The Supply of Forest-Based CO_2 Removal

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Abstract: Forestation is viewed as a way to remove CO_2 from the atmosphere and thereby reduce net CO_2 emissions. But how much CO_2 can be removed, where, 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 where precipitation patterns can potentially support forest growth, and accounts for land opportunity, tree planting, and forest maintenance costs. We find 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 South America, but with sufficient data could be extended to the entire world.

JEL Classification Numbers: Q5, Q57, C6

Keywords: Forestation, land opportunity cost, feasible forestation, CO_2 emissions, CO_2 removal, net emissions, Amazon rainforest, Atlantic forest.

Highlights:

- A supply curve for forest-based CO_2 removal integrating economic-ecological factors.
- Use of spatially disaggregated data on climate, vegetation, and costs.
- Determine target zone, forestation potential, costs, and CO_2 absorption rates.
- Supply curve shows marginal cost of CO_2 removal, by location.
- Find 2.5 Gt of CO_2 can be removed annually in South America at cost below $90/ton.

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1 Introduction

Global CO_2 emissions continue to rise, and even if they were to decline, the atmospheric CO_2 concentration will keep growing for many years. That is why policy objectives often focus on the need to remove CO_2 from the atmosphere. Planting trees (afforestation and reforestation) may be a promising solution, but where to plant 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]

How much CO_2 could be removed by planting trees? Here are some rough numbers:

1. Estimates vary depending on climate, type of tree, and tree density, but on average a mature (10- to 20-year old) hardwood tree absorbs about 20 kg of CO_2 per year.
2. Again, the numbers vary 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. Using satellite data, one recent study puts the global number of hectares that could be forested at about 1 billion. Taking this number at face value, full forestation of all available land could remove $1 \times 10^9 \times 500 \times .02 = 10$ Gt (billion tons) of CO_2 per year from the atmosphere.[3] Global CO_2 emissions are now about 40 Gt per year, so net emissions could potentially be reduced by about 25% by foresting all 1 billion hectares.

The world is indeed planting trees, but cutting down many more. Deforestation occurs because land can be used for agriculture, cattle grazing, mining, and other economic activities.[4] Afforestation requires land, making it costly. The nature and extent of these and other costs, which vary greatly across regions, will be explored in this paper.

We use $0.5^\circ \times 0.5^\circ$ resolution land grid data to develop a supply curve for forest-based CO_2 removal. We focus on forested and forestable areas in South America, which include the

[1] Considerable ongoing R&D is 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 absorption potential is limited.

[2] 1 hectare = .01 square kilometers $\approx$ 2.47 acres.

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

[4] During 2015–2020, global net forest loss was about 6 million hectares per year. 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).

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 forested but experienced forest loss, as well as areas that were never forested and instead existed as savanna or grassland. However, some recent studies have suggested that the forestation of areas that never existed as forest can have negative environmental repercussions, and thus some argue should be avoided.[5] Flora and fauna that can survive in a savanna, for example, might not survive in a dense forest, so turning savanna into forest could reduce biodiversity. We do not take a stand on this issue, but for comparison, we also develop a supply curve that restricts potentially forestable land to those areas that were previously forested.

We account 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. Land has economic value, and foresting a hectare of land means it cannot be used for other purposes.

2. *Planting and maintenance costs.* Forestation begins with planting and growing seedlings, and then replanting those seedlings with fertilizer, water, and insecticides. Later, the trees must be protected from severe weather and pruned as they mature, and sometimes replanted. Mature trees have ongoing maintenance costs, which includes continual addition of fertilizer and insecticides, 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.

Given these costs, we determine where and how many trees can feasibly be planted. We mentioned water as a critical input; indeed forestation in areas with limited rainfall is usually prohibitively expensive, and most areas suitable for forestation have considerable rainfall. We therefore 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 the precipitation patterns (rainfall and lengths of dry periods) that make it economical to plant trees. Then, turning to South

[5]See, e.g., Pörtner et al. (2021) and Holl and Brancalion (2020).

America, we identify the land grid elements where those patterns hold, and, depending in part on current tree cover, determine the number of trees that should be planted on each element. For each of those land grid elements, we estimate the land opportunity, tree planting and forest conservation costs. 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 for each land grid element. 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 sole objective of removing atmospheric CO_2.

Trees eventually die and when they do, most of the carbon they have sequestered is released into the atmosphere as CO_2. However, trees can live for up to a few hundred years, and if they are in an area that is fully or nearly fully forested, after they die regeneration will occur naturally. Thus, trees planted now will sequester CO_2 over the 50-year time horizon on which our supply curve is based, and with regrowth for many years afterwards.

In the next section we review the prior literature on the use of forestation to absorb CO_2, and clarify how our approach differs. Section 3 provides an overview of our data. Section 4 shows how we identify areas with high potential for increased tree cover. Section 5 presents estimates of land opportunity, tree planting and forest conservation costs. In Section 6 we use these results to build a supply curve for forest-based CO_2 removal, and we examine the sensitivity of the supply curve to certain assumptions in Section 7. Section 8 concludes with some caveats, policy implications, and suggestions for further work.

2 Related Studies

Other studies have addressed the potential of forestation for atmospheric CO_2 removal. Here we briefly review several of them and highlight how they differ from our approach.

Some studies have estimated the marginal cost of carbon sequestration based on local cost data and forest carbon accumulation rates. For example, Moulton and Richards (1990) estimated the average cost of carbon sequestration for 10 United States regions, accounting for land opportunity costs, planting costs, and total amount of carbon sequestered. As we do, they constructed a supply curve by ordering the marginal costs from lowest to highest, and plotting them against cumulative carbon sequestration. Nielsen, Plantinga and Alig

(2014) extended this work to refine cost estimates for carbon sequestration, with afforestation restricted to areas in the United States where temperature and moisture availability support forest growth. They found that at a carbon price of $50 ($100) per ton, approximately 200 (300) million tons of carbon could be sequestered annually through afforestation.

Others have used a revealed preference approach to estimate country-specific relationships between land-use choices and relative returns in the forest and agricultural sectors. For example, Stavins (1999) estimated the marginal costs of carbon sequestration based on landowners' behavior when confronted with the opportunity costs of alternative land uses. Lubowski, Plantinga and Stavins (2006) extended this work by modeling six major uses of private land (forest, crop, pasture, range, urban, and the federally designated Conservation Reserve Program). Key commodity prices were treated as endogenous, and carbon storage changes were predicted using a carbon sink model. Their econometric estimates were then used to simulate landowner responses to sequestration policies in the United States.

Favero, Mendelsohn and Sohngen (2017) combined a "global dynamic forest model" and a "global mitigation model" (an integrated assessment model) to study whether forestland is best used for biomass burning versus carbon storage given alternative carbon price paths. Their model describes the dynamics of woody biomass and forest carbon sequestration demand and supply, and for each price path determines the optimal amount of forest, the mix of managed versus natural forest, and optimal planting and rotation length on managed land. 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. Their 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 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.

In another regression study, Busch et al. (2024) estimated land opportunity and tree planting costs in low and middle-income countries worldwide, and then developed a GHG abatement cost curve for natural regeneration and new planting. They used spatially disaggregated data (as we do), but their land opportunity cost is based on actual revenue and household survey data, while ours is based on potential revenue and average rental values.

They found that for 138 low- and middle-income countries, about 2 billion tons of CO_2 per year can be abated via reforestation at a cost below \$50 per ton of CO_2.[6]

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 forest conservation and restoration 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 217 and 224 Gt of carbon below its full potential, of which 123 and 152 Gt are in 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 accounts for 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, which, if it materializes over 50 years, implies that global annual CO_2 removal from natural forest growth could reach $(138 \times 3.67)/50 = 10$ Gt CO_2.

Lastly, Araujo, Costa and Sant'Anna (forthcoming, 2025) estimate a model of land use in the Brazilian Amazon forest, using a panel dataset that classifies land use at 30 meters resolution – far more spatially disaggregated than our work – with the objective of determining the carbon-efficient forest cover. Once they have estimated the parameters of the model that describes farmers' optimal land use decisions, they can then determine how those decisions would change were farmers to internalize the social cost of carbon. They find that even a small carbon tax (\$10 per ton) would push farmers' decisions close to the optimal. Our study is less ambitious; we simply want to determine the marginal cost of removing CO_2 by planting and maintaining new trees. Some point on our supply curve might correspond to a carbon-efficient use of land, but we do not try to determine where that point is.

In this paper, we present an approach to developing a supply curve for forest-based atmospheric CO_2 removal that is relatively easy to implement, and that integrates economic with ecological factors that affect cost. Unlike some of the studies mentioned above:

[6]Potential revenue better reflects land users' opportunity costs over the long run (e.g., 50 years), while actual revenue may be adequate for the short run. Other differences between their study and ours include options for alternative land use and forest recovery techniques, the approach for identifying the forestation target zone, and whether agroforestry systems and forest conservation costs are accounted for.

- We identify and delineate a "forestation target zone," i.e., areas where precipitation patterns support forest growth. This is important because land suitable for agriculture may lack the necessary precipitation patterns (rainfall volume and dry season intensity) required for forest growth, meaning it cannot be converted into a forest, regardless of land opportunity and planting costs.[7]

- We allow for planting new trees on lands already classified as forests to enhance tree densities. We use tree cover data ("current" and "target") to estimate forestation potential, costs, and CO_2 absorption rates. Land grid elements with different tree cover percentages have distinct forestation costs and CO_2 absorption rates.

- Our use of spatially disaggregated data allows us to identify forestation costs at particular locations. We estimate land opportunity costs in each land grid element by considering three alternative land uses: temporary crops, permanent crops, and livestock. We account for the fact that areas with tree cover below 5% are too difficult to forest (e.g., urban and industrial areas, or areas of lakes, rivers, and rocky soil).[8]

- We define the tree cover "target" for each land grid element so as to prevent fire spread feedbacks from driving the ecosystem toward a savanna state. And we incorporate agroforestry systems, where trees are planted alongside or among crops or pastureland.

To estimate a supply curve that covers all of South America, some compromises were required because of data limitations. Most importantly, we have extensive cost data for Brazil, but less for the rest of the continent. We explain these limitations and how we dealt with them in the next section, which discusses our data in detail.

3 Data

To build the supply curve we must determine where in South America it is economical to plant trees, how many trees can be planted, and the full cost of planting and maintaining those trees. Table A1 in the Appendix shows summary statistics for key variables, and Table A2 summarizes the input data and corresponding web-based data sources.

[7]Nielsen, Plantinga and Alig (2014) incorporated data on Holdridge life zones to limit afforestation in U.S. locations where temperature and moisture availability hinder forest growth.

[8]Busch et al. (2024) also use spatially disaggregated data, as explained above. Moulton and Richards (1990) and Nielsen, Plantinga and Alig (2014) identify costs of forestation for particular U.S. counties. None of these studies distinguish between temporary and permanent crops.

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 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° 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). 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 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 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), Sullivan et al. (2020*b*), 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 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. About 60% of the Amazon forest is in Brazil, 13% in Peru, 10% in Colombia, and smaller amounts in six other countries. About 92% of the Atlantic forest is in Brazil, 6% in Paraguay, and 2%

[9]MODIS is a satellite-based sensor used for earth and climate measurements, and MODIS/VCF contains annual tree cover data (from March through February). MODIS/VCF provides a global representation of surface vegetation cover at a 250-meter spatial resolution, with three components: percent tree cover, percent non-tree cover, and percent non-vegetated (DiMiceli et al. (2020)). CRU/TS is a widely used climate dataset with $0.5^\circ \times 0.5^\circ$ resolution 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)).

in Argentina. About half of the Gran Chaco region is in Argentina, a third in Paraguay, and the rest in Bolivia. We obtained the borders of the Amazon rainforest from the Brazilian Institute for Space Research (INPE), the borders of the Atlantic forest and Gran Chaco region from the MapBiomas Project (http://mapbiomas.org), the borders of South American countries from the Global Administrative Database (GADM), and the borders of Brazilian states 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 revenues. It is instead gross revenue minus total operating costs, where the latter excludes rents or other costs associated with the use of the land. Revenue and operating cost data are sparse, but opportunity cost should also equal the rental price of the land, for which data are more available. Thus we measure opportunity cost as the rental price of land for specific agricultural activities.

Actual or imputed land rental prices in Brazil for the most important temporary crops (soy and corn), permanent crops (coffee and oranges) and livestock (bovine meat and milk) were obtained from the Brazilian Confederation of Agriculture and Livestock (CNA). The CNA data represent the average values of typical leasing agreements in different regions over the period 2018–2020. The CNA conducts meetings with farmers, input providers, and technical experts in Brazilian states and cities to check whether these average values are in line with local rental conditions. Meeting participants may request adjustment, and the CNA will seek consensus among the participants, usually based on farmers' rental.

Brazil has 26 states and one federal district, grouped into five regions. The CNA data do not cover all of the states, but only several states in each region. Using that data, we estimated land opportunity costs for each Brazilian state as the average rental value for each agricultural activity in the corresponding region. We do not have land opportunity cost data for South American countries other than Brazil. However, land areas that are close together have similar environmental characteristics and thus similar land opportunity costs, so for other countries we use the average costs in the Brazilian regions closest to their frontiers. (Also, note that Brazil accounts for 67% of the target land area.) From these numbers we

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. Future growth is uncertain, but for our base case scenario we assume they will continue to grow over the next 50 years at a rate equal to the growth rate of Brazilian gross agricultural production value during 2010 to 2020. Gross production values for temporary and permanent crops were obtained from the Brazilian Institute of Geography and Statistics (IBGE), and for livestock (bovine meat and milk) 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, 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 came from the Brazilian Institute of Geography and Statistics (IBGE), and the land areas used for raising livestock came 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 came from the United Nations' Food and Agriculture Organization.

4 Forestation Targets

Water is critical, so we must determine the areas where precipitation patterns make it economical to plant new trees, and the number of trees that could be planted in each area.

4.1 Determining the target zone

We first investigate 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 pre-

cipitation, MAP) and dry season intensity (the mean maximum cumulative water deficit MMCWD).[10] Hirota et al. (2011) found that tree cover does not increase steadily with rainfall (MAP), 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) move the ecosystem closer to either the forest or savanna state.[11] 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 examine the relationships between tree cover and rainfall volume, and between tree cover and dry season intensity, both worldwide. For each land grid element within latitudes $[-35, +15]$, we collected time series of yearly tree cover (2001 to 2018) and monthly rainfall (March 2001 to Feb. 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 the three continents, and joint distributions of ATC, MAP, and MMCWD worldwide.[12]

Figure 1 shows 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%) and savanna (around 20%). This is consistent with models of forest evolution that show how low and high tree covers are stable equilibria.[13] Figures 2a and 2b show kernel density estimates of the joint probability

[10]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 MCWD calculation is described in Aragão et al. (2007). The annual precipitation (AP) and the MCWD are calculated for several years and averaged to yield the means (MAP and MMCWD).

[11]Fire spread depends on a continuous grass layer, so the higher the tree cover, the lower the fire spread is (i.e., the more fire-resilient the forest is), and vice-versa (Staver, Archibald and Levin (2011)). Franklin and Pindyck (2018) show how deforestation can tip an ecosystem from the forest to the savanna state.

[12]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 routines in R, geom_density and stat_density2d, with 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.

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

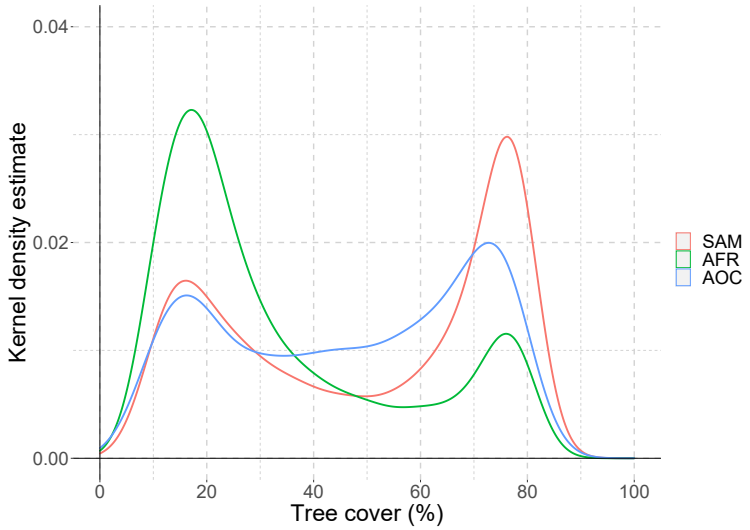


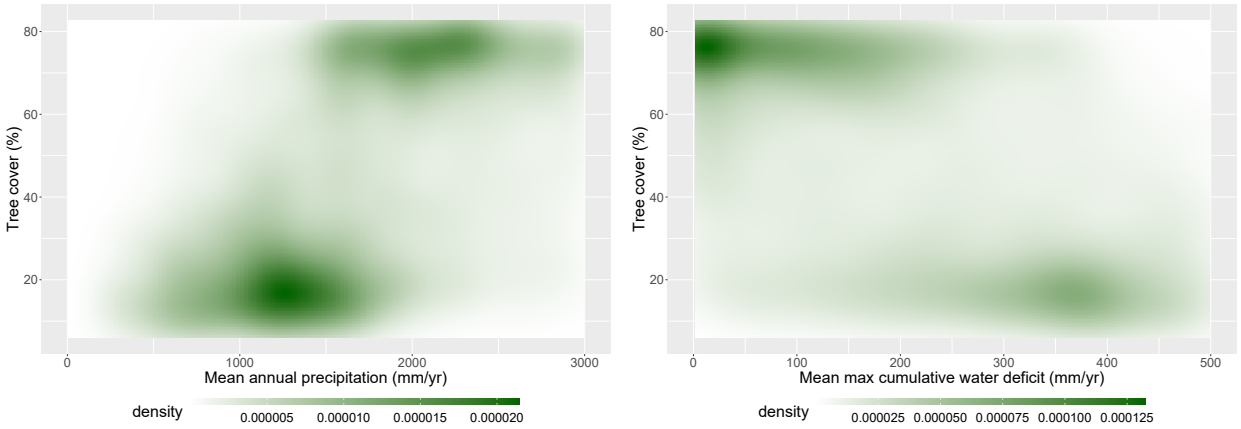
Figure 1: Probability Distributions of Average Tree Cover from 2001 to 2018 in Tropical and Subtropical Regions of South America (SAM), Africa (AFR), and Asia and Oceania (AOC). Note the peaks at low (10 to 30%) and high (70 to 80%) tree cover, corresponding to savanna and fully forested, respectively.

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 1, these graphs show that the characteristic tree covers of forest and savanna dominate. But the graphs also show that high tree cover occurs in areas where MAP $>$ 1,000 mm/yr *or* MMCWD $<$ 400 (mm/yr), and low tree cover in areas with low MAP and/or high MMCWD.

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 target zone is shown in Figure 3.

4.2 Target tree cover and forestation potential

We estimate the forestation potential for each land grid candidate for forestation in the target zone based on the characteristic tree cover of the biome that previously existed there. Thus, for land grids that during the past 50 years were once densely forested but experienced forest loss, including areas of the Amazon rainforest, Atlantic forest and Gran Chaco region, we use a 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 to 75% may not be feasible over the long run. Figures 1 and 2 show that the tree cover rarely remains between 40 and 60% over a



(a) Tree cover and annual precipitation.

(b) Tree cover and max. cumulative water deficit.

Figure 2: Bivariate Probability Distributions for 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.

sustained period. Thus, for land grids that are in the target zone but existed as savanna (e.g., Cerrado) or grassland (e.g., 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%.

The forestation potential for each land grid candidate is the difference between the target tree cover (either 75% or 40%) and current tree cover. Figure 4 shows the average tree cover observed from remote sensing (MODIS/ VCF) in 2016-2018, and the forestation potential calculated for each land grid candidate. We treat areas 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 trees it contains (or will contain following forestation). Organic carbon accumulates in both above and below ground biomass (AGB and BGB). Patterns of above ground biomass (stems, bark, branches) are well understood, but we know less about below ground biomass (roots) because it is difficult to observe and measure root biomass. The below ground biomass is usually expressed as a fraction of the above ground biomass using an estimated "root-to-shoot" ratio, which is the amount of plant tissue with supportive functions (root biomass) divided by the amount with growth function (shoot biomass).[14]

To estimate the CO_2 absorption rate per tree, we start with the above ground biomass

[14]Mokany, Raison and Prokushkin (2006) review root-shoot ratio estimates for major terrestrial biomes.

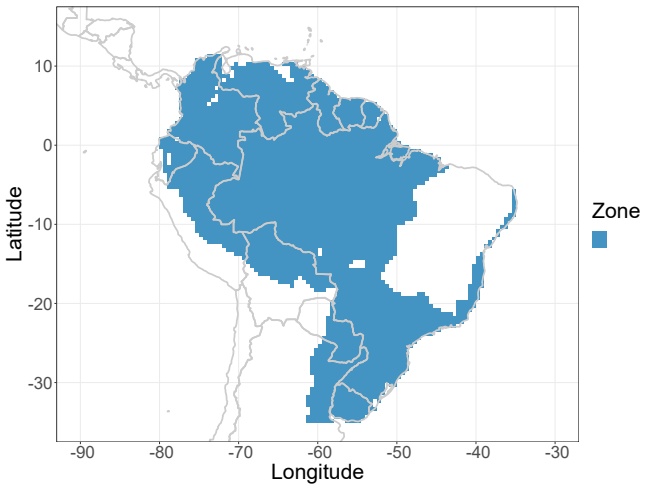


Figure 3: Forestation Target Zone. Areas where precipitation patterns support forest growth (i.e., MAP $\geq$ 1,000 and MMCWD $\leq$ 400 mm/yr) are in blue.

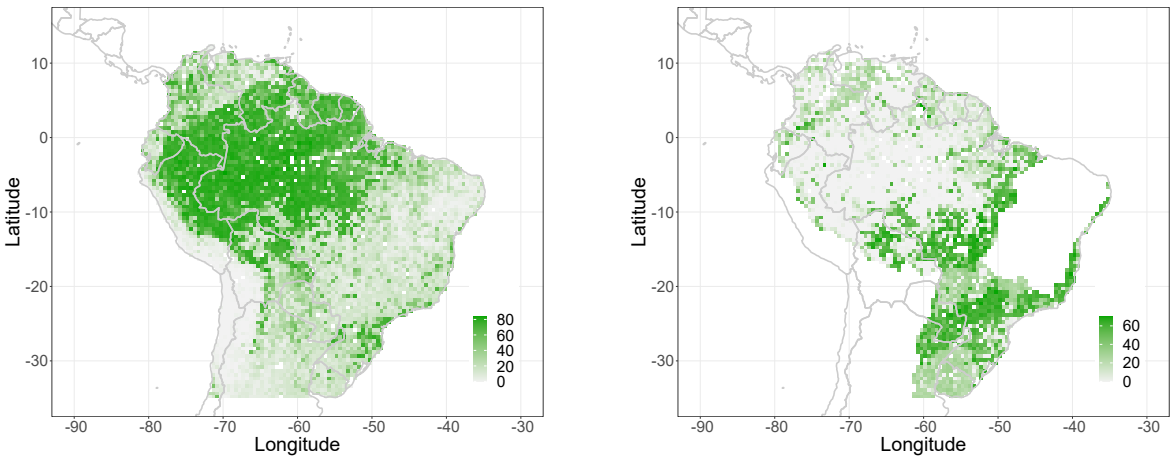
(AGB). As trees age, the rate at which they absorb carbon falls; a 5 to 10 year old tree will absorb twice as much carbon as the same tree when it is 50 years old. Forestation involves planting new trees which, with maintenance and possible replanting, will last at least 50 years, so we want the average carbon absorption rate over 50 years. For trees in tropical moist forests, several studies put the average carbon stock accumulation above ground at about 2.4 tons of carbon per hectare per year.[15] The AGB absorption can vary, depending on tree density and location; using the data package provided by Sullivan et al. (2020*b*) (available at Sullivan et al. (2020*a*)), we derived the distribution for the above ground carbon accumulation, and calculated a mean and standard deviation of 2.4 and 0.6 respectively. These numbers are consistent with estimates by others of carbon stock accumulation, as shown in Table A4 in the Appendix.

For the below ground biomass (BGB), we use a root-shoot ratio of 0.26.[16] Multiplying the AGB by 1.26, 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, the average CO_2 absorption rate is $11,000/600 = 18.33$ kg CO_2 per tree per year. These estimates apply to trees in tropical moist forests; we use them because precipitation patterns in the target zone are similar to those in tropical forests.

This value of 18.33 kg likely underestimates the rate of CO_2 absorption, because the data

[15] See Fig. 6 in ForestPlots.net et al. (2021), Fig. 1 in Sullivan et al. (2020*b*), and Sullivan et al. (2020*a*).

[16] 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).



(a) Current tree cover (%). (b) Forestation potential (%).

Figure 4: Current Tree Cover (2016-2018) and Forestation Potential over the Forestation Target Zone. Each pixel represents a 0.5° resolution land grid element.

from Sullivan et al. (2020*b*) we used to calculate the mean AGB absorption rate applies to a mix of trees with an average age close to 50 years.[17] Smith et al. (2016) found the net atmospheric removal of carbon for 40 year old trees to be 3.4 tons of carbon per hectare per year, or, with 600 trees per hectare, $(3.4 \times 3.67)/600 \approx 21$ kg CO_2 per tree per year. We use the 18.33 kg estimate to be conservative, and because it is based on publicly available data.

Consider a one percentage point increase in tree cover (e.g., going from 40% to 41% tree cover, with an upper limit of 75%, the characteristic tree cover of forest). A fully forested hectare has 600 trees, so a 1 percentage point increase means planting $600/75 = 8$ new trees. We assume these 8 trees are planted so as to allow for the combination of agriculture and trees, while occupying an area of $8/600 = 0.01333$ hectare.[18] 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

[17] Fig. 1 in Sullivan et al. (2020*b*) shows that the average carbon residence time in their sample of 273 forest plots is slightly above 50 years. The carbon residence time, calculated as the ratio of living carbon stocks to carbon gains, is a rough measure of tree age.

[18] This assumes an agroforestry system where trees are grown among crops or pastureland. A density of 600 trees per hectare implies a tree spacing of $(100/(600^{0.5}) = 4.082$ meters, so each tree occupies $4.082^2 = 16.663$ m^2. For more information on agroforestry, see https://www.fao.org/forestry/agroforestry/80338/en/.

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. With an average tree density of 600 trees per hectare, $216,645 \times 600 = 130$ million trees can be added to these two land grids.

Summing the forestation potential over all land grids inside the target zone (see Figure 4b) yields 68,400 percentage points. Multiplying 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 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 can be higher or lower than the sum of the areas used for agriculture and livestock. It will be higher, for example, if a large area has been deforested for wood or mining as opposed to agriculture. It will be lower if the area is not completely inside the target zone.

5 Forestation Costs

We estimate the land opportunity, tree planting and forest conservation costs for each land grid element in the target zone. These costs vary over time; land opportunity costs grow as food demand grows, and planting costs are highest during the first few years of forestation, and then fall. However, we treat the CO_2 absorption rate as constant over a 50-year horizon, so to estimate the marginal cost of absorbing CO_2 we smooth out these costs over time.

We calculate the 50-year present value of each flow of cost, and then convert these present values into 50-year annualized costs. 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) and elsewhere.

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.

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

Geographic unit	**Temporary crops ($/(ha yr))**	**Permanent crops ($/(ha yr))**	**Livestock ($/(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

Of Brazil's five 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. Land opportunity cost data are unavailable for other South American countries; given that Brazil accounts for 67% of the entire potentially forestable area of South America, we use the average cost in the Brazilian region(s) closest to the frontier of each country. We assume land opportunity costs will continue to grow over the next 50 years at the 4% real growth rate of the Brazilian gross value of agricultural production from 2010 to 2020.

Using data for 2018-2020, 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 into annualized costs. Table 1 shows these annual land opportunity costs for each agricultural activity.[19]

To illustrate, consider a land grid element with 55% tree cover in northern Brazil, which is used for raising livestock, so its land opportunity cost is $131 per hectare per year (Table

[19]The 50-year present value of an annuity of $1, discounted at 5%, is $(1-(1+5\%)^{-50})/5\% = 18.26$. The 50-year present value of a growing annuity that begins at $1 but increases at a 4% annual rate, discounted at 5%, is $(1-(1+4\%)^{50}\times(1+5\%)^{-50})/(5\%-4\%) = 38.03$. Thus, Table 1 was derived by multiplying each dollar cost estimate by $38.03/18.26 = 2.08$.

1). Suppose we increase the tree cover to 75%. A land grid covers 250,000 hectares, so a 1 percentage point increase in tree cover requires $8 \times 250,000 = 2$ million trees, occupying 1.33% of 250,000 = 3,333 hectares that 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, and – most importantly – current tree cover. Different forest recovery techniques imply different activities and inputs, and thus different costs. These activities and inputs can also vary for the same recovery technique, depending on soil and access conditions.

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 and enabling the spontaneous restoration of native species; (ii) "enhancing tree density and enrichening," where a large number of trees are planted 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 used 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 with forestation potential of at least 10%. Areas with current tree cover below 5% are too difficult or expensive to forest (e.g., urban and industrial areas, or areas of lakes, rivers, and rocky soil), and are ignored. Areas with tree cover greater than 65% are left for (passive) natural regeneration. 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.[20]

From the present value estimates in Benini and Adeodato (2017), we calculate the average

[20] According to Kishinami and Watanabe Jr. (2016), "facilitating natural regeneration" requires a high density of regenerative trees, and is recommended when tree cover is 50 to 80%, whereas "enhancing tree density and enrichening" is recommended for areas with moderate natural regeneration, with tree cover of 30 to 60%. Other factors also affect the choice of forest recovery technique (e.g., soil degradation, possibility of mechanization, etc.). Without 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."

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

Biome and forest recovery technique	**Present values**		**Annualized costs**
	($/ha)*	**($/tree)**	**$/(tree yr)**
Amazon rainforest, Atlantic forest, Gran Chaco region:			
Facilitating natural regeneration	420	3.50	0.192
Enhancing tree density and enrichening	1,100	4.23	0.232
Total planting (seeds and seedlings) up to 75%	2,700	5.87	0.322
Savannas and grasslands:			
Total planting (seeds and seedlings) up to 40%	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%.

tree planting cost per hectare for each forest recovery technique in the Amazon and Atlantic forests. These 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 is 8 times the difference between the target tree cover (either 75% or 40%) and its midrange tree cover.[21] We convert these present values into 50-year annualized costs. Table 2 shows resulting tree planting costs for different forest recover techniques and biomes.

Returning to our example of a land grid element in northern Brazil with 55% tree cover, the forest recovery technique is "facilitating natural regeneration," so the annualized tree planting cost is $0.192 per tree per year (Table 2). The 20% increase in tree cover requires 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, 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 conservation

[21] 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. The number of trees actually planted may exceed the number added because some trees die and must be replanted.

cost over 2005-2014 was about $(1.1 \times 10^9)/(340 \times 10^6) = \$3.20$ per hectare.

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

To summarize this example, the total annualized cost to reach and maintain a tree cover of 75% is \$8.7 million (land opportunity cost) + \$7.7 million (tree planting cost) + \$0.3 million (forest conservation cost) = \$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 $16.7/0.73 = \$23$.

6 A Supply Curve for Forest-Based CO_2 Removal

For each land grid in the target zone, we consider increasing its current tree cover up to its target level (75% or 40%). We know the current tree cover, target tree cover, forestation potential and CO_2 absorption rate, tree planting and forest conservation costs, and land opportunity cost for each agricultural activity. But to determine the land opportunity cost, we need to identify which agricultural activities can potentially be performed there.

The areas used for temporary crops, permanent crops, and livestock in the forestation target zone are not georeferenced, so we cannot determine which activity is conducted 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 (Table A3). We use these percentages to estimate the potentially forestable area from each agricultural activity, and the land opportunity cost for each land grid element.

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 A3, 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.[22]

Starting with all land grid elements inside the target zone with current tree cover above 5%, 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 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.

We then 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 cost agricultural activity. If it is, we perform the 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, consider a land grid candidate for forestation in Brazil-PR with a current tree cover of 55% and target tree cover of 75%, currently used for livestock. The increase in forested area from the proposed conversion is $(75 - 55) \times 3,333 = 67{,}000$ hectares, and the potentially forestable area from livestock is 2.069 ($= 0.19 \times 10.892$) million hectares (Table A3). The potentially forestable area from livestock exceeds the increase in forested area from the proposed conversion ($2.069 > 0.067$), so we perform the conversion and update the potentially forestable area to $2.069 - 0.067 = 2.002$ million hectares. As we try to forest more land in Brazil-PR and deplete the potentially forestable area from livestock, we will shift the remaining land grid elements to the next lowest cost activity, temporary crops, for which $0.80 \times 10.892 = 8.714$ million hectares are available.

We then pick the next land grid element with lowest total forestation cost per ton of CO_2 removed, and repeat the above steps. We continue 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 is reduced to zero.

6.2 The supply curve

There are 3,662 land grid elements inside the forestation target zone, of 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 poten-

[22]Recall that the potentially forestable area need not equal the sum of the areas currently used for agricultural activities (Section 4.3). The potentially forestable area in Brazil-PR is lower than the sum of these areas: $10.892 < 10.741 + 0.121 + 2.626 = 13.488$.

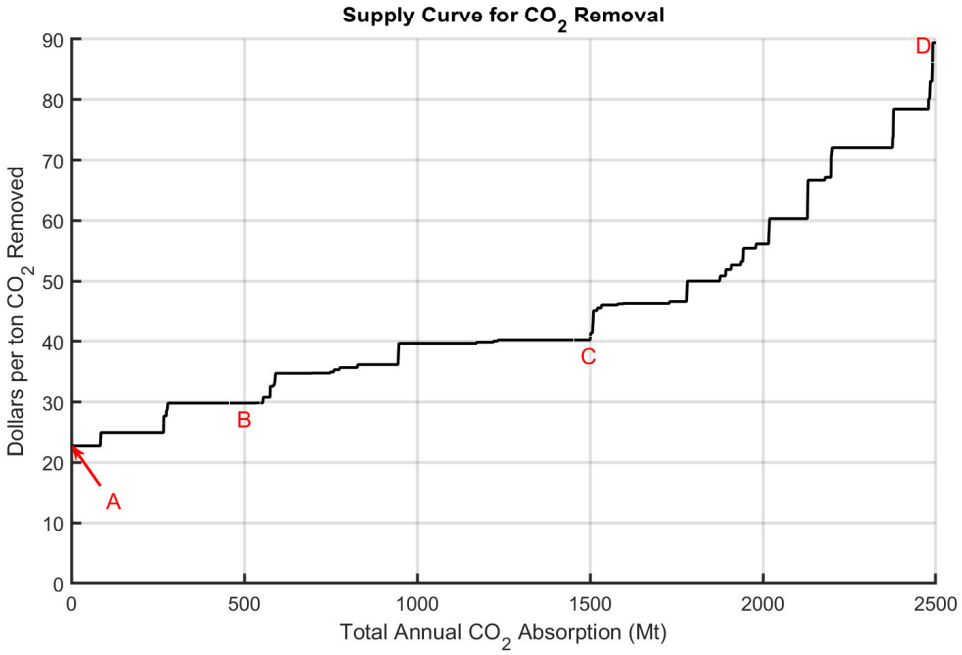


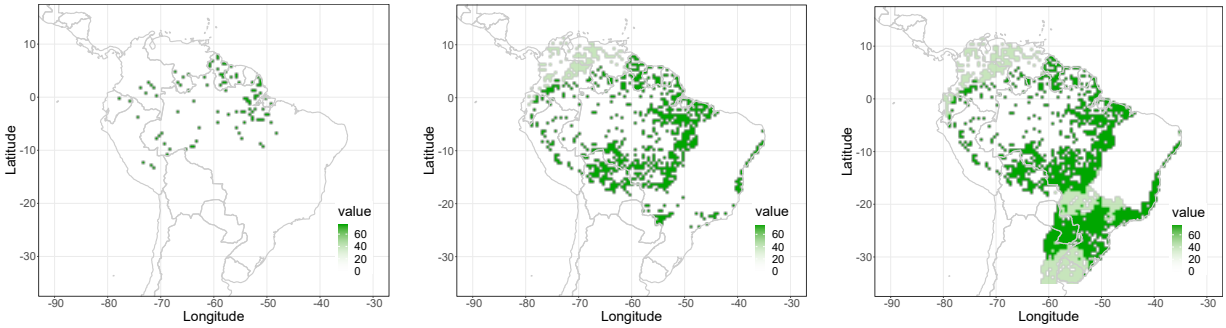
Figure 5: Supply Curve for Forest-Based Atmospheric CO_2 Removal in South America. The curve shows the marginal cost (in 2020 US dollars) of removing one ton of CO_2 as a function of total forest-based CO_2 removal. Each point corresponds to a $0.5° \times 0.5°$ resolution land grid element.

tial), leaving 3,545 – 1,784 = 1,761 candidates for forestation. After completing the above steps for the entire target zone, all 1,761 land grid elements were completely forested (either at 75% or 40% tree cover), and the total forested area reached 228 million hectares (the forestable area shown in Section 4.3), with 137 billion new trees planted.

Figure 5 presents the resulting supply curve. 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. Note that a carbon price of \$20/tCO_2 will have no impact on CO_2 sequestration, a price of \$45/tCO_2 can induce the sequestration of 1.5 Gt of CO_2 per year, and a price of \$90/tCO_2 can induce the sequestration of 2.5 Gt of CO_2 per year.

Point A on the curve applies to a land grid element in the Brazilian Amazon, state of Pará, at location (-57.75° longitude, 1.25° latitude). Here the cost of removing CO_2 from the atmosphere is lowest (\$23 per ton), because of plentiful rainfall and relatively low tree planting and land opportunity costs.[23] Point B is also in the Brazilian Amazon at location (-49.25°, -4.25°). Here, too, 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 Brazilian Amazon at location (-

[23]There are 160 land grid elements with the same \$23 marginal cost spread across 8 Amazon countries. They are all on the short horizontal line that begins at Point A. One degree latitude or longitude near the equator is equivalent to 111 km, so 0.5° in the tropics is approximately 50 km.



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

Figure 6: Land Grids Selected for Forestation and Tree Cover Evolution. Dark green pixels show areas in the Amazon rainforest, Atlantic forest and Gran Chaco region forested at 75% tree cover; light green pixels show savanna and grassland areas forested at 40% tree cover.

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.

Figure 6 shows the first 100, 880 and 1,761 land grid elements selected for forestation. Note from Figure 6a that the first 100 land grid elements are in the northern Amazon, across 8 countries, where land opportunity and tree planting costs are lowest. Figure 6b shows that among the first 880 land grid elements, most are in the Amazon rainforest, some in the Atlantic and Gran Chaco forests (higher land opportunity costs), and a few in northern South American savannas (higher tree planting costs). Figure 6c shows that most areas of savanna and grassland are at the higher end of the supply curve, i.e., these are the most expensive candidates for forestation.

7 Sensitivity of Results

Several assumptions underlie the supply curve in Figure 5: 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.

Three alternative supply curves are shown in Figure 7, where SC1 is the base case curve shown in Figure 5. SC2 is the supply curve that results when the discount rate is lowered from 5% to 2.5%. It is very close to SC1 because lowering the discount rate raises the

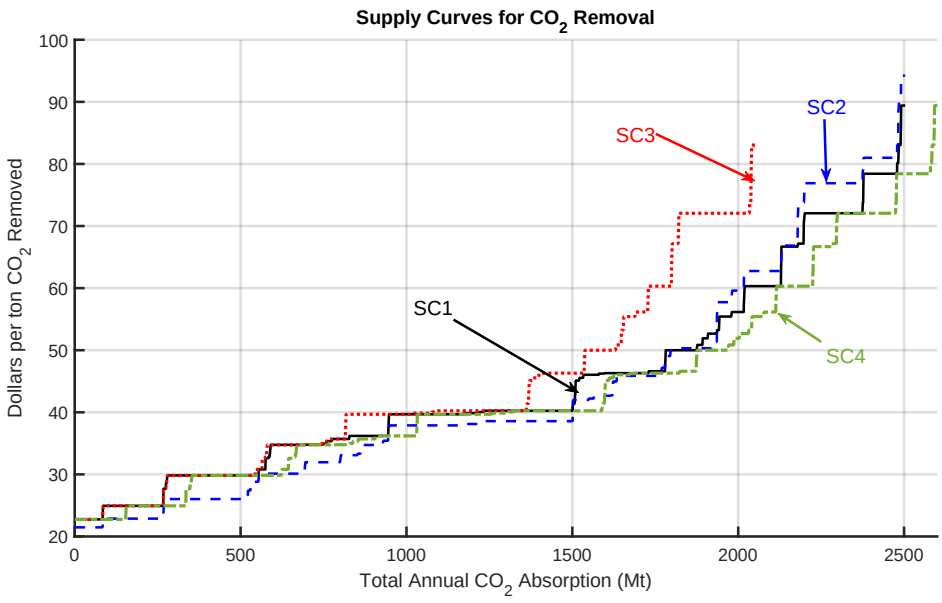


Figure 7: Alternative Supply Curves: SC1 (black) is the base case curve in Figure 5. SC2 (blue) uses a 2.5% discount rate (instead of 5%). SC3 (red) is the supply curve that only includes areas previously forested, and SC4 (green) is the result of including all land grids with any forestation potential (instead of only those with forestation potential above 10%).

present value of the flow of expenditures, but lowers the corresponding annualized costs, leaving annual expenditures nearly unchanged.

To generate SC3, we assumed that only land previously forested during the past 50 years could be reforested now, and excluded land that was never forested. (Some argue that foresting areas that never existed as forests could reduce biodiversity and should be avoided.) As expected, SC3 is well above SC1, and 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 savanna or grassland could reduce biodiversity (we take no stand on this), but excluding such land is expensive. In any case, Figure 6 shows that areas of savanna and grassland are in the higher end of the base case supply curve (SC1), and these areas are the most expensive to forest.

Finally, SC4 includes *all* land grids with forestation potential, instead of only those with potential above 10%. This change lowers the supply curve, but the difference is small, and only noticeable when total annual CO_2 absorption is above 1.7 Gt.[24] (At a total of 2 Gt 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.

[24]The recovery technique "facilitating natural regeneration" is used when tree cover is between 65 and 75%, and "total planting (seeds and seedlings, up to 40%)" is used when tree cover is between 30 and 40%.

8 Conclusions

Forestation is seen as a promising way to remove CO_2 from the atmosphere. But where and how many trees 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. The curve traces out the marginal cost of removing a ton of CO_2 as a function of total CO_2 removal. We work at the level of $0.5^\circ \times 0.5^\circ$ resolution land grid elements, and each point on the curve corresponds to a specific location (grid element), and accounts for land opportunity, tree planting and maintenance costs.

For our base case supply curve, over a billion tons of CO_2 could be removed annually via forestation at a cost below \$45 per ton, and about 2.5 billion tons could be removed at a cost below \$90 per ton. Global annual CO_2 emissions are about 40 Gt, so removing 2.5 Gt would reduce net emissions by about 6 percent. But even at a cost below \$90 per ton (per our base case curve), this reduction is not cheap; a cost of \$90 per ton implies an annual expenditure of \$225 billion. However, if payments are at marginal cost (e.g., \$23 per ton for Point A), the total annual cost of removing 2.5 Gt, found by integrating the area under the supply curve from 0 to 2.5 Gt, would be \$110 billion.

Those costs and CO_2 absorption rates apply to South America. By how much could net CO_2 emissions be reduced worldwide, and at what cost? South America accounts for 21% of the world's forested area (FAO, 2020), 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, reducing net emissions by 25 percent.[25] That would cost about $10 \times 90 = \$900$ billion annually if payments were \$90 per ton, or $4 \times 110 = \$440$ billion (less than 0.5% of world GDP) if payments were at marginal cost.

One could take issue with several aspects of our analysis. First, we did not account for the lifetime of trees. When trees eventually die, the carbon they sequestered is released back into the atmosphere as CO_2. 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 they need to be replanted. Also, in a fully forested area with 75% tree cover, trees that die are replaced by natural regrowth (which is why 70 to 80% is an equilibrium tree cover). Our supply curve is based

[25] Applying our results to the rest of the world is a stretch. But Figure 6 in ForestPlots.net et al. (2021) shows probability distributions of tree density and carbon gain in tropical forests in South America, Africa and Asia. Tree densities in these three continents are similar, and carbon gains (and hence CO_2 removal rates) in South America and Africa are similar but a little lower than in Asia.

on a 50-year horizon, during which most of the trees planted will survive.

We have ignored potential demand shifts and innovations in agriculture and in forestry that might occur over the coming decades. If consumers' food preferences shift from meat to grains and vegetables, so less land is used for livestock and more for temporary and permanent crops, land opportunity costs will change. Also, if large amounts of land are taken out of agricultural production, land opportunity costs will change and may not grow at the assumed rate. 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 from forestation, such as water recycling and erosion control. 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, and we have not accounted for the carbon harvested and stored in wood products, nor the net revenue from the sale of wood products.

Trees of different ages and species have different growth rates and therefore store carbon at different rates over time. As explained in Section 4.3, we are taking the average carbon stock, tree density, and CO_2 absorption rate in tropical moist forests in light of the mix of trees already there. We are not considering the impact of forest management on forest growth and carbon stock accumulation. We leave this for further work.

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.

Finally, how might forestation in South America (and elsewhere) take place? Article 6 of the Paris Agreement (2015) sets out how countries can voluntarily cooperate to reach their climate targets,[26] but there are still issues regarding the validation and verification of forest generated carbon credits. Investigations have revealed that some projects overstate their emissions impact, for instance, by protecting forests that were never in danger of being cut down. But reforestation and afforestation projects that grow trees on degraded land is more straightforward, and passive natural regeneration does not take place in areas with low tree cover. Thus, standards regarding tree cover targets and forestation potential may set out

[26]In particular, Article 6.2 allows countries to exchange mitigation outcomes bilaterally, report their trade, and use them towards their nationally determined contributions (NDCs); and Article 6.4 establishes a new international carbon crediting mechanism for the validation, verification and issuance of carbon credits.

the conditions under which carbon removals from reforestation and afforestation are counted towards a carbon credit. Then, our supply curve can show how many carbon credits are expected to be sold at each carbon price, under each set of assumptions.

Table A1: 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 A2: Input data and corresponding web-based data sources.

Data type	**Source**
Monthly precipitation data worldwide from Mar/2001 to Feb/2019 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/2019 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), ForestPlots.net et al. (2021), Sullivan et al. (2020*b*), 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 (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 A3: Planted, pasture, and potentially forestable areas in the Brazilian states and South American countries covered by the forestation target zone. Values in million hectares.

Geographic unit	**Planted and pasture areas in 2020**						**Potentially forestable area (MM ha)**
	Temp. crops (MM ha (%))		**Perm. crops (MM ha (%))**		**Livestock (MM ha (%))**		
Brazil							
South (S)							
PR	10.741	(80%)	0.121	(1%)	2.626	(19%)	10.892
RS	9.373	(94%)	0.159	(2%)	0.393	(4%)	10.618
SC	1.436	(62%)	0.076	(3%)	0.791	(34%)	3.240
Southeast (SE)							
ES	0.080	(3%)	0.485	(19%)	1.979	(78%)	3.033
MG	4.640	(18%)	1.193	(5%)	19.320	(77%)	9.134
RJ	0.076	(4%)	0.035	(2%)	1.884	(94%)	1.849
SP	8.068	(61%)	0.795	(6%)	4.353	(33%)	12.456
Central-West (CW)							
GO	6.900	(35%)	0.041	(0%)	13.015	(65%)	1.520
MS	5.947	(30%)	0.010	(0%)	13.871	(70%)	13.321
MT	17.150	(45%)	0.039	(0%)	20.935	(55%)	36.552
Northeast (NE)							
AL	0.420	(22%)	0.047	(3%)	1.404	(75%)	0.710
BA	3.229	(16%)	0.907	(5%)	15.932	(79%)	3.048
MA	1.700	(19%)	0.019	(0%)	7.217	(81%)	3.681
PB	0.337	(21%)	0.032	(2%)	1.224	(77%)	0.102
PE	0.704	(20%)	0.092	(3%)	2.770	(78%)	0.573
RN	0.245	(28%)	0.082	(9%)	0.564	(63%)	0.158
SE	0.219	(13%)	0.060	(4%)	1.377	(83%)	0.523
North (N)							
AC	0.070	(3%)	0.012	(1%)	2.192	(96%)	0.814
AM	0.102	(4%)	0.021	(1%)	2.649	(96%)	3.347
AP	0.036	(13%)	0.003	(1%)	0.235	(86%)	2.038
PA	1.364	(6%)	0.652	(3%)	21.477	(91%)	19.569
RO	0.722	(8%)	0.092	(1%)	8.749	(91%)	6.919
RR	0.084	(8%)	0.010	(1%)	1.026	(92%)	2.279
TO	1.547	(20%)	0.005	(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%)	0.251	(1%)	33.000	(91%)	13.724
Colombia	1.850	(4%)	2.505	(6%)	39.504	(90%)	10.006
Ecuador	0.823	(16%)	1.443	(28%)	2.939	(56%)	2.318
French Guiana	0.011	(37%)	0.006	(18%)	0.014	(45%)	0.331
Guyana	0.370	(37%)	0.028	(3%)	0.594	(60%)	3.467
Paraguay	4.262	(26%)	0.090	(1%)	11.985	(73%)	13.332
Peru	0.909	(4%)	2.262	(10%)	18.800	(86%)	3.529
Suriname	0.053	(72%)	0.005	(7%)	0.016	(22%)	1.298
Uruguay	1.827	(13%)	0.039	(0%)	12.000	(87%)	5.223
Venezuela	1.950	(9%)	0.700	(3%)	18.200	(87%)	6.840
Total	132.885	(26%)	13.827	(3%)	366.220	(71%)	227.924

Table A4: Estimates for carbon stock accumulation following reforestation and afforestation

Reference	**Carbon stock accumulation (tC/(ha yr))**	**Notes**
ForestPlots.net et al. (2021)	2.4 (AGB)	Tropical moist forests in South America. Estimate derived from Fig. 6, which shows probability distribution of carbon gains, for average tree age of about 50 years.
Sullivan et al. (2020*b*)	2.4 (AGB)	Tropical forests in South America. Estimate calculated from data package at Sullivan et al. (2020*a*), for average tree age of about 50 years.
Busch et al. (2019)	1.7 (AGB)	Tropical moist forests. Estimate derived from Suppl. Figure 1 for 50 year old trees.
Smith et al. (2016)	3.4 (AGB+BGB)	Mixed types of forests. Forest regrowth over 40 years to maturity.
Griscom et al. (2017)	2.8-5.5 (AGB+BGB)	Maximum mitigation potential in tropical, subtropical and temperate forests. No information about the trees' age.

References

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).

Araujo, Rafael, Francisco Costa, and Marcelo Sant'Anna. forthcoming, 2025. "Efficient Conservation of the Brazilian Amazon: Estimates from a Dynamic Model." *Review of Economic Studies*, 92.

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." *Annual Review of Economics*, 15: 723–754.

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, Jacob J. Bukoski, Susan C. Cook-Patton, Bronson Griscom, David Kaczan, Matthew D. Potts, Yuanyuan Yi, and Jeffrey R. Vincent. 2024. "Cost-Effectiveness of Natural Forest Regeneration and Plantations for Climate Mitigation." *Nature Climate Change*, 14: 996–1002.

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, T. W., H. B. Glick, K.R. Covey, C. Bettigole, D. 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.

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.

Griscom, B.W., Justin Adams, Peter W. Ellis, Richard A. Houghton, Guy Lomax, et al. 2017. "Natural climate solutions." *Proc Natl Acad Sci*, 114(44).

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, et al. 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.

Lubowski, Ruben N., Andrew J. Plantinga, and Robert N. Stavins. 2006. "Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function." *Journal of Environmental Economics and Management*, 51(2): 135–152.

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, et al. 2023. "Integrated global assessment of the natural forest carbon potential." *Nature*, 1–10.

Moulton, Robert J., and Kenneth R. Richards. 1990. "Costs of Sequestering Carbon through Tree Planting and Forest Management in the United States." US Department of Agriculture, Forest Service, GTR WO-58 Report.

Nielsen, Anne Sofie Elburg, Andrew J. Plantinga, and Ralph J. Alig. 2014. "New Cost Estimates for Carbon Sequestration through Afforestation in the United States." Gen. Tech. Rep. PNW-GTR-888. Portland, OR: US Department of Agriculture, Forest Service, Pacific Northwest Research Station. 35 p. 888 Report.

Paris Agreement. 2015. "United Nations Framework Convention on Climate Change." Paris, France.

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.

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

Smith, P., S. Davis, F. Creutzig, S. Fuss, J. Minx, et al. 2016. "Biophysical and economic limits to negative CO_2 emissions." *Nature Climate Change*, 6: 42–50.

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.

Stavins, Robert N. 1999. "The Costs of Carbon Sequestration: A Revealed-Preference Approach." *The American Economic Review*, 89(4): 994–1009.

Sullivan, Martin J. P., Simon L. Lewis, Kofi Affum Baffoe, Carolina Castilho, Flávia Costa, et al. 2020*a*. "Data from Sullivan et al. (2020) Long-term thermal sensitivity of Earth's tropical forests. Science. DOI: 10.1126/science.aaw7578."

Sullivan, M. J. P., S. L. Lewis, K. A. Baffoe, C. Castilho, F. Costa, et al. 2020*b*. "Long-term thermal sensitivity of Earth's tropical forests." *Science*.

Walker, W.S., S.R. Gorelik, S.C. Cook-Patton, A. Baccini, M.K. Farina, K.K. Solvik, P.W. Ellis, J. Sanderman, et al. 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 Comm.*, 8(14681).