 | 268 | 335 | 1188 | 274 |
| Average tree cover (%) | 0 | 27 | 37 | 84 | 29 |
| GPV for temporary crops (US$/ ha) | 319 | 848 | 992 | 2457 | 724 |
| GPV for permanent crops (US$/ ha) | 399 | 2242 | 2434 | 6254 | 1990 |
| GPV for livestock (US$/ ha) | 51 | 126 | 464 | 6067 | 2240 |
| LOC for temporay crops (US$/ ha) | 116 | 118 | 155 | 286 | 66 |
| LOC for permanent crops (US$/ ha) | 146 | 344 | 322 | 449 | 122 |
| LOC for livestock (US$/ ha) | 63 | 94 | 112 | 224 | 58 |

(*) GPV stands for Gross Production Value; LOC stands for Land Opportunity Cost.

Table A3: Input data and corresponding web-based data sources.

| Data type | Source |
|---|---|
| Monthly precipitation data worldwide from Mar/2001 to Feb/2018 at 0.5° resolution (CRU/TS). | Climatic Research Unit, accessed on 2024-02-24 through the link: https://crudata.uea.ac.uk/cru/data/hrg/. |
| Tree cover data worldwide from Mar/2001 to Feb/2018 at 250-meter spatial resolution (MODIS/VCF). | Moderate Resolution Imaging Spectroradiometer/Vegetation Continuous Fields, accessed on 2024-02-24 through the link: https://lpdaac.usgs.gov/products/mod44bv006/. |
| Tree densities, carbon gains and $CO_2$ absorption rates in the tropics. | Crowther et al. (2015), Busch et al. (2019), ForestPlots.net et al. (2021), and Mokany, Raison and Prokushkin (2006). |
| Geographic borders of the Amazon forest. | Brazilian Institute for Space Research, accessed on 2024-02-24 through the link: http://terrabrasilis.dpi.inpe.br/en/download-2/. |
| Geographic borders of the Atlantic forest and Gran Chaco region. | MapBiomas Project, Annual Series of Land Use and Land Cover Maps of Brazil (Collections 2.0 and 4.0), accessed on 2024-02-24 through the link: https://code.earthengine.google.com/?accept_repo=users%2Fmapbiomas%2Fuser-toolkit&scriptPath=users%2Fmapbiomas%2Fuser-toolkit%3Amapbiomas-user-toolkit-lulc.js. |
| Geographic borders of South American countries. | Database of Global Administrative Areas, accessed on 2024-02-24 through the link: https://gadm.org/download_country.html. |
| Geographic borders of Brazilian states. | Brazilian Institute of Geography and Statistics, accessed on 2024-02-24 through the link: https://www.ibge.gov.br/geociencias/organizacao-do-territorio/malhas-territoriais/15774-malhas.html. |
| Land opportunity costs for temporary crops, permanent crops and livestock in Brazil. | Obtained by request from the Brazilian Confederation of Agriculture and Livestock (CNA): https://cnabrasil.org.br/. |
| Tree planting costs. | Kishinami and Watanabe Jr. (2016) and Benini and Adeodato (2017). |
| Forest conservation costs. | Cunha et al. (2016) and Assunção, Gandour and Rocha (2023). |
| Gross production values for temporary and permanent crops in Brazil, and the respective planted areas. | Brazilian Institute of Geography and Statistics, accessed on 2024-02-24 through the link: https://www.ibge.gov.br/estatisticas/economicas/agricultura-e-pecuaria/9117-producao-agricola-municipal-culturas-temporarias-e-permanentes.html?=&t=resultados. |
| Gross production values for livestock in Brazil. | Brazilian Ministry of Agriculture and Livestock, accessed on 2024-02-24 through the link: https://www.gov.br/agricultura/pt-br/assuntos/politica-agricola/valor-bruto-da-producao-agropecuaria-vbp. |
| Pasture areas for livestock grazing in Brazil. | MapBiomas Project, accessed on 2024-02-24 through the link: https://plataforma.brasil.mapbiomas.org. |
| Planted and pasture areas for temporary crops, temporary meadows and pastures, permanent crops, and permanent meadows and pastures in South America. | United Nations' Food and Agriculture Organization, accessed on 2024-02-24 through the link: https://www.fao.org/faostat/en/#data/RL. |

Table A4: Land opportunity costs in the Brazilian regions and South American countries covered by the forestation target zone (*). Data from 2018-2020 (2020 US dollars).

| **Geographic unit** | **Temp. crops (US$/(ha yr))** | **Perm. crops (US$/(ha yr))** | **Livestock (US$/(ha yr))** |
|---|---|---|---|
| Brazil | | | |
| South (S) | 286 | 295 | 224 |
| Southeast (SE) | 118 | 344 | 150 |
| Central-West (CW) | 118 | 344 | 115 |
| Northeast (NE) | 174 | 449 | 94 |
| North (N) | 116 | 146 | 63 |
| Argentina | 286 | 295 | 224 |
| Bolivia | 117 | 245 | 89 |
| Colombia | 116 | 146 | 63 |
| Ecuador | 116 | 146 | 63 |
| French Guiana | 116 | 146 | 63 |
| Guyana | 116 | 146 | 63 |
| Paraguay | 202 | 320 | 170 |
| Peru | 116 | 146 | 63 |
| Suriname | 116 | 146 | 63 |
| Uruguay | 286 | 295 | 224 |
| Venezuela | 116 | 146 | 63 |

(*) For South American countries other than Brazil, because of the lack of appropriate cost data, we use the average land opportunity costs for temporary crops, permanent crops and livestock observed in the Brazilian regions closest to their frontiers.

Table A5: Planted, pasture, and potentially forestable areas in the Brazilian states and South American countries covered by the forestation target zone. Values in thousand hectares.

| **Geographic unit** | **Planted and pasture areas in 2020** | | | | | | **Potentially forestable** |
|---|---|---|---|---|---|---|---|
| | **Temp. crops** | | **Perm. crops** | | **Livestock** | | **area ('000 ha)** |
| | **('000 ha (%))** | | **('000 ha (%))** | | **('000 ha (%))** | | |
| Brazil | | | | | | | |
| South (S) | | | | | | | |
| PR | 10,741 | (80%) | 121 | (1%) | 2,626 | (19%) | 10,892 |
| RS | 9,373 | (94%) | 159 | (2%) | 393 | (4%) | 10,618 |
| SC | 1,436 | (62%) | 76 | (3%) | 791 | (34%) | 3,240 |
| Southeast (SE) | | | | | | | |
| ES | 80 | (3%) | 485 | (19%) | 1,979 | (78%) | 3,033 |
| MG | 4,640 | (18%) | 1,193 | (5%) | 19,320 | (77%) | 9,134 |
| RJ | 76 | (4%) | 35 | (2%) | 1,884 | (94%) | 1,849 |
| SP | 8,068 | (61%) | 795 | (6%) | 4,353 | (33%) | 12,456 |
| Central-West (CW) | | | | | | | |
| GO | 6,900 | (35%) | 41 | (0%) | 13,015 | (65%) | 1,520 |
| MS | 5,947 | (30%) | 10 | (0%) | 13,871 | (70%) | 13,321 |
| MT | 17,150 | (45%) | 39 | (0%) | 20,935 | (55%) | 36,552 |
| Northeast (NE) | | | | | | | |
| AL | 420 | (22%) | 47 | (3%) | 1,404 | (75%) | 710 |
| BA | 3,229 | (16%) | 907 | (5%) | 15,932 | (79%) | 3,048 |
| MA | 1,700 | (19%) | 19 | (0%) | 7,217 | (81%) | 3,681 |
| PB | 337 | (21%) | 32 | (2%) | 1,224 | (77%) | 102 |
| PE | 704 | (20%) | 92 | (3%) | 2,770 | (78%) | 573 |
| RN | 245 | (28%) | 82 | (9%) | 564 | (63%) | 158 |
| SE | 219 | (13%) | 60 | (4%) | 1,377 | (83%) | 523 |
| North (N) | | | | | | | |
| AC | 70 | (3%) | 12 | (1%) | 2,192 | (96%) | 814 |
| AM | 102 | (4%) | 21 | (1%) | 2,649 | (96%) | 3,347 |
| AP | 36 | (13%) | 3 | (1%) | 235 | (86%) | 2,038 |
| PA | 1,364 | (6%) | 652 | (3%) | 21,477 | (91%) | 19,569 |
| RO | 722 | (8%) | 92 | (1%) | 8,749 | (91%) | 6,919 |
| RR | 84 | (8%) | 10 | (1%) | 1,026 | (92%) | 2,279 |
| TO | 1,547 | (20%) | 5 | (0%) | 6,113 | (80%) | 5,344 |
| Brazil (Subtotal) | 77,965 | (33%) | 5,431 | (2%) | 154,487 | (65%) | 151,721 |
| Argentina | 39,744 | (34%) | 1,068 | (1%) | 74,681 | (65%) | 16,136 |
| Bolivia | 3,121 | (9%) | 251 | (1%) | 33,000 | (91%) | 13,724 |
| Colombia | 1,850 | (4%) | 2,505 | (6%) | 39,504 | (90%) | 10,006 |
| Ecuador | 823 | (16%) | 1,443 | (28%) | 2,939 | (56%) | 2,318 |
| French Guiana | 11 | (37%) | 6 | (18%) | 14 | (45%) | 331 |
| Guyana | 370 | (37%) | 28 | (3%) | 594 | (60%) | 3,467 |
| Paraguay | 4,262 | (26%) | 90 | (1%) | 11,985 | (73%) | 13,332 |
| Peru | 909 | (4%) | 2,262 | (10%) | 18,800 | (86%) | 3,529 |
| Suriname | 53 | (72%) | 5 | (7%) | 16 | (22%) | 1,298 |
| Uruguay | 1,827 | (13%) | 39 | (0%) | 12,000 | (87%) | 5,223 |
| Venezuela | 1,950 | (9%) | 700 | (3%) | 18,200 | (87%) | 6,840 |
| **Total** | 132,885 | (26%) | 13,827 | (3%) | 366,220 | (71%) | 227,924 |