Avoiding deforestation: The implications for global markets

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Abstract

The projected growth in population and incomes as implied by various shared socioeconomic pathways is expected to create pressure to convert forestland into farmland. At the same time, the increasingly negative climate impacts are expected to generate further pressure to enhance the terrestrial carbon sink. These goals are potentially incompatible as reversing the deforestation trend by afforesting cropland might result in negative market impacts such as higher food prices, especially in low agricultural productivity/high population growth scenarios. In order to better grasp the interrelationship and the magnitude of harm that might be caused by prioritizing the goal of mitigating deforestation, this analysis connects two respected global economic models: the Global Trade Analysis Project (GTAP) model and the Global Timber Model (GTM). Results from the model suggest that it is possible through fiscal policy to preserve 144.2 million hectares of forestland that otherwise would be converted to agricultural land by 2033. As to the economic price for doing so, the avoided deforestation would in most regions of the world result in less agricultural output and higher market prices. This is estimated to impact the well-being of global consumers by $92.1 billion, which translates to a global average cost of $10.6 per person in 2033.

1 Introduction

In 2020, there were 4.1 billion hectares of forestland globally covering roughly 31.4% of the land (FAO and UNEP 2020). These forests play an important role in maintaining and growing the land-based carbon sink by sequestering about 30% of GHG emissions currently (Roe et al. 2019). This is because of forests proven ability to sequester carbon not only in the stems of trees (Davis, Sohngen, and Lewis 2022) but in their soils as well (Guo et al. 2021). With increasingly negative climate impacts, the pressure to enhance the terrestrial sink is growing, and one of the tools to achieve this is afforestation. As such, there is growing attention being placed globally to afforestation efforts, which is highlighted by the UN's declaration of the years from 2021 through 2030 as the UN Decade of Ecosystem Restoration (Sewell, Esch, and Lowenhardt 2020). Many of the Nationally Determined Contributions (NDCs) countries have submitted, which detail their plans to keep warming under the 2C threshold, also rely to a significant degree on afforestation projects (Roe et al. 2019).

The global gains that can be realized from afforestation, however, are uncertain, with broad estimates of cumulative sequestration ranging from 42 gigatonnes to 700 gigatonnes by the end of the century (Bastin et al. 2019a, 2019b; Humpenöder et al. 2014; Sathaye et al. 2006; Doelman et al. 2020). In addition, the amount of land conversion that would be required also varies greatly, with estimates ranging from 0.3 billion hectares to 2.8 billion hectares (Bastin et al. 2019a, 2019b; Humpenöder et al. 2014; Doelman et al. 2020). In many cases, these results suggest massive losses in the amount of pasture and cropland that would be available. This puts into question the feasibility of attaining these results, as almost 90 percent of deforestation worldwide is undertaken to expand the amount of agricultural land (FAO 2021). There are many reasons for this. For example, as nations develop and disposable incomes rise, consumers often change to more meat-based diets. Population growth is also a driver. Currently, the United Nations' medium variant population projections suggest that between 2023 and 2033 the worlds' population will grow by 8.8 percent, a gain of 707.1 million people (Nations 2023). And where population growth is especially high, which is the case at present throughout most of Africa (2023 to 2033 population growth: 25.0%: 360.6 million), this puts extreme pressure on policymakers to allow greater conversion of forestland into farmland. Still, some research has suggested that substantive gains in the carbon sink (+23.8PgCo2e/yr) can be made without sacrificing agricultural land (Griscoma et al. 2017).

If such efforts are to be made, it is important to understand where to target them, as afforestation is thought to not provide equal benefits in every region. For example, afforestation in boreal zones has been shown to provide the smallest net benefits, as the carbon sequestrations benefits of conifer forests are mitigated by the reduction in albedo in winter (Mykleby, Snyder, and Twine 2017; Li et al. 2015). Coniferous forests have also been shown to increase soil organic carbon less than broadleaf forests (Guo et al. 2021). Conversely, tropical forests have been linked with a strong positive result from afforestation, as the carbon sequestration benefit is complemented by a cooling impact due to changes in both albedo and evapotranspiration, and with temperate forests, the impact of afforestation is also shown to be positive, albeit less strongly so due to a winter warming effect (Li et al. 2015).

South America and Sub-Saharan Africa are thus two regions that show much potential for afforestation. It is estimated that these two regions hold at least 50% of the potential for global gains while regions such as Northern Africa and the Middle East show little promise as forest growth rates are quite low (Doelman et al. 2020). Thus, it is promising that the African Forest Landscape Restoration Initiative (AFR100), which aims to afforest 100 million hectares by 2030, has roughly 70% of its commitments coming from Sub-Saharan nations (AUDA-NEPAD 2023). While many of these nations may be well-suited in biophysical terms for afforestation, there is concern about how long-lasting any investment may be due to proximate zones of political instability. There are other nations that have a big potential for gains from afforestation, but they also face challenges. India, for example, has a great potential to increase its carbon sequestration through afforestation, but its massive population and food security worries limit its ability to consider such actions. The United Nations suggests that India's population will grow slightly less fast than the world average between 2023 and 2033 (+8.5%), but due to its sizable base, that will equate to an increase in population of 120.5 million. Thus, its NDC does not entertain the idea of agricultural land being re-purposed and instead primarily considers targeting wastelands that may not be well suited for afforestation (Amjath-Babu et al. 2019). Moreover, as land-use decisions in one country also tend to have impacts that spillover into many others (Meyfroidt, Rudel, and Lambin 2010; Lambin and Meyfroidt 2011), analysis needs to be conducted at a global scale.

Several notable modeling attempts have been made in this direction. Steinbuks and Hertel (2012) developed their global partial equilibrium FABLE model (Forestry, Agriculture, Biofuels, Land Use, and Environment) to identify the optimal land use choices given the competing demands of meeting greenhouse gas targets and satisfying demand for food, bioenergy, forest products, and ecosystem services. While FABLE is a powerful tool for examining the optimal trajectory of various land uses under specific demand assumptions, it is focused on specific sectors of the economy and neglects general equilibrium and household welfare effects (Steinbuks and Hertel 2012; T. W. Hertel 2017). Other efforts have used the Global Trade Analysis Project (GTAP) computable general equilibrium model to address such questions, but its standard model does not well account for land-use changes. This prompted the creation of the Land Use and Land Cover Database within the GTAP framework, which incorporates forestry remote-sensing products (Baldos 2012). The GTAP Agro-Ecological Zone (GTAP-AEZ) model further strengthened the GTAP model's ability to analyze land use changes, with the use of spatially explicit global land use data and through the incorporation of intra- and inter-regional land and land-based greenhouse emissions heterogeneity (H.-L. Hertel T. W. 2008). While the GTAP-AEZ model benefits from the inclusion of competition among different crops, grazing, and forest-based uses, it has limitations, primarily due to its infrequent updates. The KLUM@GTAP framework integrated the Kleines Land Use Model (KLUM) with an extended yet static version of GTAP called GTAP-EFL to evaluate the impact of climate change on cropland allocation. KLUM is a global agricultural land-use model that connects the economy to global crop allocation to maximize producer returns under specific risk assumptions, and GTAP-EFL separates energy factors from intermediate inputs and incorporates them into capital, while also considering CO2 emissions. KLUM@GTAP substitutes the land allocation mechanism within GTAP-EFL by utilizing regionally aggregated area changes in cropland determined by KLUM to update cropland shares in GTAP-EFL (Ronneberger and Tol 2009).

More recent modeling attempts of land-use change have begun to move away from comparative static analysis though. For example, the dynamic GTAP model, supported by the GTAP-AEZ database, considers land market effects, which were identified as significant in driving results by Stevenson (2013). This model has been utilized to evaluate the impact of crop intensification on land use. It, however, has been critiqued, as global aggregates may mask localized shifts that can have implications for ecologically significant areas (Byerlee 2014). In addition, in the standard GTAP model, it is difficult to model a sector individually. There are 68 market sectors covered in the latest version of the GTAP database. The GTAP model's general equilibrium nature means that all these markets are cleared with market-clearing prices. As the model applies nested CES production functions to all sectors and differentiates them by parameters only, to model one sector, in this case forestry, differently from the rest would require a major redesign of the model. While not impossible, this project will attempt to get around these concerns and assess the impact of various likely land-use scenarios by melding the dynamic GTAP model with the Global Timber Model (GTM), which is a dynamic optimization model that has been specifically designed to analyze the relationship among land rents, forested land cover, and carbon sequestration through forests and thus is better able to examine the impact of afforestation or avoided deforestation on the carbon sink (Sohngen, Mendelsohn, and Sedjo 2001). The latest versions of both models were used. For the GTAP model, this meant using data which has 2017 as its base year. This data was then updated to the base year (2023) using data from the Centre for Prospective Studies and International Information (CEPII) (Fontagné and Santoni 2022) to account for the projected changes in gross domestic product (GDP), population, and productivity for each country in the world. Similar steps were taken to update and recalibrate the GTM model.

2 Connecting the GTAP and GTM models

The rationale for joining these two models is that, by passing outputs back and forth between the models until a dual-state equilibrium is achieved, any limitations of either model should be minimized and more robust results should, therefore, be attained. Establishing a connection between the GTAP model and the GTM model required a two-step process. First, we had to identify the set of variables that are common to both models and their closures. From those, we selected which variables would be determined endogenously by one model and held as exogenous in the other model. In our case, we decided to model the return on land using the GTAP model and feed those results into the GTM model as exogenous. The GTM model then endogenously determined the amount of land available for crop and livestock production, and we fed that back into the GTAP model as an exogenous input. In the second step, we established the connection between the models on the software level. This step required that the GTAP model, which is written in GEMPACK, be able to handle inputs from the GTM model, which is written in GAMS, and submit the outputs back to the GTM model. As GEMPACK and GAMS were developed long before software integration became important or even possible, we settled on the use of R (R Core Team 2021) to create the user functions that executed both models, collected their outputs, and automatically created parameter files.

Once R was able to control the interactions between both models, we were then able to formulate the combined solution as a fairly simple math program that is solved in R:

$$\text{GTAP} : V_1 \rightarrow V_2 \tag{1}$$

$$\text{GTM} : V_2 \rightarrow V_1 \tag{2}$$

$$s.t. V_2 = V_1 \tag{3}$$

where V_1 is a vector of all the variables in both systems, i.e., all variables in GTAP and all variables in GTM. Of import, V_1 includes the land change variables, which are exogenous to the GTAP model. V_1 is then used by the GTAP model (represented by function GTAP) and its outputs are passed to GTM as a vector of variables V_2. This output vector contains the change in rents, which is treated as exogenous in the GTM model. GTM then processes the V_2 variables as inputs and passes its solution back to GTAP as V_1. To solve the system simultaneously, we require that V_1 and V_2 be equal. With several iterations, the system converges to the change in land and land rent that is consistent across the models, i.e., the land change results in the land rent changes that, when entered into the GTM model, result in the same land changes as assumed by the GTAP model.

3 Changes under the baseline projections

To understand the impact of potential regional and global afforestation actions, an important first step was creating a realistic baseline scenario that depicts the likely changes over the decade under study, 2023–2033. Data for this were drawn from CEPII (Fontagné and Santoni 2022). To build our scenario, we use two of their variables that we determined to be key: population and GDP. The CEPII projections do not contain any

Table 1: GDP, population, and agricultural land growth under the baseline scenario (Source: CEPII and GTM)

	Real GDP (%)	Population (%)	Agricultural land (%)
Oceania	52.7	24.0	27.6
China	189.8	0.8	0.0
Japan	20.6	-10.4	-34.9
East Asia	46.0	-2.6	-1.1
SE Asia	138.5	15.0	11.7
South Asia	308.6	17.8	12.8
Canada	41.3	15.2	2.6
United States	38.6	10.6	-0.5
Central America	74.1	18.3	16.7
Brazil	20.8	7.8	13.9
Other Latin America	64.8	15.8	25.8
West/Central Europe	25.4	0.9	4.5
EU II	113.1	8.7	3.1
Russia	41.8	-4.7	4.4
Sub-Saharan Africa	172.9	55.7	17.4
North Africa/Middle East	58.2	27.8	7.8
ROW	44.4	36.8	0.0

information on land use. To build a more complete baseline, we also include the projections on forested land change included in the Global Timber Model (GTM). Using the GTAP model in connection with the GTM model (to assure that the changes in land are consistent between the two models), we calculate the overall change in factor quantity/productivity growth required to achieve the targeted values in 2033. In Table 1, we show the projected population and GDP growth per region. GDP increases for all regions of the world with the largest percentage changes occurring in South Asia (+308.6%), China (+189.8%), and Sub-Saharan Africa (+172.9%). Population also is projected to grow in most regions with the largest changes happening in Sub-Saharan Africa (+55.7%). Japan, Russia, and East Asia are projected to see their populations decline by 10.4%, 4.7%, and 2.6%, respectively. As for the projected change in agricultural land, our baseline prjoections show significant growth in Oceania (+27.6%), Rest of Latin America (+25.8%), Sub-Saharan Africa (+17.4%), Central America (+13.9%), and Brazil (+13.9%). Japan is the only nation that sees a significant decline (-34.9%) in agricultural land, which is likely tied in part to the population decline just described.

Focusing on the absolute area of the forested areas, as generated by the GTM model, we estimate that between 2023 and 2033, 144.2 million hectares (3.6%) of global forests will be converted to agricultural lands with the largest decline expected to happen in Sub-Saharan Africa, which is estimated to lose 39.7 million hectares (7.0%) of its forestland (Table 2). Southeast Asia, Brazil, and the rest of South America also see forestland shrink significantly, with decreases of 22.6 million hectares (9.3%), 19.0 million hectares (3.8%), and 23.5 million hectares (6.7%), respectively. Conversely, the United States is estimated to add 1.3 million

Table 2: Forestland by region in 2023 and estimated change by 2033

	Forestland in 2023	Forestland in 2033	Δ (Mha)	Δ (%)
United States	248.4	249.7	1.3	0.5
China	164.6	164.8	0.1	0.1
Brazil	498.2	479.2	-19.0	-3.8
Canada	412.8	407.9	-5.0	-1.2
Russia	838.1	828.6	-9.5	-1.1
West/Central Europe	186.7	175.5	-11.1	-6.0
EU II	40.1	36.1	-4.1	-10.1
South Asia	47.8	42.5	-5.3	-11.0
Central America	94.6	91.2	-3.4	-3.6
Other Latin America	348.5	325.0	-23.5	-6.7
Sub-Saharan Africa	564.6	525.0	-39.7	-7.0
SE Asia	243.9	221.3	-22.6	-9.3
Oceania	199.2	196.1	-3.1	-1.5
Japan	23.7	26.9	3.2	13.7
North Africa/Middle East	33.8	30.9	-2.9	-8.5
East Asia	14.5	14.6	0.1	0.7
Total	3959.5	3815.3	-144.2	-3.6

[a] Southeast Asia includes Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, Timor-Leste, and Vietnam.

[b] Oceania includes Australia, Cook Islands, Fiji, French Polynesia, Kiribati, Marshall Islands, Micronesia, Nauru, New Caledonia, New Zealand, Palau, Papua New Guinea, Samoa (Western Samoa), Solomon Islands, Tonga, Tuvalu, and Vanuatu.

[c] Rest of South America includes Argentina, Bolivia, Czech Republic, Chile, Colombia, Ecuador, the Falkland Islands, French Guiana, Guyana, Paraguay, Peru, South Georgia, the South Sandwich Islands, Suriname, Uruguay, and Venezuela.

[d] Western & Central Europe includes Austria, Belgium, Bulgaria, Croatia, Denmark, Estonia, Finland, France, Hungary, Iceland, Italy, Ireland, Germany, Greece, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Monaco, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and the United Kingdom.

[e] Other Europe includes Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Georgia, Kosovo Kazakhstan, Kyrgyzstan, Moldova, Tajikistan, and Ukraine.

hectares (0.5%) to its forestland.

4 Modeling the impact of possible measures to mitigate deforestation/promote afforestation

Against the backdrop of the baseline scenario, we turn to the question of what policy could prevent global deforestation in the period of 2023–2033. Because the area of forestland is mostly determined by the relative returns of land in agriculture and forestry, in our policy scenario we modify the return to land in agriculture by applying a uniform global tax on the use of land in the production of agricultural output. Solving the two models together shows that it would require a tax of roughly 70 percent to be assessed on the use of land for the deforestation rate to fall globally to zero. The economic impact of such a policy measure would not

Table 3: Changes in key variables relative to baseline under a uniform land tax of 70 %

	Real GDP (%)	Agr. land (%)	Agr. prices (%)	Agr. output (%)
Oceania	-0.1	-23.9	2.8	-2.5
China	0.0	-2.5	1.1	0.0
Japan	-0.3	-60.8	7.8	-6.3
East Asia	-0.2	-15.0	5.4	-5.0
SE Asia	-0.3	-9.0	2.9	-1.7
South Asia	-0.3	-7.9	3.0	-1.0
Canada	0.0	-7.9	0.7	1.9
United States	0.0	-2.1	0.7	1.0
Central America	-0.2	-15.6	2.7	-2.0
Brazil	-0.1	-8.6	1.3	0.6
Other Latin America	-0.4	-23.1	3.8	-3.2
West/Central Europe	0.0	-6.1	1.0	0.7
EU II	-0.1	-3.2	1.3	0.3
Russia	-0.1	-9.3	1.1	0.3
Sub-Saharan Africa	-0.2	-4.0	1.4	-0.2
North Africa/Middle East	-0.1	-10.2	2.0	-0.7
ROW	0.0	0.0	0.8	0.9

be limited to the cost of the tax, it would also impact food production and its prices. For example, with this policy in place, most regions of the world would see significant declines in the amount of agricultural land in 2033 relative to the baseline scenario where land conversion was not taxed. For the United States, there would be 2.1 percent less agricultural land (Table 3). Larger decreases would happen in other major agricultural production regions such as China (-2.5 percent), South Asia (-7.9 percent), Brazil (-8.6 percent), and Russia (-9.3 percent).

These reductions in the amount of agricultural land would then impact the quantity of agricultural goods that could be produced. For example, the 15.0 percent decrease in agricultural land in East Asia and the 9.0 percent decrease in agricultural land in Southeast Asia would result in large declines in percentage terms in agricultural production of 5.0 percent and 1.7 percent, respectively. Surprisingly, Brazil and the United States, despite their decreases in available agricultural land compared to the baseline 2033 scenario, are estimated to see increased agricultural output of 0.6 percent and 1.0 percent, respectively. This may be tied to the sharp declines in other regions prompting greater intensity of production to satisfy external demand.

When we examine how this impacts exports of agricultural goods, we find that exports from Japan and the United States grow the most, increasing 8.8 percent and 3.5 percent, respectively (Table 4). The regions where agricultural exports drop most significantly are East Asia, South Asia, Southeast Asia, and Central America who see decreases of 14.5 percent, 5.9 percent, 5.1 percent, and 5.0 percent, respectively.

Overall, this tax policy, which results in zero net deforestation globally, has a rather significant negative

Table 4: Percentage change in the amount of forested land in 2033 with deforestation mitigation policy in place (Source: Authors' calculations)

	Forestland in 2023	Forestland in 2033	Δ (Mha)	Δ (%)
United States	248.4	254.8	6.4	2.6
China	164.6	174.8	10.2	6.2
Brazil	498.2	492.2	-6.0	-1.2
Canada	412.8	423.2	10.4	2.5
Russia	838.1	849.7	11.6	1.4
West/Central Europe	186.7	191.1	4.5	2.4
EU II	40.1	40.3	0.2	0.4
South Asia	47.8	46.2	-1.6	-3.3
Central America	94.6	94.9	0.3	0.3
Other Latin America	348.5	348.1	-0.3	-0.1
Sub-Saharan Africa	564.6	535.6	-29.0	-5.1
SE Asia	243.9	240.5	-3.5	-1.4
Oceania	199.2	199.0	-0.1	-0.1
Japan	23.7	23.5	-0.1	-0.6
North Africa/Middle East	33.8	34.9	1.1	3.4
East Asia	14.5	15.8	1.3	9.3
Total	3959.5	3964.9	5.3	0.1

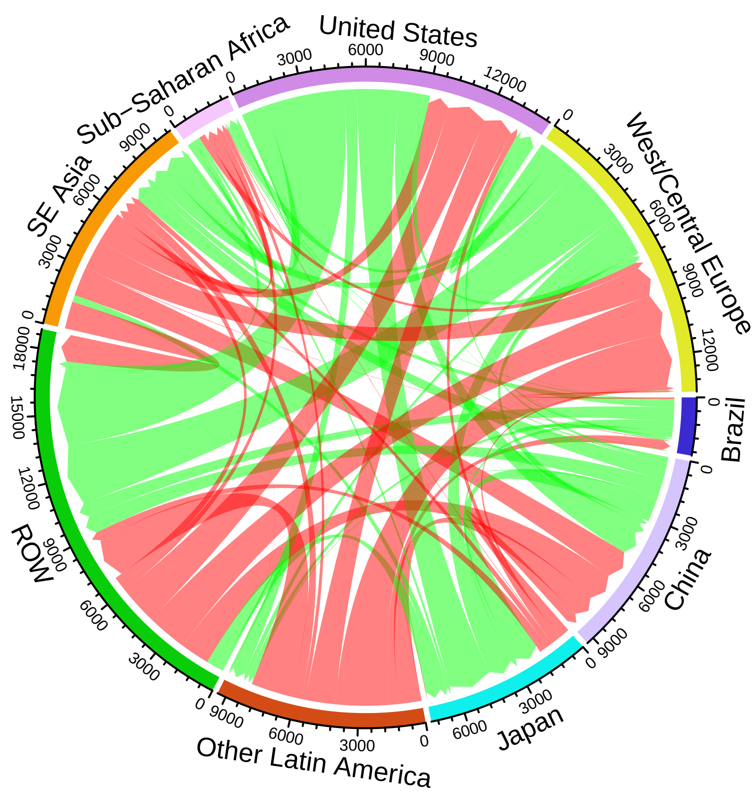

Figure 1: Changes in ag trade volumes (red arrows denote reductions, green arrows denote increases)

Table 5: Change in consumer well-being in 2033, by region, in billions dollars, with deforestation mitigation policy in place

	Baseline (B$)	Scenario (B$)	Δ (B$)
Oceania	863.7	861.8	-1.9
China	23,275.9	23,260.0	-15.9
Japan	1,052.6	1,036.1	-16.5
East Asia	1,168.4	1,163.0	-5.4
SE Asia	3,886.2	3,872.4	-13.9
South Asia	9,493.4	9,465.6	-27.8
Canada	713.1	713.5	0.4
United States	7,497.2	7,496.4	-0.9
Central America	1,241.2	1,236.4	-4.8
Brazil	423.0	422.4	-0.6
Other Latin America	1,242.6	1,233.2	-9.4
West/Central Europe	5,126.7	5,118.8	-8.0
EU II	839.3	838.7	-0.6
Russia	706.2	704.9	-1.3
Sub-Saharan Africa	2,766.7	2,758.8	-7.8
North Africa/Middle East	1,715.9	1,710.7	-5.3
ROW	13.9	13.9	0.0
Total	62,026.3	61,906.6	-119.7

economic impact on all regions except Japan and Canada who see an increase in consumer well-being of \$977.1 million and \$166.9 million, respectively (Table 5). Consumer well-being is a measurement of equivalent variation and here measures the benefit/harm consumers experience in terms of income as a result of the policy changes. The United States, along with 10 other regions, see well-being drop by more than \$1 billion. The most negatively impacted regions are South Asia (-\$28.0 billion), China (-\$14.5 billion), and Southeast Asia (-\$13.6 billion). In total, this tax-driven policy is estimated to decrease global consumer well-being in 2033 by \$92.1 billion relative to the scenario where no tax on forestland conversion was in place.

Much of this loss in well-being may be the result of higher prices. Japan is the only nation that sees any price impacts that are beneficial for consumers resulting from this policy, with the price of agricultural goods decreasing 0.3 percent (Table 6). All other regions, for both agricultural and non-agricultural products, see prices rise between 0.3 and 5.1 percent.

5 Discussion

This analysis shows that, at an estimated tax rate of 70.3 percent of the value of each hectare of land that is converted to agricultural land, global net deforestation would drop to roughly zero by 2033, preserving 144.2 million hectares of forestland that otherwise would have been converted to agricultural land. In the United States, as USDA-NASS (Land Values 2022 Summary (August 2022)) valued the average hectare of farmland

Table 6: Percent change in market prices for agricultural goods in 2033, with deforestation mitigation policy in place, relative to baseline

	Ag prices
Oceania	2.8
China	1.1
Japan	7.8
East Asia	5.4
SE Asia	2.9
South Asia	3.0
Canada	0.7
United States	0.7
Central America	2.7
Brazil	1.3
Other Latin America	3.8
West/Central Europe	1.0
EU II	1.3
Russia	1.1
Sub-Saharan Africa	1.4
North Africa/Middle East	2.0
ROW	0.8

in 2022 at $1,537.8, the tax would equate to $1,081.1/hectare. In Brazil, CEIC valued the average price of Brazilian land at roughly 2,500 Brazilian Reals, which would put the tax at roughly $82.2 per hectare. The economic price of this would likely be transfered to consumers through less agricultural output and higher market prices. Overall, such an action is estimated to reduce consumer well-being by $92.1 billion or $10.6 per every person in 2033. Governments might be wary of farmer discontent were they to take such fiscal actions and thus might be reluctant to impose such taxes on them. Thus, policymakers who wish to see deforestation stopped might have to resort to import tariffs on products produced on land converted from forestland for agricultural use.

We also show the utility of joining two major economic models. GTAP has long been valued for its ability to provide robust information on global trade flows and prices, and GTM has proven its utility in understanding the impact of forestry decisions on the carbon sink and land rents. By combining these models through the use of R and allowing the models to pass inputs and outputs back and forth iteratively, the benefits of both models have been maintained and their weaknesses greatly minimized. This advance holds great promise for advancement on a variety of fronts for researchers and policymakers interested in climate change, agricultural trade, and their inter-dependencies.

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