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Insights into the challenges posed by climate change and land competition to Brazil's Midwest pulpwood market

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I investigated the effect of climate change in one of the few expanding markets in the world in Brazil. In the last decades the demand for pulpwood increased from zero to 11 million tons, leading to an expansion of 700 thousand hectares of Eucalyptus plantation. In 2024, a new mill will start operating increasing the consumption of wood fiber by 8.2 million tons (+49%). I used mathematical programming to investigate how different scenarios of productivity and land will affect the market. My results showed that around 946,000 hectares (+124%) of additional timberland will be necessary in the upcoming decades. The first impact will be an increase in the production cost of around US$550 million (+16.4%) in 25 years. If the rate of land cover change remains constant, the broad development of the local market would be constrained, discouraging future investments, and reducing potential positive externalities in the region.

DEDICATION

I dedicate this work to Catarina, my niece.

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Introduction

Climate disturbances have triggered numerous environmental and social-economic damages worldwide. Losses associated with rising sea levels, agriculture, tourism, and forestry drive a vast increase on expenditures related to climate change mitigation and adaptation (Bosello et al., 2012). For example, the United States (US) government will spend up to 92% of its Gross Domestic Product (GDP) on mitigating climate change effects by 2100, while the European Union and Latin America might experience shares of 125.9% and 192.1% of their respective GDPs (Estrada & Botzen, 2021).

In the forest sector, the impact of climate change on forest production has mixed results. On one hand, forest resources could face losses in productivity and biodiversity, and increase the incidence of pests and diseases (Almeida et al., 2010; Battles et al., 2008; Elli et al., 2020; Ghini et al., 2011; Palma et al., 2021; Tang et al., 2021). In Californian forests, for example, the average productivity for mixed conifer could decrease 25% by 2100 (Battles et al., 2008). On the other hand, some species might experience higher growth rates. In the southern US, loblolly pine (*Pinus taeda*) forests, for instance, could increase productivity up to around 40% by 2030 (Susaeta et al. 2016).

In Brazil, the expected yield loss driven by climate change for *Eucalyptus* plantations ranges between 5% and 40% (Almeida et al., 2010; Elli et al., 2020; Palma et al., 2021). These losses could cause a tremendous economic impact in the Brazilian forest industry. Eucalyptus plantations cover around 77% of the total Brazilian timberland area, followed by pine forests (19%) and other species (4%) (IBGE, 2021). In 2021, the Brazilian forest industry output was around US$17.1 billion, 7.3% of the total industrial production; and employed more than 550 thousand people directly and supported 1.59 million indirectly (IBA, 2022). According to the Food and Agriculture Organization (FAO, 2021a), Brazil is the largest exporter of wood pulp (16.4 million tons) and the second largest producer (23.1 million tons), behind only the United States (49.7 million tons produced in 2021).

Also, there is no region in the world with such an aggressive greenfield investment over the last decade like the ones observed in Brazil. Between 2000 and 2017, the Brazilian planted forest area grew around 49%; the largest compared to other countries in South America (47%), and worldwide (31%) (UN environment programme, 2023). Only in the state of Mato Grosso do Sul, for example, the area of planted forest expanded 2.7 times, from around 299,000 hectares in 2010 to 806,000 hectares in 2020 (Figure 1). In Figure 1, I present the geographic distribution and trend over the last decades. In Figure 1A, it is possible to observe the distribution of Brazil's wood baskets, where the South and Midwest (highlighted) are the country's most important ones. Figure 1B shows the pulpwood forest coverage trend index over the last decades for each Brazilian region.

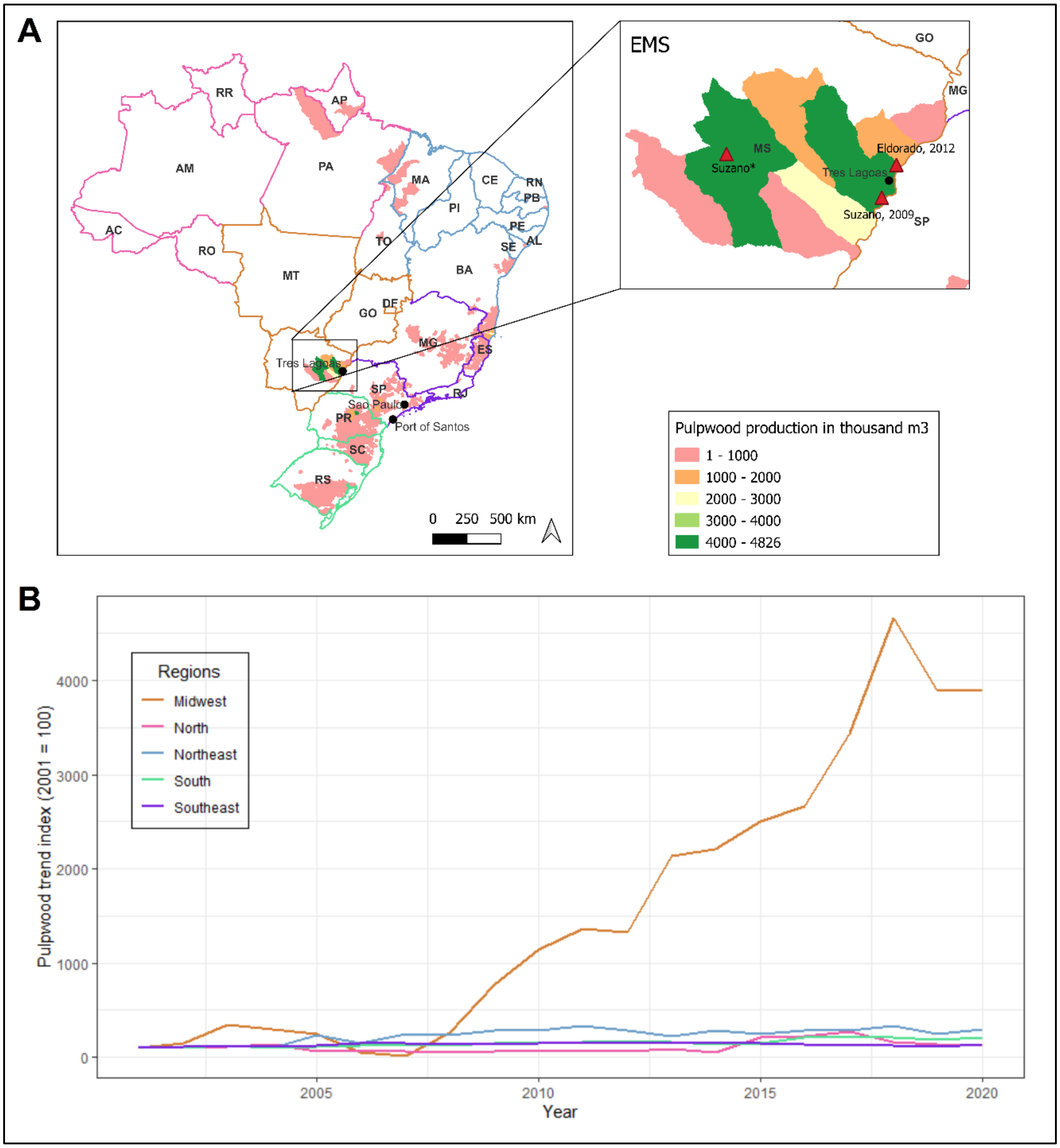

Figure 1 A) Geographic distribution of the production of pulpwood in Brazil in 2020 B) Pulpwood coverage trend by Brazil's regions from 2001 to 2020

Source: IBGE (2021)

The industrial expansion of the forest sector in the state of Mato Grosso do Sul started in the municipality of Três Lagoas in 2009 (Figure 1) when Suzano, a pulp and paper industry giant, installed a pulp mill that consumes 10.5 million m^3 per year. In 2012, an investment group installed the Eldorado pulp mill (consuming an additional 6.3 million m^3 per year) 76.3 km from Suzano's mill. Both mills have boosted land conversion to planted forest, turning Mato Grosso do Sul into one of the most prominent wood baskets in the country. A third mill (also owned by Suzano) is expected to start operating by the end of 2024, with a demand of 8.2 million m^3 per year (Suzano S.A., 2021a). In addition, forest investors expect a fourth mill in the upcoming years with a capacity of around[1] 5 million m^3 (Valor International, 2022), increasing the local demand for pulpwood to 28 million m^3 per year. This expansion is uncommon in developing countries, or any other place. In the US, for example, a new pulp mill has not been announced since the 1980s. Finnpulp, a Finnish company in Europe, abandoned a recent investment of US$1.7 billion in the Kuopio region, Eastern Finland (EUWID PULP AND PAPER, 2022).

Greenfield investments in the pulp and paper industry involve a significant capital investment and require a meticulous analysis of various variables, including labor, inputs, infrastructure, and taxes. Of these, wood fiber shares the largest cost, being essential to ensure healthy financial returns in both the short and long term (Hussain & Bernard, 2017). Ideally, the wood procurement division in these pulp mills must guarantee a constant flow of timber under competitive costs to avoid any loss in capital invested and compete in the paper and cellulose market. Thus, uncertainty related to timber production could disrupt this supply chain and put pulp mill operations at risk. My study investigates the impacts of climate change on Brazil's Midwest, specifically in the state of Mato Grosso do Sul. Given the expansion dynamics mentioned above, this region is a perfect opportunity to understand the expansion of greenfield investments in the pulp and paper industry.

[1] I assumed a Eucalyptus roundwood density of 500kg/m3. To calculate the density, I took the average of different Eucalyptus species commonly planted in Brazil from previous studies (Magaton et al., 2009; Mendes et al., 1980).

I built a Mixed-Integer Problem (MIP) to account for new players entering the wood pulp market. I analyzed multiple scenarios involving uncertainties in timber production and land use change to answer the following questions: (1) will the supply of pulpwood be enough to support the current and future demand in the market? (2) what will be the impact on the industry's returns if forest productivity changes due to climate change? (3) where would the new plantation grow? and (4) where will the new mill be built?

My results indicate that the market is more exposed to negative variations in productivity. Extreme negative scenarios can decrease the Net Present Value (NPV) by 3.4%, while the best positive scenario would increase the NPV by no more than 0.4%. Transportation costs have the highest impact on financial returns, followed by land conversion and management costs.

This chapter has the following structure: (1) first, I present the literature review, going through previous works on harvest schedule, facility location, and transportation costs modeling, and the climate change impact on the forestry sector; (2) the following section contains my methodological approach (heuristics proposed, site division, land cover analysis, model description, and solution), and data description; (3) I then discuss the results and the implications to the decision maker; (4) last, I conclude by suggesting topics for future research based on my findings.

Literature Review

My study contributes to three main topics in forest resource economics: (1) impact of climate change on forest production, (2) industrial expansion, and (3) harvest schedule. In this section I briefly review the current literature of each of these items, how their finding and/or approach founded my research, and how I expand their work.

Impact of Climate Change on Forest Production

The impact of climate change on forest production is a complex and multifaceted issue. Climate change is expected to lead to warmer temperatures and longer growing seasons, which could potentially increase tree growth (Elli et al., 2020). These positive effects might be offset by more extreme weather events, such as droughts and floods, reducing wood fiber production (Almeida et al., 2010).

The consequences of climate change in forest plantations are not equal among regions. In Portugal's eucalyptus forests, for instance, lower temperatures and higher precipitation could increase trees' production by around 20%; on other hand, higher temperature and lower precipitation, could decrease productivity by around 27% (Garcia-Gonzalo et al., 2016). Elli et al. (2020)[2] show that in Brazil, eucalyptus plantations could gain up to 15% in the region of Minas Gerais or lose up to 12% in the region of Mato Grosso in the following decades under a scenario with higher temperature (RCP8.5). In Brazil, Favero et al. (2022) found that planted area might increase, while native forest decreases, especially in the Amazon, under both scenarios RCP2.6 and RCP8.5, resulting in a loss of global market share and a reduction of up to 25% in the

[2] The authors used two climate scenarios (RCP2.6 and RCP8.5). The acronym RCP stands for Representative Concentration Pathways, and each of them assumes different levels of greenhouse gases emissions. The RCP2.6, for example, is a low-emission scenario that assumes a 2.6 watts per square meter radiative forcing by 2100, while the RCP8.5 is a high-emission scenario assuming an 8.5 watts per square meter radiative forcing by 2100.

producer's surplus. The authors found that forestry variables in Brazil and Latin America are more sensitive to socio-economic (e.g., timber prices) fluctuations than climate ones.

These studies highlight the uncertainty created by changes in the current climate pattern and emphasize the importance of including climate variables in strategic planning and modeling to prevent and mitigate potential financial losses. Harvest Schedule (HS) models play a vital role in sustainable forest management and planning. By incorporating the biological dynamics of forests and accounting for climate variables, these models enable the identification of optimal harvest regimes.

Timber Harvest Scheduling (HS)

HS models can tackle a variety of forest management problems, such as wildfires, carbon sequestration, wind damage, and compare different Ecosystem Services (ES) in optimal timber harvesting regimes (Daniel et al., 2017; Díaz-Balteiro & Romero, 2003; Kolo et al., 2020; Neilson et al., 2006; Potterf et al., 2022; Reed & Errico, 1986). Forest scientists have also used HS models to investigate the impact of climate change on forest composition and inventory (e.g., Creutzburg et al., 2016; Daniel et al., 2017; Locher et al., 2012; Palma et al., 2015).

Palma et al. (2015), for instance, studied adaptive management regimes as a response to climate change in cork oak (*Quercus suber L.*) stands in Portugal. They found that higher temperatures could postpone harvesting operations due to lower productivity. Similarly, Daniel et al. (2017), assessed the impacts of climate change on the boreal forest in Canada; their results indicate drier conditions and warmer winters would lead to more frequent and severe wildfires, resulting in a 23% reduction in the harvestable volume.

Often HS models incorporate transportation costs and capture the spatial and temporal dynamics in strategic planning (Bellavenutte et al., 2020; Naderializadeh & Crowe, 2020; Restrepo et al., 2022; Troncoso & Garrido, 2005). As the scope and refinement of applied studies increase, the inclusion of spatial variables significantly amplifies the magnitude and size of the problem. To enhance both solution quality and efficiency, many studies have directed their attention toward developing new formulations and solution methods. For instance, Naderializadeh & Crowe (2020) developed an integrated HS model that minimized transportation costs and optimized circuit selection. Their model was able to reduce the computing time and the root Linear Programming (LP) gap compared to previous methodologies. Similarly, Bellavenutte et al. (2020) proposed a strategy of partitioning large-scale problems into smaller subsets, which were subsequently merged into an MIP framework. Similarly, Restrepo et al. (2022) introduced an approach based on a non-centralized chi-square distribution to validate and compare solutions for large-scale scenarios.

Different authors also assessed the impact of transportation planning into timber trade restrictions, greenhouse gases emission, forestry policy evaluations, and log bucking operations (Arce et al., 2002; Dems et al., 2017; Hieu & Harrison, 2011; Oberscheider et al., 2013; Stennes & Wilson, 2005).

While previous studies have made valuable contributions to decision-making under productivity uncertainties, they oversimplified the demand assumption by supposing that existing mills would expand their capacities. In reality, significant increases in wood fiber consumption are often related to the installation of new mills. Therefore, optimization models could be useful not only for decision-makers allocating forest resources, but also for mill investors seeking to determine the optimal time and location to install their facility. Facility location models can provide more comprehensive and realistic insights for both decision-makers and investors by incorporating a dynamic expansion of demand for wood fiber.

Industrial Expansion Modelling

Facility Location (FL) models assist decision makers to have a fair estimation of the optimal location of a new facility, e.g., a pulp mill. They normally consider several variables and parameters, such as distance to warehouses, tax benefits, labor market, consumer market development, household income, and access to water (Ozgen & Gulsun, 2014).

In forestry, these models are used to find optimal harvestable units, the most efficient road network, and potential mills sites (Aksoy et al., 2011; Chan et al., 2009; Contreras & Chung, 2007; Philippart et al., 2012; Troncoso & Garrido, 2005; Vahid, 2011; Venn & McGavin, 2021).

Troncoso and Garrido (2005) studied suitable locations for expanding current mills and expanding new ones in Chile. The authors combined FL and HS formulations by considering variables such as the distance to ports, distance to forest units, and costs to operate a mill.

In Alabama, FL models were applied to identify the most profitable destination sites for wood biomass (Aksoy et al., 2011). Similar limitations apply to a study conducted in Cameroon, where Philippart et al. (2012) focused solely on the costs of hauling, skidding, and the value of leaving designated trees uncut, without considering a time horizon. A recent application of an FL model in Australia optimized the gross financial margin of hardwood sawmills (Venn & McGavin, 2021). Similar to Aksoy et al. (2011), the authors majorly considered logistic costs when formulating their model; despite identifying a relatively optimal site, their optimization approach was static, which missed future changes in demand and supply.

Contribution to Current Literature

The objective of this study is to investigate the effect of alteration in productivity due to climate change in an expanding pulp and paper industry market located in the Midwest of Brazil. I contributed to the current literature in the following ways: (1) I investigate an expanding forestry market, where the capacity of timber supply for the current mills is uncertain in one of the most attractive regions in the world for forest investment. The Midwest of Brazil gathers all conditions to the expansion of not only the pulp and paper industry, but for the entire forest sector. (2) I link the FL with HS problems in a single model; contrary to previous approaches, I use multiple periods, and allow a new pulp mill to enter the market at the optimal spatial and temporal location. This feature provides a more realistic outcome for decision makers in the pulp and paper industry. And, last (3) I use multiple climate change and land cover change scenarios from historical data and current literature. By combining market expansion, climate change, and land availability, agents can consider a range of possibilities and equip themselves to anticipate fluctuations in timber resources and changes in the market.

Methods and Data

In this section I describe the study area and parameters used in this study. My research area surrounds the East region of Mato Grosso do Sul (EMS) in Brazil, from herein referred as EMS (Figure 2). The EMS region accounts for almost 20% of the total wood pulp produced in Brazil (IBGE, 2021), and is located 668 km from the São Paulo state capital, and 755 km from the Port of Santos (see Figure 2B), the second largest port in South America and the Caribbean (ECLAC, 2019). The land use is somewhat diverse, but with higher occurrence of pasture; there are currently 806,000 ha of planted forest, 4,728,301 ha of pasture, and 901,901 ha of agriculture (Souza et al., 2020).

Figure 2 is a map of Brazil's Midwest pulpwood market. In Figure 2A, I present, in light orange, the area covered by pasture, and in light green, the area covered by planted forest. In the same figure, is shown the real location of the operating mills as well as EMS's neighboring states. In Figure 2B, is presented the locations of Três Lagoas, São Paulo, and the Port of Santos, as well as the São Paulo's railway network. Lastly, Figure 2C is a zoom-in of the EMS market, showing the land organization among planted forests, pasture, and mill.

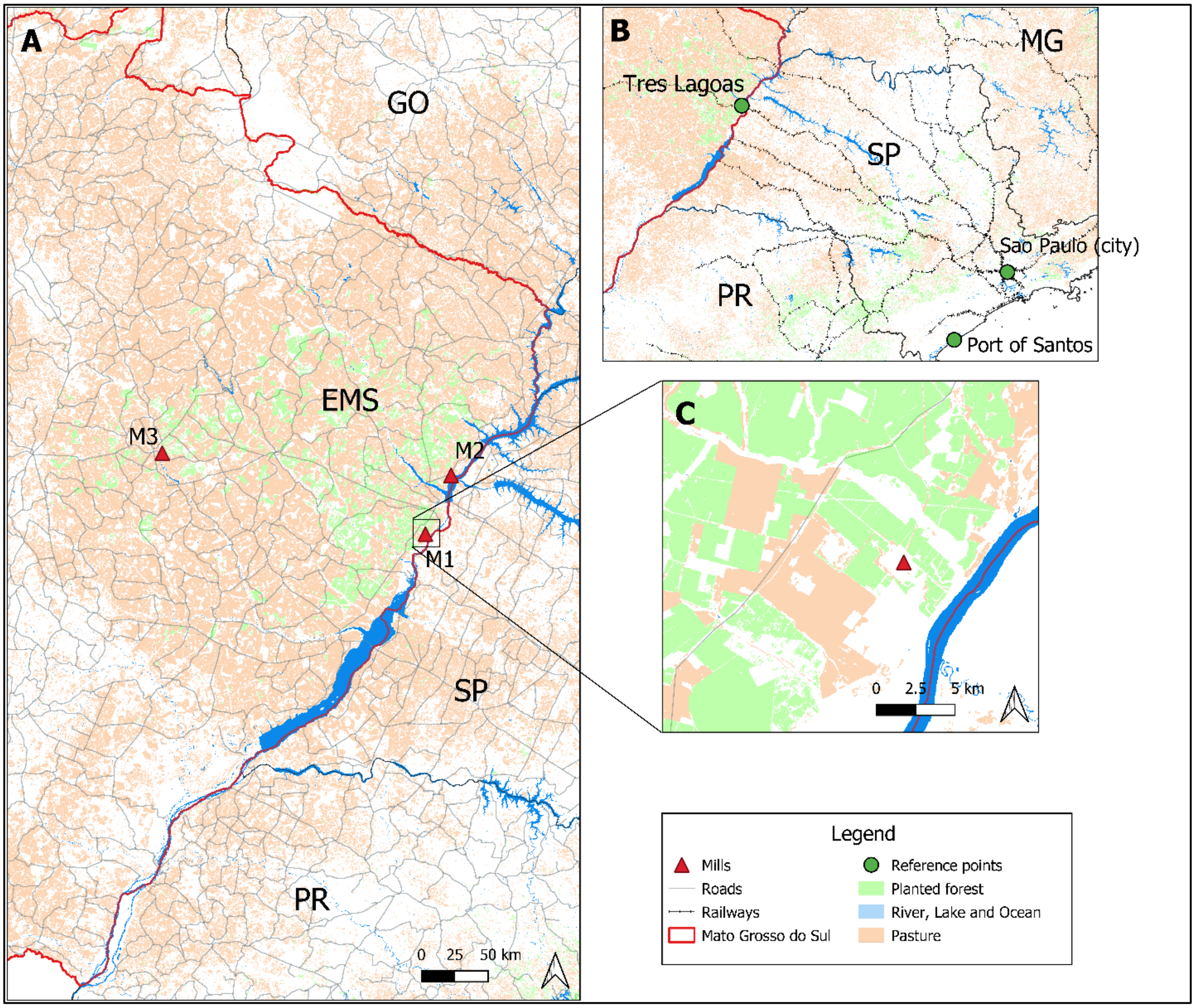

Figure 2 East region of Mato Grosso do Sul (EMS). (A) the map of Brazil and the location of the EMS, (B) The EMS and the location of Suzano – Três Lagoas (M1), Eldorado – Três Lagoas (M2) and Suzano – Ribas do Rio Pardo (M3). (C) An example of the spatial distribution of the current forest plantations and pasture. The state acronyms are MS = Mato Grosso do Sul, PR = Paraná, SP = São Paulo, and MG = Minas Gerais.

Sources: MapBiomas (2023)

Demand

Two pulp mills operate currently in the region: (1) Suzano (M1) and (2) Eldorado (M2), with a demand for pulpwood of 10.5 and 6.3 million m^3 per year, respectively (Figure 2A). Suzano invested[3] around US$2.8 billion to install a third mill (M3), which will start operating in 2024 and increase the demand for pulpwood by 8.2 million m^3 per year (Suzano S.A., 2021a). A fourth mill will be installed in 2028 with a demand of 2.5 m^3 per year (Valor International, 2022).

Regional Grid

I aggregated the timber supply and demand to cells of 10x10 km to facilitate the computational process and interpretation of results (Figure 3). Figure 3A presents the location of the current operating mills (M1 and M2) and the future one (M3). The grid cells in blue represent locations where new mills can be installed; they are all located near a river, given the nature of wood pulp production. Figure 3B shows the current planted forests in green and pasture in light orange. Each grid cell with planted forest has the timber volume and area by age class.

The distances between these markets were collected from the road distance data in the OpenStreetMap platform. To calculate the distance between the supply and demand grids, I assumed that they are located in the grid centroid. Although I recognize this setup might oversimplify the model, it does facilitate data collection and finding the optimal solution. Altogether, there are 1,026 grids of possible suppliers, 356 grid candidates for a new mill, and 3 demanders before the third year, 3 demanders between the third and seventh year, and 4 after the seventh period. Among the suppliers, 434 already have some level of timber inventory that can be expanded; the remaining 592 nodes are potential supply centers in which pasture could be converted to timberland, if optimal.

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[3] See <https://www.suzano.com.br/en/suzano-to-invest-2-8-billion-in-the-first-fossil-free-pulp-plant-in-brazil/>.

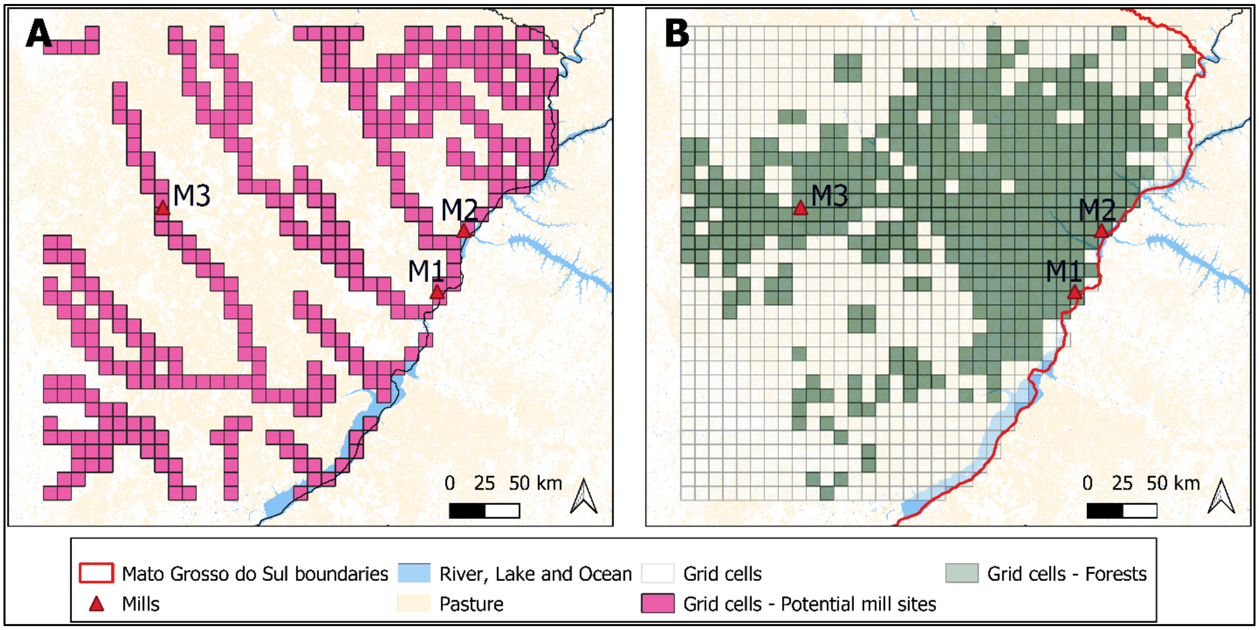

Figure 3 A) Location of the current pulp mills and possible future locations of a new pulp mill (pink), B) Location of the current planted forest, pasture, and current mills.

Inventory and Pulpwood Production

I gathered information about initial inventory volume and yield curves in partnership with the consulting company GePlant[4], based in Brazil; I used the database from MapBiomas (MapBiomas, 2023a) as the landcover reference. Figure 4A shows the age distribution of the planted forest, ranging from three to eleven years old and averaging around six years old. Figure 4B shows the average Eucalyptus yield curves with its underlying standard deviation and was formulated using 3PG models by GePlant (GePlant, 2022). Each grid has its own yield curve of projected pulpwood volume from 3- to 25-year-old forests.

[4] https://geplant.com.br/

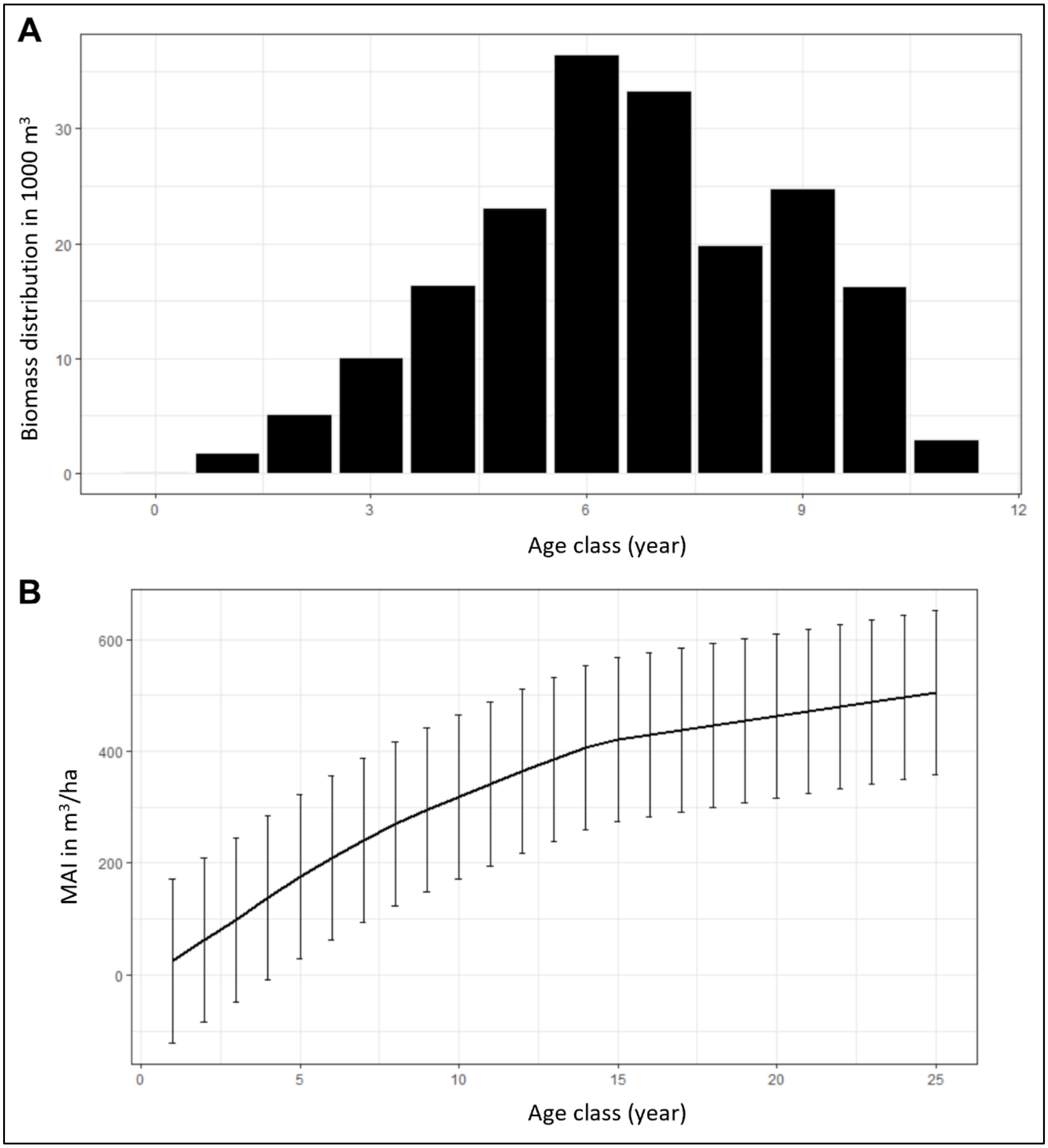

Figure 4 (A) Current inventory distribution by age class in EMS region. (B) Average yield curve in EMS region with standard deviation at each age class.

Pulpwood Flow

The EMS has complex market dynamics and interaction with other pulpwood baskets. For instance, the current supply of timber in EMS is complemented by importing pulpwood from the state of São Paulo. And a small amount of pulpwood from EMS is also exported to pulp mills in São Paulo. After exchanging information with local experts, I assume that 250,000 m^3/year (10% of the volume of the fourth mill installed in EMS) is exported from EMS to the state of São Paulo within 337 km (assuming that this timber is being exported from Três Lagoas).

Land Cover Change

The landscape in EMS is characterized by intensive pasture, with 4,728,301 ha (almost six times the timber area – 806,000 ha) (Souza et al., 2020). The EMS's new areas of forest plantations are normally from conversion of low productive pasture (annual average between 41,500 ha and 45,000 ha). I, therefore, restricted the land conversion to forest plantations only from pasture. I also allowed a conversion from pasture to forest since the rents from pasture can be higher and technology could improve productivity in the future. I incorporated these dynamics by using the Land Cover Change (LCC) collected from 2004 to 2020 (the period when the companies started installing their mills in the region) and calculating the probability of conversion for each grid cell to timberland. Equation 1 demonstrates how I calculated the probability of LCC for each grid cell i ($P(LCC)_i$).

$$P(LCC)_i = \frac{\sum_{t=2004}^{2020}\left[\frac{Pasture_{t-1,i} - Pasture^c_{t-1,i}}{Pasture_{t-1,i}}\right]}{2020-2004}, \qquad \forall i \in I \tag{1}$$

where $Pasture_{t-1,i}$ is the pasture area in the grid cell i at period $t-1$ and $Pasture^c_{t-1,i}$ is the area of pasture that was converted to forest in the same grid cell i and period $t-1$.

Figure 5A shows the distribution of the probability of LCC from pasture to forest, while Figure 5B shows the distribution of available land or pasture covered land, in ha, for each grid cell.

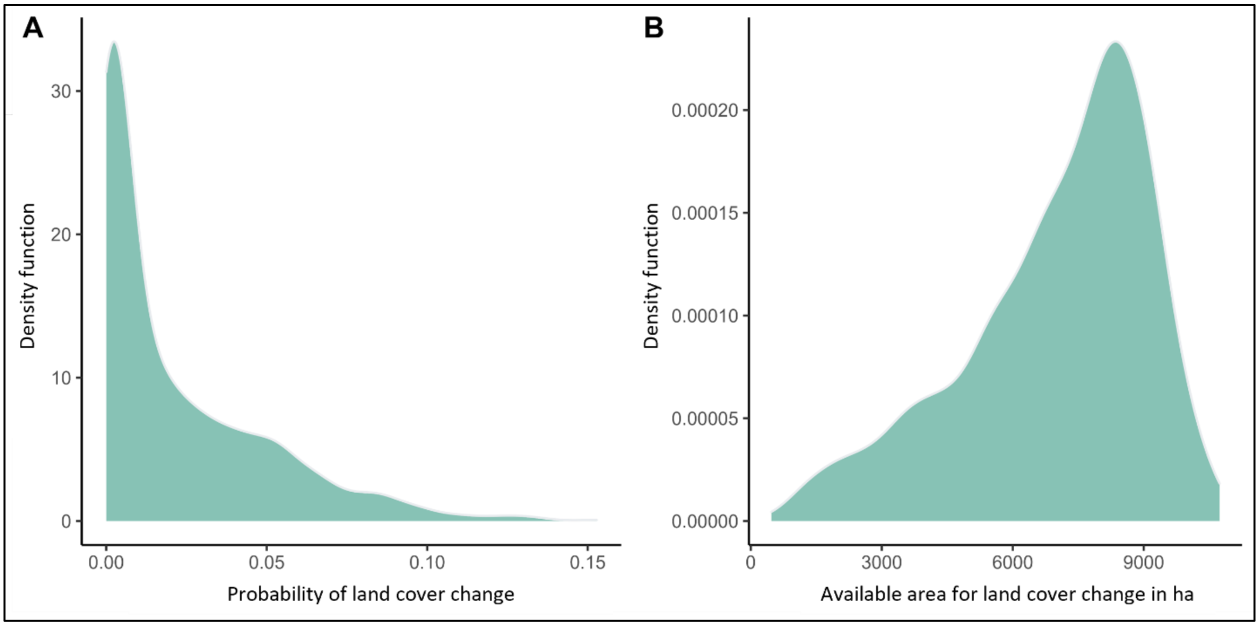

Figure 5 A) Distribution of LCC probabilities from pasture into forest in the EMS regions based on historical probabilities, in the horizontal axis is the P(LCC) – Equation(1) - from pasture to forest and the vertical axis is the density; B) Distribution of pasture land across the EMS region, that land represents the amount of land available to be converted into planted forests.

Land Price

I gathered land price information from the National Institute of Colonization and Agrarian Reform (INCRA) database at the municipality level for the EMS region (INCRA, 2023). The available prices were for seven municipalities (Dourados, Ivinhema, Nova Andradina, Campo Grande, Três Lagoas, Chapadão do Sul, and Paranaíba). To compensate for missing data in certain regions, I performed an inverse distance-weighted spatial interpolation to estimate land prices. Figure 6 shows the outcome of the spatial interpolation in the EMS market, where the darker the color, the higher the land price, in US$/ha.

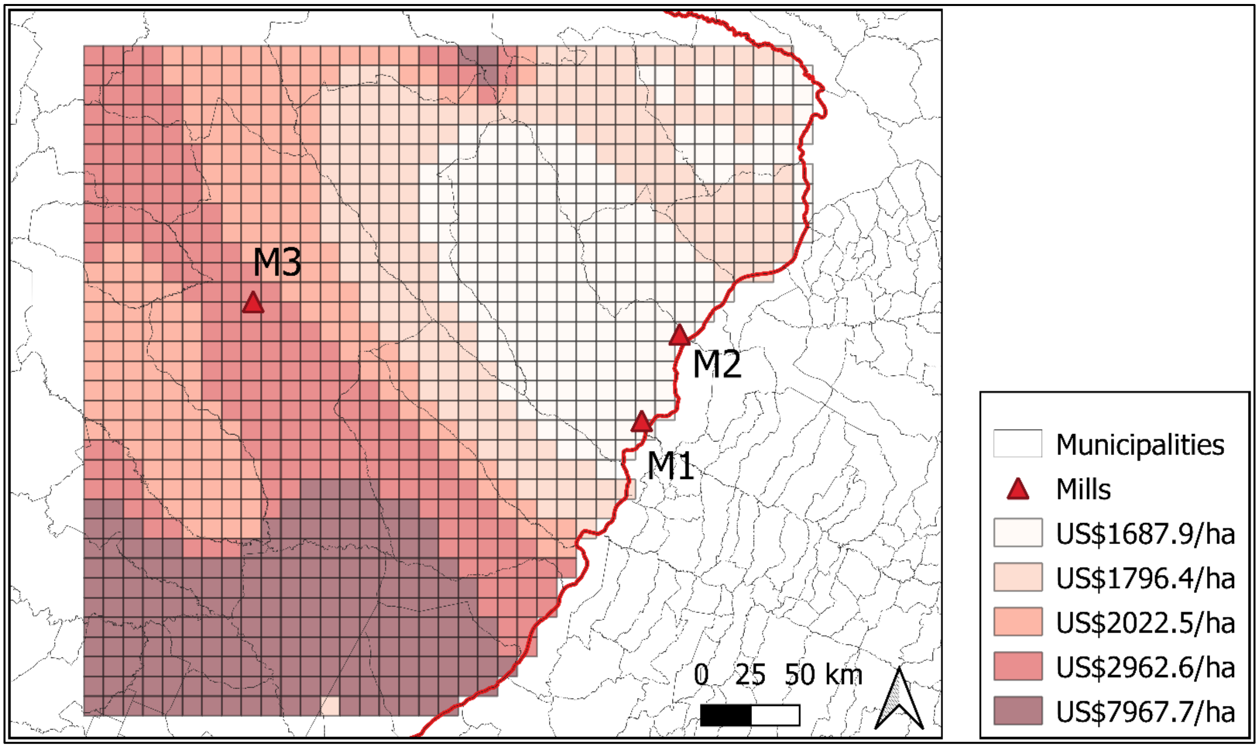

Figure 6 Land prices geographic interpolation for the EMS region in US$/ha and current mills location.

Scenarios

I proposed 18 scenarios from the combination of different values for the P(LCC) and the yield curves (Table 1). For the LCC, I defined three scenarios based on the historical average and standard deviation. The historical average is 23,980.5 ha/year, while the standard deviation (SD) is 28,240 ha/year. With that, my three LCC scenarios establish an upper bound for land to be converted into forest yearly. The first bound is 52,220.5 ha/year, which is the mean plus one standard deviation, the second is 66,340.5 ha/year, and the third is 38,100.5 ha/year, the average plus half SD. I summarized all scenario's parameters in Table 1.

The yield curves shifts were based on the literature; results in Almeida et al. (2010) indicate that eucalyptus productivity could decrease by 38% under a drought scenario, while Palma et al.

(2021) suggested a reduction in productivity between 3% to 5% due to changes in precipitation patterns. Furthermore, results from Elli et al. (2020) indicate that changes in eucalyptus productivity could range between minus 12% and positive 5%. Thus, I defined six climate scenarios: (i) the historical average, (ii) two positives (+15% and +5%), and (iii) three negative (-3%, -12%, and -38%).

To investigate the marginal effect of adding a new mill, I also evaluate a scenario without the addition of a new pulp mill with the historical average and productivity.

Table 1 Summary of scenarios parameters used

Scenarios	Yield Curve Shift	Maximum allowed LCC	MAI at 5-years*
S1	Historical average**	52,220.5 ha/year	175.5 m^3/ha
S1***	Historical average	52,220.5 ha/year	175.5 m^3/ha
S2	Historical average	66,340.5 ha/year	175.5 m^3/ha
S3	Historical average	38,100.5 ha/year	175.5 m^3/ha
S4	+5%+	52,220.5 ha/year	184.3 m^3/ha
S5	+5%	66,340.5 ha/year	184.3 m^3/ha
S6	+5%	38,100.5 ha/year	184.3 m^3/ha
S7	+15%+	52,220.5 ha/year	201.8 m^3/ha
S8	+15%	66,340.5 ha/year	201.8 m^3/ha
S9	+15%	38,100.5 ha/year	201.8 m^3/ha
S10	-3%++	52,220.5 ha/year	170.2 m^3/ha
S11	-3%	66,340.5 ha/year	170.2 m^3/ha
S12	-3%	38,100.5 ha/year	170.2 m^3/ha
S13	-12%+	52,220.5 ha/year	154.4 m^3/ha
S14	-12%	66,340.5 ha/year	154.4 m^3/ha
S15	-12%	38,100.5 ha/year	154.4 m^3/ha
S16	-38%#	52,220.5 ha/year	108.8 m^3/ha
S17	-38%	66,340.5 ha/year	108.8 m^3/ha
S18	-38%	38,100.5 ha/year	108.8 m^3/ha

*Mean Annual Increment; **GePlant; ***No mills allowed to enter the market; +Elli et al. (2020); ++ Palma et al. (2021); #Almeida et al., 2010

Table 2 shows the summary of each parameter.

Table 2 Summary of parameters and data used in the model

Parameter	Description	Value*	Source
Pulpwood demand	Suzano 1	10.5 million m^3/year	Company report[5,6]
	Suzano 2 – 2024 (three year after simulation starts)	8.2 million m^3/year	
	Eldorado	6.3 million m^3/year	
	4th mill (2028)	2.5 million m^3/year	Valor, 2022
Pulp price	March/23	US$1,329/ton	Cepea[7]
Average land price		US$2,265.12/ha (US$841.32/ha)	INCRA[8]
Import distance		400km	
Tax to import		10%	
Imported pulpwood price		US$22.4/$m^3$	
Exchange rate		US$0.18/R$	Central Bank of Brazil

*Standard deviation in parenthesis

Model Overview

I formulated a MIP model to assess the impact of current and new pulp mills in the inventory and harvest dynamics in the eastern region of Mato Grosso do Sul (EMS - Brazil) under climate and land market uncertainties. My model maximizes the NPV of the pulpwood industry and searches for the best location to install a new pulp mill.

I decided to model the entire EMS market as a unit instead of individual models due to market specifics. Many forest markets around the world are highly competitive, with agents competing for scarce resources such as land, labor, and inputs. In the forest industry, land plays a vital role.

[5] https://www.eldoradobrasil.com.br/wp-content/uploads/2022/11/plano-de-manejo-florestal-base-2021.pdf
[6] https://www.suzano.com.br/a-suzano/documentos/?tag=manejo-florestal-sustentavel
[7] https://www.cepea.esalq.usp.br/upload/revista/pdf/0012887001681756483.pdf
[8] https://www.gov.br/incra/pt-br/assuntos/governanca-fundiaria/relatorio-de-analise-de-mercados-de-terras/ramt_sr16_2020.pdf

In the US forest market, for example, the land market is characterized by significant fragmentation, encompassing various ownership types, including individual (40.6%), corporate (21.9%), and government (35%) ownerships (Butler et al., 2022).

In Brazil, however, the market is vertically structured, which means that forest companies own and manage their land. Another important characteristic of the Brazilian forest industry is its high concentration, with only a few players operating in the market. This situation often leads to cooperation among companies. This mutual market relationship encompasses various aspects, including asset exchanges involving forest lands.

In 2007, for instance, two companies traded assets valued at around US$2 billion, which included two mills and 178,000 hectares of forest land (Naime, 2006). More recently, in 2020, Suzano sold approximately 21,000 hectares of forest land in São Paulo to Bracell (Valor, 2020). Because of this market organization, I found it reasonable to model the EMS problem by assuming the market as a single unit, rather than conducting individual optimizations. For that, I used the Python package Pyomo (Hart et al., 2017) to build the computational model and solved it using Gurobi (versions 9.5.2 and 10.0). The mathematical formulation is defined as follows:

SETS:

$i \in I$: Grid cells

$j \in J$: Potential pulp mill sites, where $J \subseteq I$

$k \in K$: Current pulp mill sites, where $K \subseteq J$
$t \in T$: Time;

$a \in A$: Age classes.

Objective Function

The objective function is the sum of the pulp mill's NPV and forest investments (Equation 2 to 2.3). The model maximizes the objective function by allocating optimal harvest volume, inventory, land, and forest management.

$$\max\left\{\sum_{j=1}^{J}\sum_{t=1}^{T}\rho_t\left[R_{j,t}-C_{j,t}\right]-\sum_{t=1}^{T}\rho_t L'_t\right\} \tag{2}$$

where, ρ_t is the discount factor with discount rate r for each period t,

$$R_{j,t}=P_x\left(W_j\right)+\sum_{i}^{I}TV_{i,t=25} \tag{2.1}$$

$$C_{j,t}=C'_{j,t}+C''_t \tag{2.2}$$

$$C'_{j,t}=\sum_{i=1}^{I}\left[\underbrace{d_{i,j}p^{freight}X_{i,j,t}}_{section\ (1)}+\underbrace{p^{imp}\left(d_j^{*}p^{freight}+p^{*}\right)V_{j,t}^{imp}}_{section\ (2)}\right] \tag{2.2.1}$$

$$C''_t=p^{land}\left(L_{1_{i,t}}^{lcc}-L_{2_{i,t}}^{lcc}\right) \tag{2.2.2}$$

$$L'_t=\sum_{i=1}^{I}\sum_{a=1}^{A}\left(c_a L_{i,a,t}\right) \tag{2.3}$$

where, Equation 2.1 is the revenue, $R_{j,t}$, formed by the wood pulp produced (W_j) and international pulp prices (P_x) in US$/ton and the sum of all terminal values ($\sum_i^I TV_{i,t=25}$), which are the combination of the biological and land values at the terminal period ($t=25$). To calculate the wood pulp volume (W_j), I converted the pulpwood consumed (m^3) to pulp (ton) using the factor of 1 m^3 of eucalyptus to 0.26 ton of cellulose (Foelkel, 2017). I assume that the producers in the pulp and paper industry act as price takers. This assumption is reasonable considering the industry's strong focus on exports, with China alone accounting for approximately 47% of EMS's total exports in the past decade (MDIC, 2023).

The cost function (Equation 2.2) estimates the expenditures of each mill j during period t ($C_{j,t}$) and is composed of logistic costs ($C'_{j,t}$) and LCC costs (C''_{t}). For the first, I divided it in two sections where Section 1 accounts for the transportation cost; that is the product of the amount of pulpwood transported ($X_{i,j,t}$), the distance traveled ($d_{i,j}$), and freight price ($p^{freight}$) from forest i to mill j at period t. Section 2 is the costs of importing pulpwood where p^{imp} is the import tax, d^{*}_{j} is the distance traveled to a supply center outside the EMS, $p^{freight}$ is the freight cost, p^{*} is the imported pulpwood price, and $V^{imp}_{j,t}$ is the volume imported. The LCC costs account for net area converted into forest ($L^{lcc}_{1_{i,t}} - L^{lcc}_{2_{i,t}}$) multiplied by the land prices (p^{land}), where $L^{lcc}_{1_{i,t}}$ is the land converted from pasture to forest, and $L^{lcc}_{2_{i,t}}$ is the timberland converted to other uses for every i and t.

Equation 2.3 is the cost with land management, where c_{a} is the cost per hectare per age class, and $L_{i,a,t}$ is the total forest area at grid cell i, at age class a, and time t.

Since this market is vertically integrated, I disregard the cost of buying pulpwood from third-party standing trees. I also did not add the cost of building a pulp mill or maintaining it because they are constant across every j; which would not change the marginal effect.

Constraints

The following set of equations guarantee market equilibrium (Equation 3), forest harvests (clearcut) (Equation 4, 5, 6, 7, and 8), forest transition (Equation 9), land cover change conditions (Equations 10 to 12), and market expansion (Equations 13 to 15).

Trade and market condition

Equation 3 ensures the market equilibrium condition, where the current mill capacities (section 1D) plus the possible new mill location (section 2D) are equal to the volume of pulpwood harvested or imported (section 1S).

$$
\underbrace{\sum_{k}^{K} D_{k,t}}_{section\ 1D} = \begin{cases} \underbrace{\sum_{i}^{I} X_{j,i,t} + V_{j,t}}_{section\ 1S}, & \forall\, j \in (M1\ and\ M2) and\ t < 3 \\ \underbrace{\sum_{i}^{I} X_{j,i,t} + V_{j,t}}_{section\ 1S} - \underbrace{\sum_{j}^{J} Y_{j,t} D_{j,t}}_{section\ 2D}, & \forall\, j \in (M1, M2, and\ M3)\ and\ t \geq 3 \\ \underbrace{\sum_{i}^{I} X_{j,i,t} + V_{j,t}}_{section\ 1S} - \underbrace{\sum_{j}^{J} Y_{j,t} D_{j,t}}_{section\ 2D}, & \forall\, j \in (M1, M2, M3, and\ M4)\ and\ t \geq 7 \end{cases} \tag{3}
$$

Section 1D is the sum of the current demand ($\sum_{k}^{K} D_{j,t}$). Section 2D is the demand of the future pulp mills ($D_{j,t}$) times a binary variable ($Y_{j,t}$), which equals to one if a pulp mill is installed at region j and period t, and zero otherwise. Notice that the mills available changes as the period t is greater than the expected installation. On the left-hand side of Equations 3a, 3b and 3c, I have the available supply of pulpwood for each period t. The supply of pulpwood can be either domestic ($X_{j,i,t}$) or imported ($V_{j,t}$). In $X_{j,i,t}$, every supplier i can feed the mill j at period t, while $V_{j,t}$ is the quantity imported outside EMS by mill j during period t.

Harvest

The harvested area constraints are described in Equations 4 to 6. Equation 4 limits the area harvested ($H_{i,a,t}$) to less than, or equal to, the current area available ($L_{i,a,t}$). Equation 5 estimates the volume harvested ($V_{i,t}^{h}$), which is the sum of the product of all age classes between area harvested ($H_{i,a,t}$) and the yield curve ($v_{i,a}$). Similarly, Equation 6 estimates the stock of pulpwood - the sum of the product of all age classes between the area available ($L_{i,a,t}$) and the yield curve ($v_{i,a}$).

$$H_{i,a,t} \leq L_{i,a,t}, \qquad \forall i \in I, a \in A, t \in T \tag{4}$$

$$V_{i,t}^{h} = \sum_{a=1}^{A} v_{i,a} H_{i,a,t}\,, \qquad \forall i \in I, t \in T \tag{5}$$

$$W_{i,t} = \sum_{a=1}^{A} v_{i,a} L_{i,a,t}\,, \qquad \forall a \in A \tag{6}$$

Eucalyptus rotations in Brazil are commonly between five and nine years (Diaz-Balteiro & Rodriguez, 2006). Therefore, I imposed that the eucalyptus rotation could not be less than four years (Equation 7), and the current stock older than nine years would be harvested within the next five years (Equation 8).

$$V_{i,a,t}^{h} = 0, \qquad \forall\, a \leq 4 \tag{7}$$

$$L_{i,a,t} = 0, \qquad \forall\, a > 9 \; and \; t \geq 5 \tag{8}$$

Transition Between Age Classes

Equation 9 outlines the age transition as the forest grows or is harvested during period t. At $t = 0$, and age class greater than zero ($a > 0$), the forest area is determined by the available area from GePlant data ($l_{i,a}$). When $t = 0$ and $a = 0$, the forest area is calculated by adding the initial area to the area converted into forest ($L_{1_{i,t}}^{lcc}$) and subtracting the land sold ($L_{2_{i,t}}^{lcc}$).

For subsequent time periods ($t > 0$) and when $a = 0$, the forest area is determined by adding the area harvested (clearcut) in the previous period for all age classes ($\sum_{a}^{A} H_{i,a,t-1}$) to the area converted into forest ($L_{1_{i,t}}^{lcc}$) and subtracting the land sold ($L_{2_{i,t}}^{lcc}$).

If $t > 0$ and $0 < a < 25$, the forest area is calculated by subtracting the land harvested in the previous age class and period ($H_{i,a-1,t-1}$) from the available land in the previous age class and period ($L_{i,a-1,t-1}$). Now, when $t > 0$ and the forest reaches its maximum allowed age ($a = 25$), the forest area calculation follows a similar pattern as before. However, it includes the area at the current age class ($L_{i,a,t-1}$) minus the harvested area at the same age class ($H_{i,a,t-1}$).

$$L_{i,a,t} = \begin{cases} l_{i,a} & , if\ t = 0\ and\ a > 0 \\ l_{i,a} + \left(L^{lcc}_{1_{i,t}} - L^{lcc}_{2_{i,t}}\right) & , if\ t = 0\ and\ a = 0 \\ \sum_{a}^{A} H_{i,a,t-1} + \left(L^{lcc}_{1_{i,t}} - L^{lcc}_{2_{i,t}}\right) & , if\ t > 0\ and\ a = 0 \\ L_{i,a-1,t-1} - H_{i,a-1,t-1} & , if\ t > 0\ and\ 0 < a < 25 \\ (L_{i,a-1,t-1} - H_{i,a-1,t-1}) + (L_{i,a,t-1} - H_{i,a,t-1}) & , if\ t > 0\ and\ a = 25 \end{cases} \quad (9)$$

Land Cover Change (LCC) Constraints

Similar to the timberland transition in Equations 9, Equation 10.1 ensures that the current area of pasture available equals the value estimated by MapBiomas ($l_{0,i}$). Equation 10.2 simulates the transition from pasture ($L^{p}_{i,t}$) to timberland between periods, where $L^{lcc}_{1_{i,t-1}}$ is the area of pasture converted to forest plantation.

$$L^{p}_{i,t} = l_{0,i}\,, \qquad \forall\ t = 0 \quad (10.1)$$

$$L^{p}_{i,t} = L^{p}_{i,t-1} - L^{lcc}_{1_{i,t-1}}, \qquad \forall\ t > 0 \quad (10.2)$$

$$L^{lcc}_{1_{i,t}} \leq p(LCC)_i L^{p}_{i,t} \quad (11)$$

$$\sum_{i=1}^{I} L^{lcc}_{2_{i,t}} \leq \sum_{i=1}^{I} \sum_{a=0}^{A} L_{i,a,t}\,, \qquad \forall t \in T \quad (12)$$

Equation 11 sets the boundary for land conversion based on the historical probability of LCC ($p(LCC)_i$) from pasture to planted forest and Equation 12 limits the selling of timberland to other uses to no more than the area available.

A New Mill Establishment

In this section I establish a series of rules to define where and when a new mill could be installed in the EMS. First, I introduce a binary variable ($Y_{j,t}$) that represents the decision either to install a mill ($Y_{j,t} = 1$) or not ($Y_{j,t} = 0$). Equation 13 restricts the pulp mill installation to a single location when the period t is equal or greater than t^* (an integer variable that indicates the earliest period a mill can be installed). It also does not allow any new pulp mill entering when t is less than t^*. A new pulp mill, j, could be installed only after seven years ($t^* \geq 7$), at which point the simulation starts since local investors of a new mill will only enter the market in 2028 (Valor International, 2022), and less than the last period ($t \leq 25$).

$$\sum_{j=1}^{J} Y_{j,t} = \begin{cases} 1, \forall \; t \geq t^* \\ 0, \forall \; t < t^* \end{cases} \tag{13}$$

Equation 14 guarantees the new mill will not shut down in My period of study; I impose that the sum of binary variables over time ($\sum_{t=1}^{T} Y_{j,t}$) should be equal to the number of periods between its opening and the final year of the analysis (T). If the model, for example, finds the optimal period to open a mill at $t = 9$, then this mill must operate for at least 17 years $(25 - 9 + 1)$. I add one to the difference to account for the last year of operation; otherwise, the mill would only have operated for 16 years.

$$\sum_{t=1}^{T} Y_{j,t} = (T - t^* + 1), \qquad \forall t \geq t^* \in T, j \in J \tag{14}$$

Last, Equation 15 ensures that once a mill, j, is selected at $t - 1$ ($Y_{j,t} - 1 = 1$), it will not shutdown or another mill would be chosen at t.

$$Y_{j,t} - Y_{j,t-1} \geq 0 \tag{15}$$

Proposed Solution

I broke down the solution process into two steps due to the large amount of data and the integer and binary variables in the problem. First, I solve the model by imposing $Y_{j,t}$ as a continuous variable, within the limits between zero and one. At this step, the solution $Y_{j,t}^{*}$ represents the share of the demand $D_{j,t}$. Second, I reduced the total possible mill's location by selecting just $Y_{j,t}^{*}$ that have a value greater than or equal to 20%[9]. Then, I run the model with $Y_{j,t}$ as binary. Figure 7 illustrates the process of model solving.

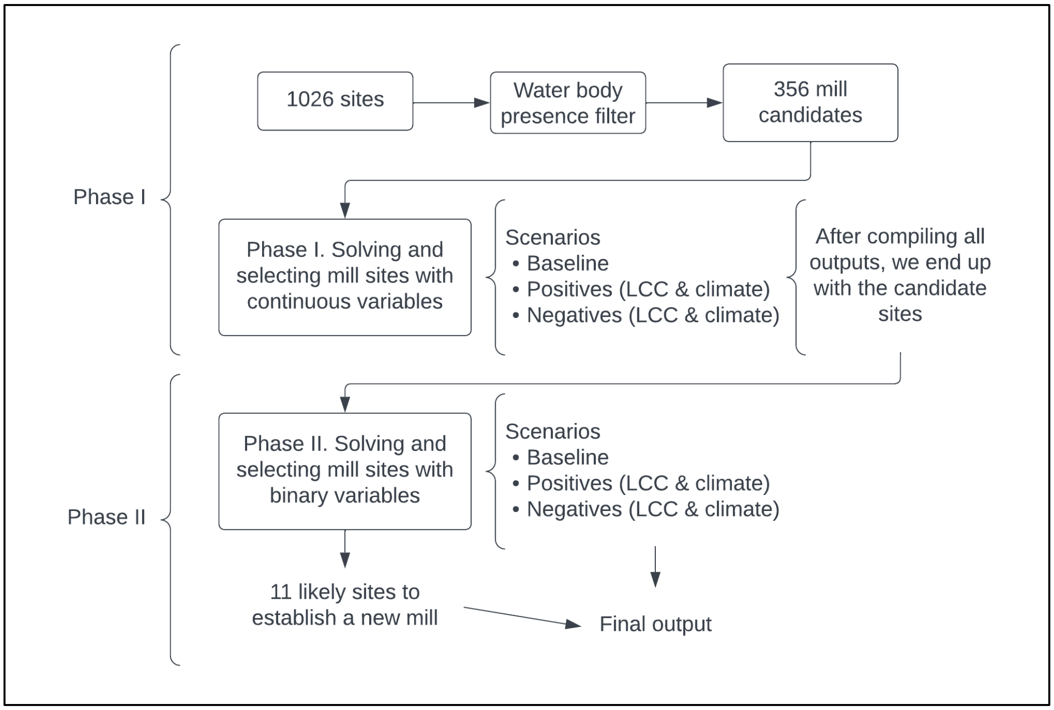

Figure 7 Solution description: Phase 1, I used $Y_{j,t}$ (Equations 15 and 16) as continuous variables to select the location s with higher demand share. In Phase 2, I use the solution of Phase 1, where I selected only the locations with a share higher than 20% of the demand consumption and run $Y_{j,t}$ as a binary variable.

[9] Although 20% is an arbitrary value, initial analysis indicated that the locations with less than 20% were never selected.

Results

My findings indicate that productivity fluctuations and restricted access to land can lead to shortage of pulpwood in negative climate scenarios. The financial returns were also more responsive to negative variations than positive ones. In the worst-case scenario, the total NPV for the following 25 years could decrease by around 3.6% under an extreme loss of productivity and increase no more than 0.2% under a positive climate scenario. Among the possible new mill's locations, the EMS Northeast region shows more potential for a new mill in 17 (S13) out of 18 scenarios.

Net Present Value

Table 3 indicates the results from scenarios S1 to S18; to facilitate the interpretation, I present the comparison between their NPV using four baselines: (i) compared to S1 (column 5), (ii) I compare the NPV within the same productivity level to capture the effect of access to land on the NPV (column 6), and (iii and iv) within both expansive and restricted land cover change rate, respectively, to capture the effects of different climate shocks on the productivity level (column 7 and 8).

In the baseline (S1), the expected NPV at a 10% discount rate is around US$79 billion, assuming the historical productivity and not allowing yearly forest LCC to be greater than 52,220.5 ha (historical average plus one standard deviation). If I suppose that each scenario had an equal probability of happening (which is not realistic), in 25 years, the EMS pulpwood market financial returns could decrease around 0.54%, or US$430 million.

In the best-case scenario (S8), the market's NPV would be no more than 0.2% greater than the baseline. In S8, I assumed a 15% gain in the average productivity and the yearly maximum forest LCC to be no greater than 66,340.5 ha, indicating the industry's access to more land. Yet, the total gross gain would be around US$130 million in 25 years. In the worst-case scenario (S18), however, the losses could reach up to US$2.7 billion in 25 years (-3.4% than baseline).

NPV – Land Access

Land access fluctuations, however, had a lower impact, on average, on the NPV than productivity ones. When I held productivity constant while testing different land scenarios (column 6), the average NPV variation was around 0.02%. However, when I held land constant while varying the productivity, the NPV change ranged from 0.57% (column 7) to 0.74% (column 8). That was expected since land conversion can offset negative variations in productivity and boost productivity gains by converting larger areas.

Table 3 Climate and LCC scenarios output summary

Scenarios	Yield Curve Shift	P(LCC) Shift	NPV @ 10% (billion US$)	Δ NPV (% from baseline - S1)	Δ NPV (% from baseline - P(LCC))	Δ NPV (% from baseline – S2)	Δ NPV (% from baseline – S3)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S1	HA**	1	78.80	-	-	-	-
S2	HA	2x	78.99	0.2%	0.2%	-	-
S3	HA	0.5x	78.65	-0.2%	-0.2%	-	-
S4	5%	1	78.86	0.1%	-	-	-
S5	5%	2x	79.05	0.3%	0.2%	0.1%	-
S6	5%	0.5x	78.72	-0.1%	-0.2%	-	0.1%
S7	15%	1	78.91	0.1%	-	-	-
S8	15%	2x	79.09	0.4%	0.2%	0.1%	-
S9	15%	0.5x	78.77	0.0%	-0.2%	-	0.1%
S10	-3%	1	78.75	-0.1%	-	-	-
S11	-3%	2x	78.95	0.2%	0.2%	-0.1%	-
S12	-3%	0.5x	78.60	-0.3%	-0.2%	-	-0.1%
S13	-12%	1	78.56	-0.3%	-	-	-
S14	-12%	2x	78.76	-0.1%	0.3%	-0.3%	-
S15	-12%	0.5x	78.38	-0.5%	-0.2%	-	-0.3%
S16	-38%	1	76.91	-2.4%	-	-	-
S17	-38%	2x	77.32	-1.9%	0.5%	-2.1%	-
S18	-38%	0.5x	76.11	-3.4%	-1.0%	-	-3.2%
Average***	-	-	78.45 (0.82)	-0.4% (1.0%)	-0.5% (1.1%)	-0.5% (0.9%)	-0.7% (1.4%)

*Negative values in parenthesis; **Historical Average; ***Standard deviation in parenthesis

I was also able to assess the marginal effect of a new player entering the market. The entrance of one mill can potentially increase the market's NPV by around 5.2% (see Table 4), or US$4.09 billion, in 25 years.

Cost Composition

Figure 8 shows the NPV cost components and its relative importance for each scenario. The cost composition was heterogeneous among all scenarios except for the extreme negative ones. Even though the transportation cost is the most expressive item (averaging around 53% of total costs), as the productivity declines, and the relative importance of import costs gets higher, the transportation costs lose importance. In S18, for example, imports accounted for 46% of total costs *versus* 26% of transportation costs, while in S1, transportation was 57%. That is because S18 has a land conversion restriction and lower productivity, reducing the compensation of loss in productivity with larger areas of forest plantation drastically. In other words, it is, to a certain limit, more profitable to purchase pulpwood in the market than owning a forest plantation.

Land Conversion Costs (LCC) and land management are two other cost components that are responsive to productivity shifts. As more land is converted into forests, the higher the management costs will be. This provides further explanation for the lower NPVs observed in scenarios S16 to S18, for instance. Despite the correlation between management costs and LCC components, fluctuations in management costs were relatively smaller compared to those in LCC costs. While LCC costs varied between 8% (S2, S10, S11, S13, S14, S15) and 46% of total costs (S18), the minimal land management cost share was 16% (S8) and was at 22% at the maximum.

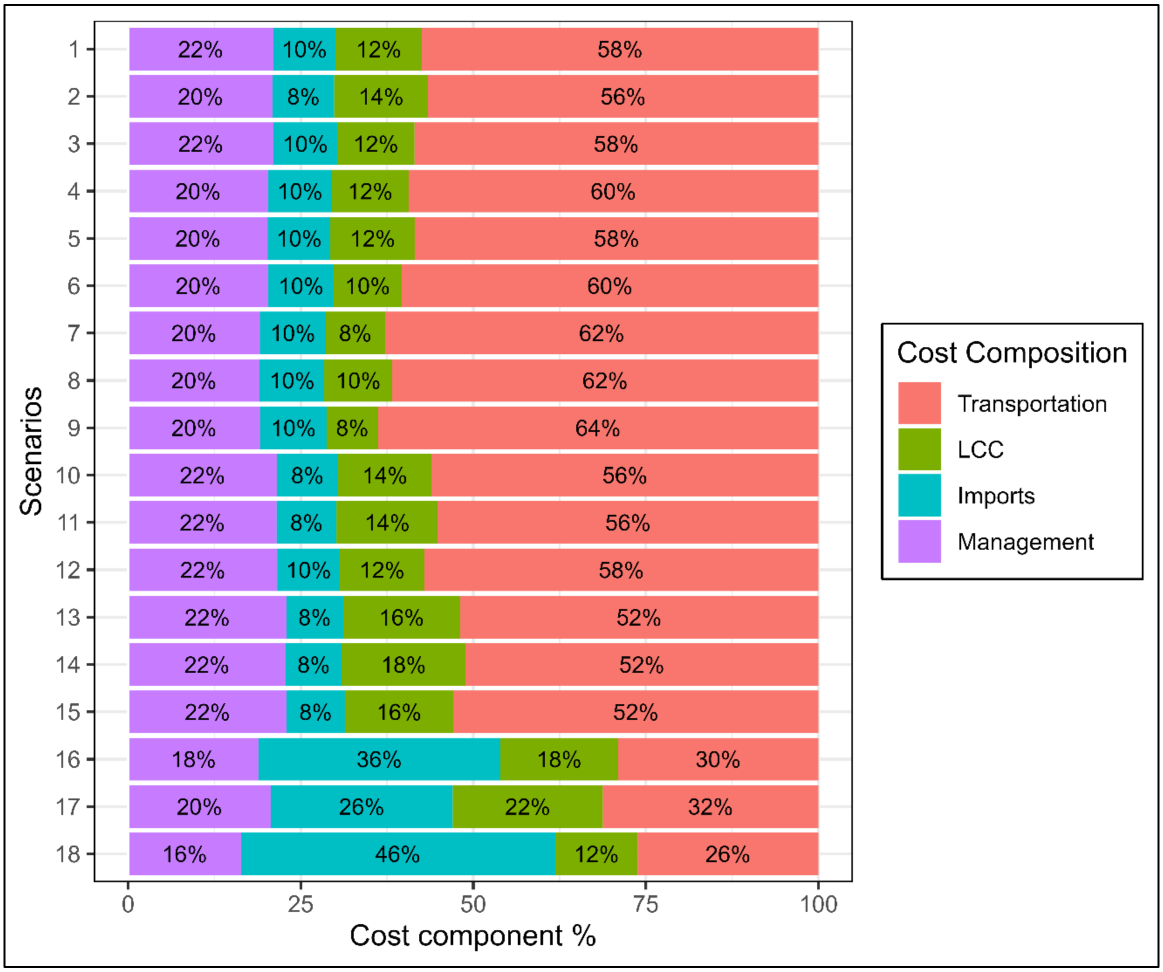

Figure 8 NPV cost components relative importance per scenario. Transportation is the timber transported within the EMS region from forest grid cells to the mills, LCC is the net converted amount of land, Imports are the costs related to importing pulpwood from outside the EMS, and Management is the cost associated with land management.

Pulpwood Supply and Shortages

Figure 9 shows the consumption of pulpwood from local (harvest) and importing sources over time. One of my constraints was that M3 would import an amount of pulpwood, that is the reason why I observe a few imports in the first years. The ratio between the volume imported and total demand is also similar among scenarios S1 to S15, averaging around 1.78% of total demand. In other words, for each 100 m^3 of pulpwood consumed, 1.78 m^3 were imported.

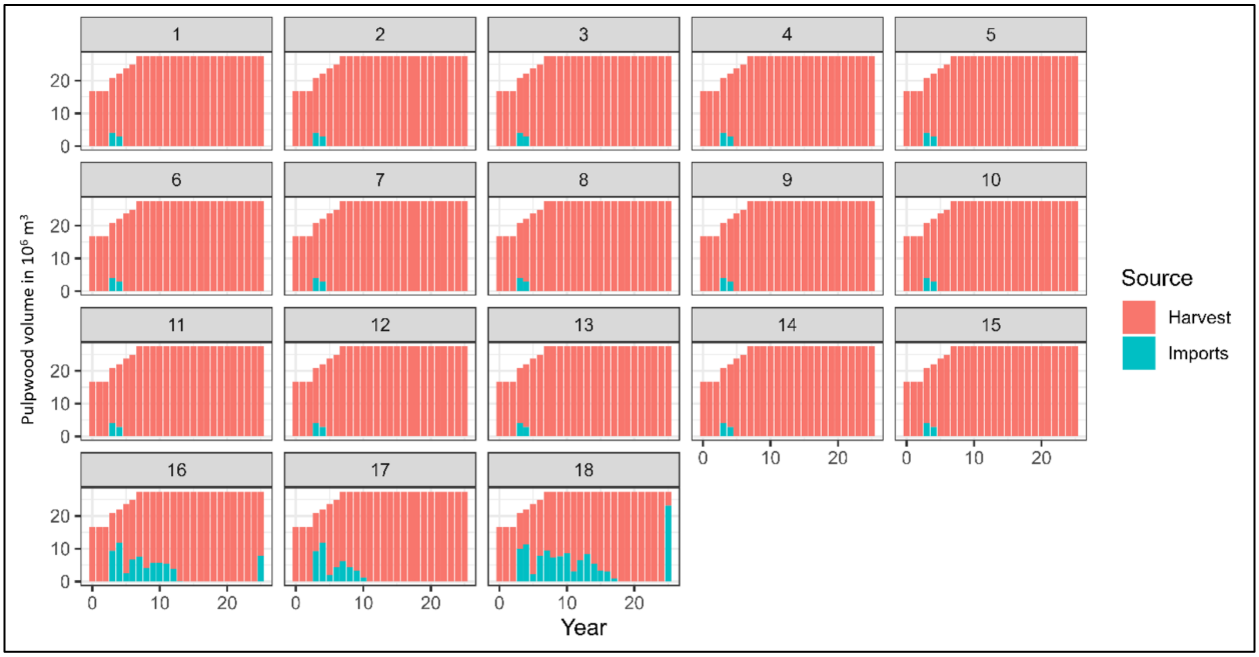

Figure 9 Demand for pulpwood per harvest source per scenario and periods. Each square represents a scenario (from S1 to S18). Harvest accounts for the pulpwood harvested within the EMS, while imports account for pulpwood imported from outside the EMS.

In my model, imports were associated with several costs that harvesting was not subject to, such as taxation, higher hauling distance, and standing timber price. Because of that, agents would only rely on imports in the face of a domestic shortage. I then understood that imports have a slack variable role in my model. In other words, excluding the imposed imports volume in the first year, every period with imports indicates a shortage of pulpwood.

I could assess that if productivity dropped by 38% (S16 to S18), there would be severe shortages of wood fiber in the long run. The imports to harvest ratio among these three scenarios averaged around 11.7%. In S16, S17, and S18, this ratio was 10.6%, 6.4%, and 18%, respectively. In S16, mills had to import between years 3 to 13, and in the last period, in which year 13 had the smallest share with less than 1% of total pulpwood consumed and period 3 the highest with 50.0% of total pulpwood consumed. In S17, the shares are smaller, but still had to be implemented in periods 3 to 10. In S18, almost all period shortages were observed. That is because this is a scenario with limited access to land, which makes it impossible for agents to offset productivity losses by planting forests.

Revenue Composition

The revenue of the EMS market is composed of three components: (1) Terminal Value, (2) Revenue from Domestic Pulpwood, and (3) Revenue from Imported Pulpwood. The first component represents the added value of both biological assets (standing pulpwood) and land value. I have chosen to divide the trading revenue into two parts to gain a better understanding of the relative significance of importing pulpwood and harvesting within the EMS region. This revenue is generated from processing pulpwood into wood pulp and subsequently exporting it.

Figure 10 illustrates the distribution of components in the total market revenue. The figure demonstrates that wood pulp traded from domestic inputs constitutes over 80% in all scenarios, with an average of approximately 94%. The terminal value, on the other hand, never comprises more than 2% across all scenarios. Wood pulp exports made from imported pulpwood contribute to around 4.1% of the total market revenue.

Scenarios 16, 17, and 18 were the ones that presented divergences in the revenue composition from the average. That is because these are scenarios with the most extreme climate variations, demanding higher volumes of pulpwood. That was then offset by importing pulpwood from outside the EMS. As the share of imported pulpwood increased, the revenue from wood pulp made with imported pulpwood also increased.

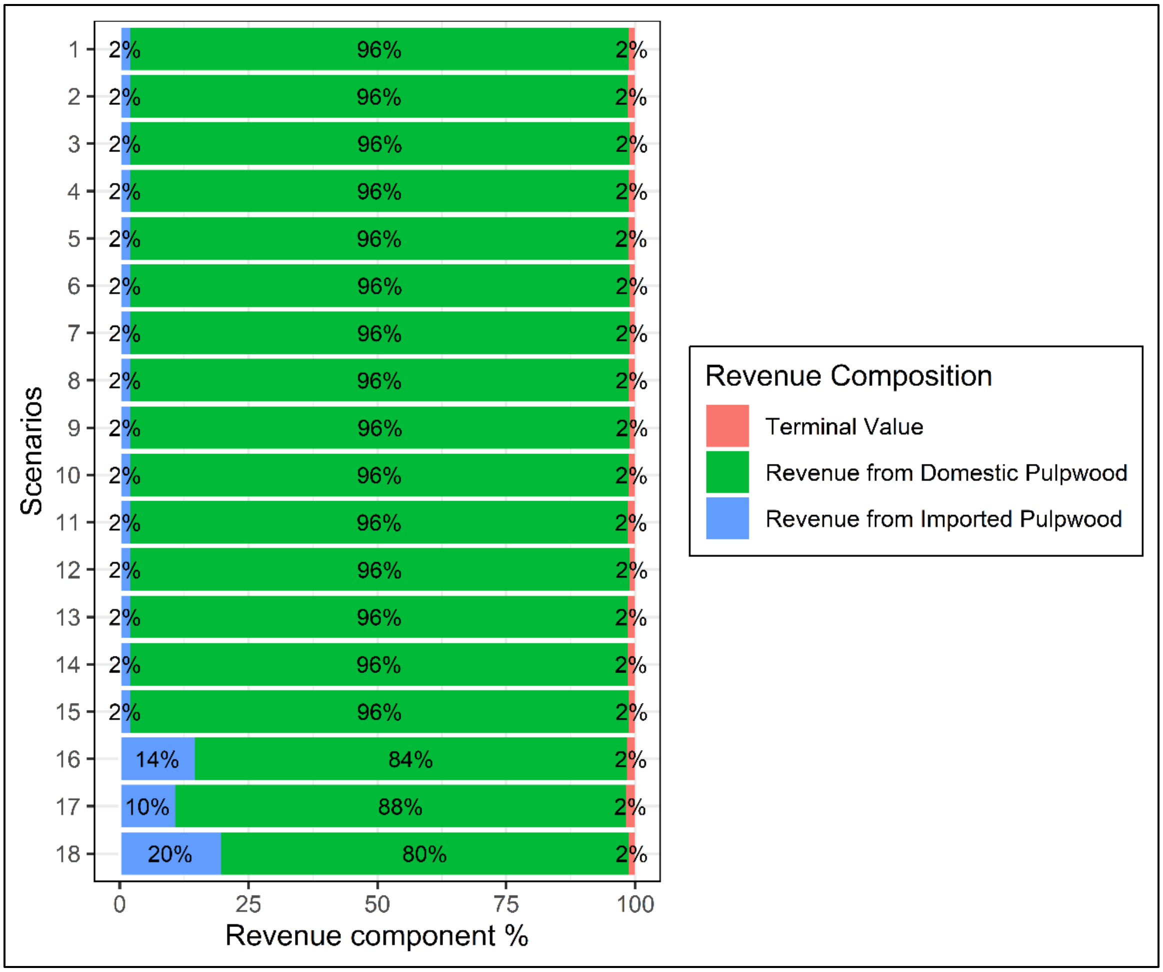

Figure 10 NPV revenue components relative importance per scenario. Terminal Value is the sum of the biological and land value at the period's end. Revenue from Domestic Pulpwood is the part of the revenue that comes from EMS's domestic forests. Revenue from Imported Pulpwood is the remaining revenue that comes from pulpwood harvested outside the EMS.

Logistics and Relative Efficiency

My research indicates a consistent decrease in haul distance over time across all scenarios, leading to timber harvests occurring closer to the mills. In the baseline scenario (S1), the average distance decreased from 125 km to 51 km, a reduction of 59%. Among the scenarios of higher productivity, the largest reduction occurred in S9, decreasing from 142 km to 45 km (68% reduction) in 25 years. Among the scenarios with lower productivity, the largest reduction (70% reduction) occurred in S18, decreasing the hauling distance from 175 km to 44 km. The hauling distance distribution curves are shown in Figure 11A. In the first plot, on the left top corner of Figure 11A, I see the distribution per scenario in year one, where curves are majorly flat. However, when I look at the last year (t=25), the curves converge almost to the same mean (~59 km).

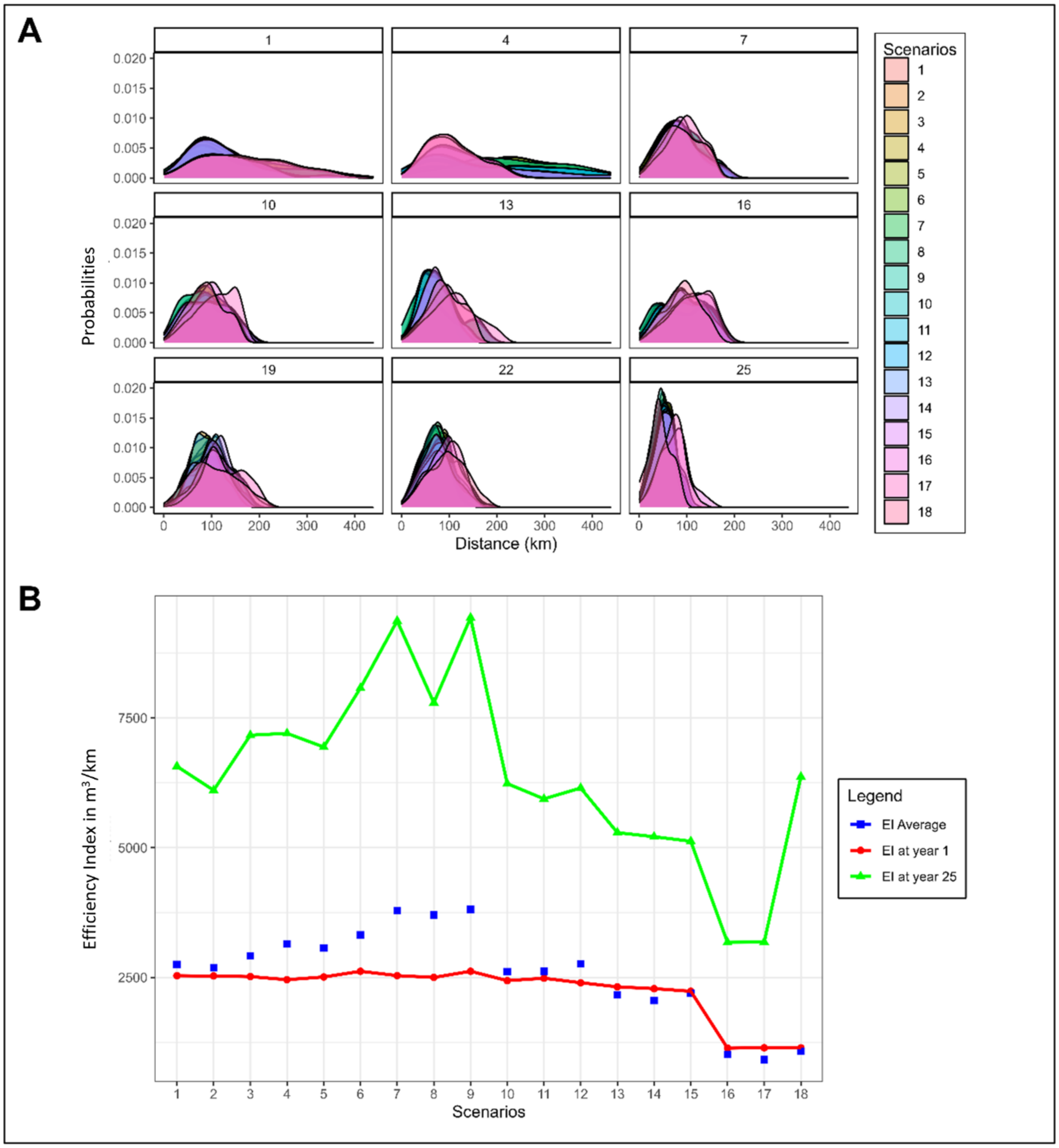

Figure 11 A) Haul distance distribution curves per climate scenario; each curve represents a different scenario B) Efficiency Index (EI) in m^3/km per scenario; the blue squares represent the average EI over time, while the green and red curves represent the EI at the end and beginning of the analysis, respectively.

Figure 11B illustrates the relative logistic Efficiency Index (EI) of pulpwood (m^3) transported per km traveled. The scatterplot shows an evident negative trend with respect to lower productivity. In other words, losses in forest's productivity reduces the market's logistic efficiency leading to lower NPVs. The baseline scenario, on average, could transport around 2,751 m^3/km, while S17, the least efficient scenario, averages around 916 m^3/km. In S9, the most efficient scenario, the EI was 3,810 m^3/km on average. Figure 8B also shows the influence of increased land availability on the behavior of EI.

LCC Dynamics

Figure 12A illustrates the cumulative timberland area over my analysis time frame for each scenario. In Figure 12B, I present the annual timberland area growth for all scenarios. Both figures reveal a similar pattern of land conversion across most scenarios, except for S16, S17, and S18. In Figure 12A, a quasi-concave-shaped curve is observed for most scenarios, whereas S16 to S18 exhibit a straight-line-shaped curve. As the productivity losses get higher, the curve tends to go from a quasi-convex to a straight line one. This can be attributed to the early land conversion in negative scenarios to mitigate productivity losses. These findings are supported by Figure 12B, where S16 to S18 deviate from the other scenarios with constant land conversion. In other words, in those scenarios, the agents were converting the maximum land available in the market to offset productivity losses.

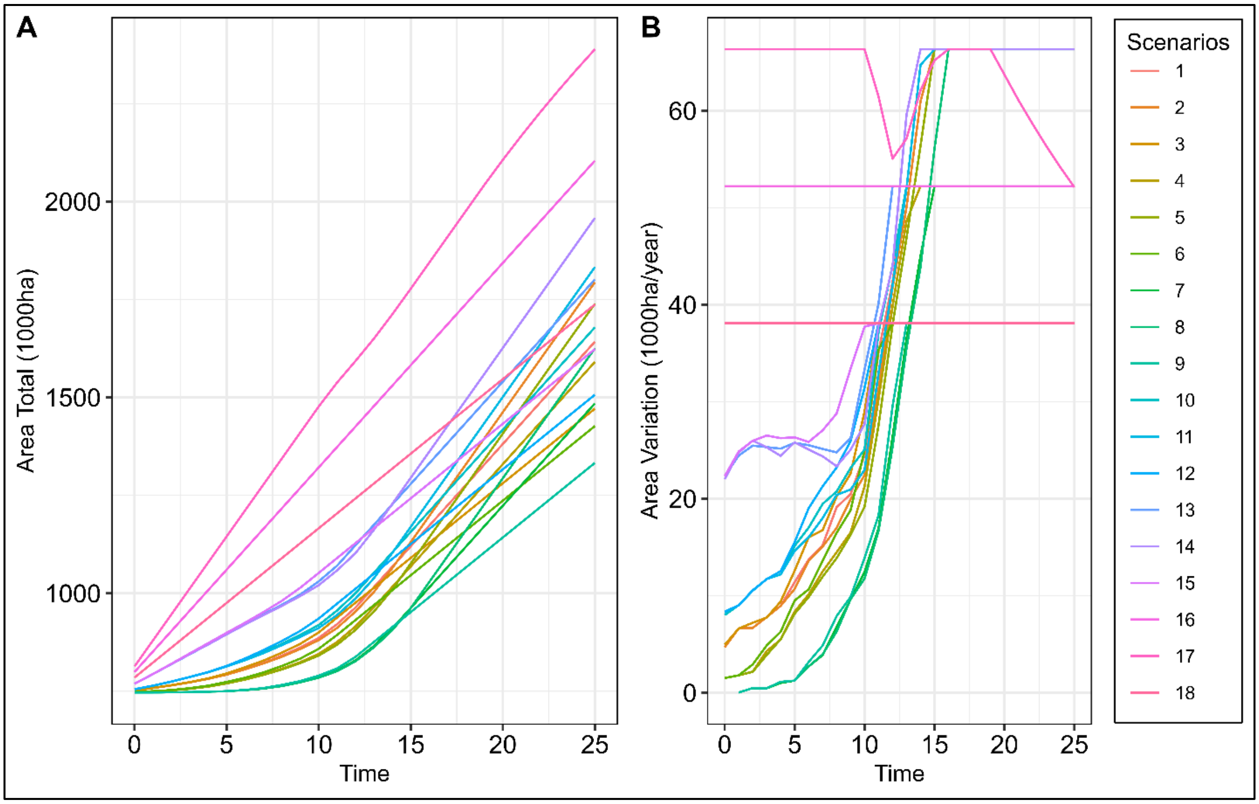

Figure 12 A) Cumulative coverage of planted forest area across all scenarios in thousands of hectares; B) Annual land conversion into planted forests across all scenarios

Mill Site Selection

Among the 18 scenarios, I found 10 potentially different sites to receive a new pulp mill. Out of the 18 locations, 17 were situated in the EMS northeast region, near Inocência (Figure 12). Figure 12 shows all the selected sites in orange circles, where their sizes indicate the frequency at which a mill was selected under different climate and land scenarios. For easier interpretation, I labeled each site with letters from A to J and displayed their distribution in Figure 13.

Only one of the remaining sites was selected in southern EMS, near Campo Grande, the capital of Mato Grosso do Sul (S13). Scenario S13 is under the climate negative assumptions (with productivity 12% lower than the baseline) and average LCC scenario.

The relatively cheaper land prices in the Northeastern region, averaging around US$1,742.2/ha (around 47% lower than the regional average), had a positive effect on mill selection in most of the scenarios.

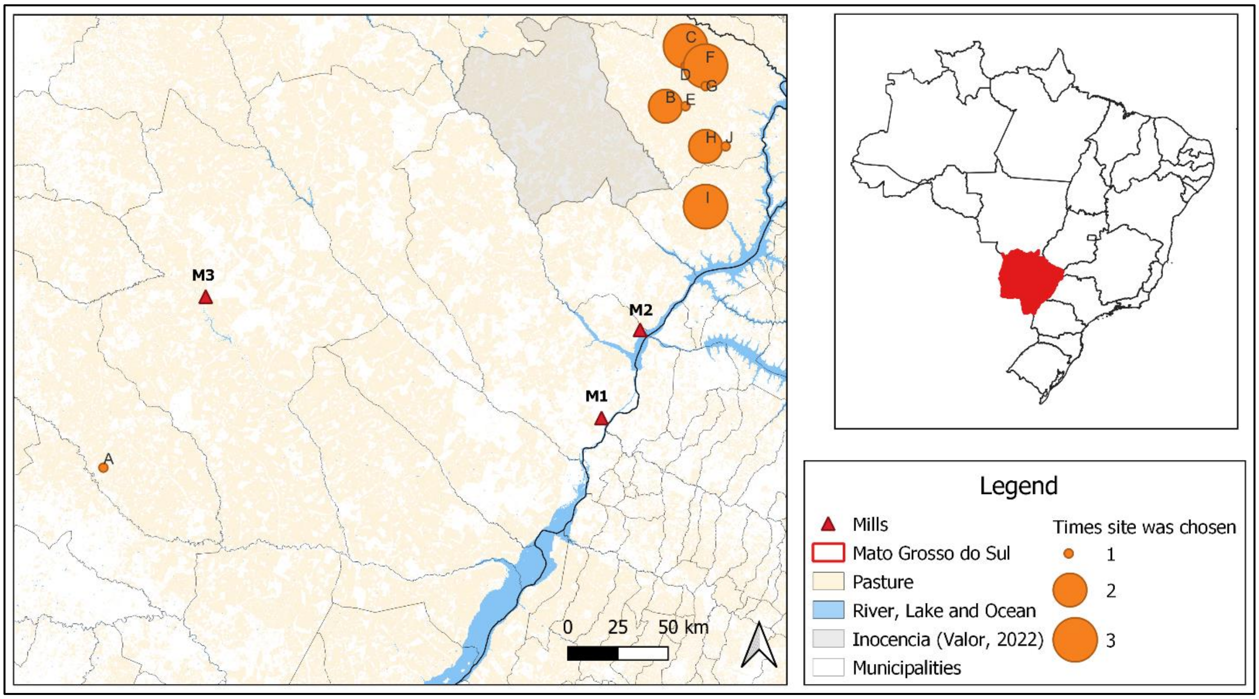

Figure 13 Selected sites for a new mill installation and current mills' location. Sites A ={S13}, B = {S5, S12}, C = {S4, S16, S17}, D = {S6}, E = {S11}, F = {S8, S14, S18}, G = {S3}, H = {S2, S10}, I = {S1, S7, S15}, and J = {S9}

Wood Pulp Price Sensitivity Analysis

In this sub-section, I tested how sensitive the NPV was to wood pulp price fluctuations and if a mill would be installed in case wood pulp prices decrease. Table 4 summarizes the NPV deviation for different wood pulp prices and an extra scenario ($S1^{\#}$) if a fourth mill never installs. I tested 5%, 10%, 15%, and 50% price negative variation (S1a, S1b, S1c, and S1d, respectively). I changed wood pulp prices in comparison to S1, keeping the LCC parameter or yield curves constant. Also, I did not impose an installation of a new mill, instead I made the constraint more flexible, where the equality in Equation 13B becomes an inequality as:

$$\sum_{j=1}^{J} Y_{j,t} \leq \begin{cases} 1, \forall \; t \geq t^* \\ 0, \forall \; t < t^* \end{cases} \tag{13B}$$

For all price scenarios, I observed that the NPV deviation to the baseline was higher than the price variation. When the price decreased -5% (S1a), the NPV reduction was around 5.2%, and when the price lowered 50%, the NPV reduced 51.5%. The demand for land and cost composition, however, remained unchanged.

Table 4 Price sensitivity analysis output

Scenarios	Wood Pulp Price Fluctuation	Yield Curve Shift	LCC	Wood Pulp Price ($/ton)	Market NPV @ 10% (in billion US$)	Δ NPV (% from baseline)
S1	-	Historical average		1,329.00	78.7	-
S1#	-			1,329.00	74.6	-5.2%
S1a	-5%			1262.55	74.7	-5.1%
S1b	-10%			1196.10	70.6	-10.3%
S1c	-15%			1129.65	66.6	-15.4%
S1d	-50%			664.50	38.2	-51.5%
Average*				1,116.4 (263.3)	67.2 (14.8)	-17.5 (19.5)

#In this scenario I assumed no market expansion; *Standard deviation in parenthesis

Figure 14 shows all the selected sites in orange circles, where their sizes indicate the frequency at which a mill was selected under different wood pulp price scenarios.

The geographical location was sensitive to changes in wood pulp prices; in contrast from what I observed in the previous section, lower pulp prices scattered the mill locations. Scenarios S1a and S1b were installed in Northeast EMS as a potential plant site. The pulp mills in S1d are in line with S9 in the Campo Grande (the MS capital) area. S1c, however, chose a site closer to the border with São Paulo, which would decrease export costs by reducing the hauling distance from the plant to the Port of Santos.

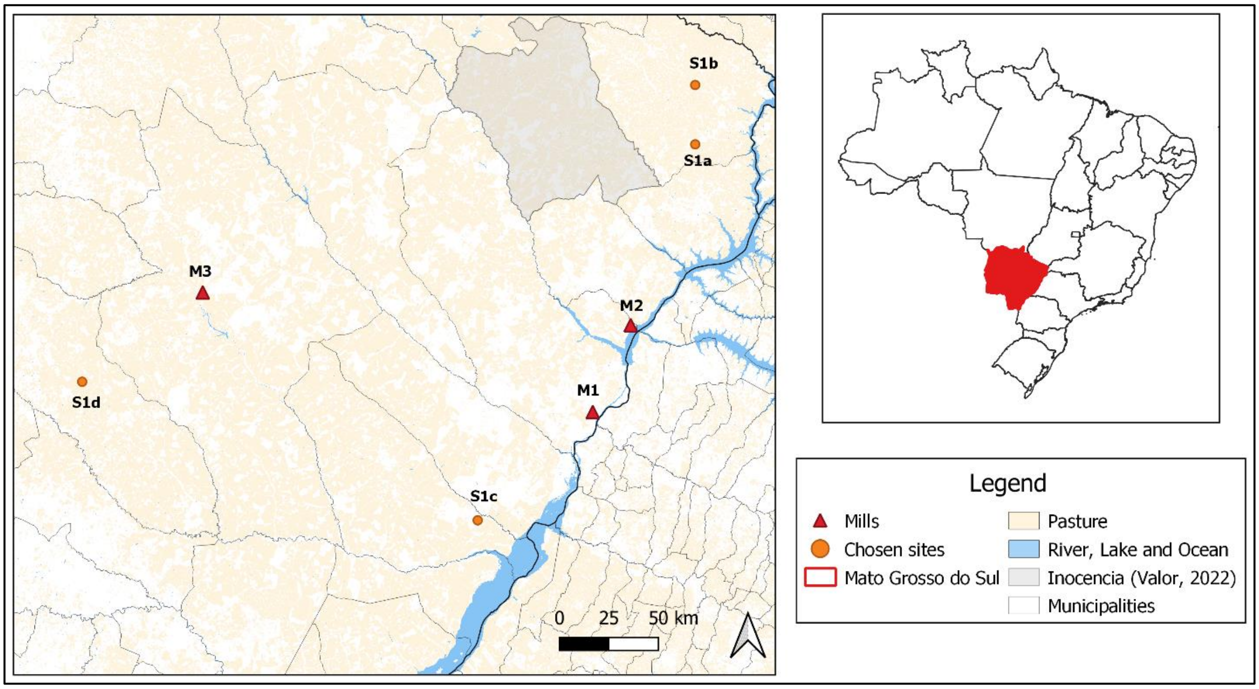

Figure 14 Selected sites for a new mill installation and current mills' location. Each orange dot represents a different site selected to install a mill for scenarios S1a to S1d. The red triangles represent the current mills.

Discussion and Conclusion

My study assessed the impact of climate change on eucalyptus forest variability in an expanding market and estimated the most suitable sites to receive a new pulp mill in the eastern region of Mato Grosso do Sul, Brazil. I used a sophisticated Mixed Integer Model that considered harvest schedule and facility location simultaneously. My study attempted to answer four questions:

(1) Will the supply of pulpwood be enough to support current and future demand in the market?

I found that shortages of pulpwood might occur under extreme negative scenarios. In the worst-case scenario, in 25 years, around 18% more pulpwood would be needed. In line with that, I also observed that the results of all scenarios showed a peak of land cover change which could indicate another possible shortage of pulpwood regardless of the climate scenario.

(2) What will be the impact on the industry's returns if forest productivity changes due to climate change?

I found that financial returns would be severely affected by land constraints and productivity fluctuations. In the worst-case scenario, the market's losses could reach up to US$2.81 billion in 25 years. From 2012 to 2021 the EMS exports of pulp products (HS47 to HS49[10]), for example, averaged around US$1.3 billion/year. So, in 25 years, the losses driven by climate change could be the same as if the EMS market stopped exporting pulp products for more than two years.

[10] Harmonized System (HS) is an international convention to classify goods and services traded globally. They consist in a series of hierarchical code that assist players in trading goods and services, governments to input taxes, and statistical analysis. HS47: Pulp of wood or of other fibrous cellulosic material; recovered (waste and scrap) paper or paperboard; HS48: Paper and paperboard; articles of paper pulp, of paper or of paperboard; HS49: Printed books, newspapers, pictures, and other products of the printing industry; manuscripts, typescripts, and plans.

Earlier studies showed that climate scenarios causing productivity losses had adverse effects on the Brazilian and Latin American markets, resulting in negative NPV variations. In Brazil, Palma et al. (2021) discovered that the short-term effect on the NPV would escalate to 15%. However, with the introduction of new genetic material in trees, this deviation from the baseline would gradually decrease and settle at around 7% in the long term. Palma et al. (2021) also found that the producer's cost in the southern Brazilian region could increase by around 10% under forest productivity loss scenarios. My findings suggest that, on average, under productivity loss scenarios, the costs could rise around 30%. If I disregard the most aggressive scenarios, such as S16, S17, and S18, the cost variation would average around 5.6%. In the worst-case scenario (S18), costs would rise 84%. In the best-case scenario (S9), with productivity gains, the total costs would reduce no more than 7%.

A separate investigation conducted by Favero et al. (2021) projected that Brazilian producers could potentially encounter surplus losses of approximately 8% by the year 2100 under a highly aggressive climate change scenario. However, it is worth noting that this study did not account for industrial and non-industrial forests, which creates discrepancies when comparing their findings to ours. For instance, the authors focused on economic losses to producers in the Brazilian Amazon, while most of the timber production in the country does not originate from the Amazon Forest.

(3) Where would the new plantation grow?

In the EMS, land conversion mainly occurred in areas near existing forests and most likely in the northeastern side. This happened because those areas had lower land prices (around 47% cheaper than region's average) and were close to current and future pulp mills, thus reducing transportation costs.

(4) Where will the new mill be installed?

Brazilian specialized media have been reporting that the Arauco mill could be installed in Inocência, which is in the northeastern EMS region. My findings suggested that in 17 out of 18 scenarios, the most suitable place would also be in the Northeastern EMS region, surrounding Inocência. Only scenario S9 did not choose a site in that region.

Despite considering several variables, some of my assumptions are conservative. I, for example, did not account for exchange rate, international price fluctuations, or distance to the Port of Santos. The reason for that is the difficulty in forecasting international forestry prices and the relatively low accuracy most models have as the time frame lengthens. Perez-Garcia et al. (2002) proposed a formulation of the Global Circulation Model to assess global supply and price trends and found a negative trend for the 2010s and 2020s. However, the price trend was positive in many regions. In Europe, from 2000 to 2020, the nominal prices rose around 60% (ResourceWise, 2023), while in Brazil, the stumpage prices doubled in the last decade (CONSUFOR, 2023).

Advances and Limitations

My work was similar in many ways to a study conducted by Troncoso & Garrido (2005) in Chile. Among the differences between both studies are the productivity fluctuations and different land access scenarios considered here. The authors, however, considered mill expansion and mill construction costs. I decided to not include the latter because it would be a constant among all scenarios, changing only the NPV level.

Among the major limitations of my model, I highlight the absence of transportation costs in the exports function and consequently the distance to nearer ports. I also have not accounted for international prices and exchange rate fluctuations. The LCC scenario is another limitation given

I based the availability of land on historical averages. Future works could incorporate a function to predict or assess the most likely places to be converted into forests, for example.

One of my main assumptions relies on the productivity change over the whole timespan, future works could also simulate random climate events (e.g., drought periods). For studies in the US, the incidence of wildfires and hurricanes could also be assessed using my model.

Conclusion

Although the empirical example used in this case study is specific to *Eucalyptus* plantations in Brazil, the comprehensive methods presented here can be used by any decision-makers who seek to understand the risks and resources allocation in an expansion of a new wood-consuming mills. In the US, for instance, this type of analysis could be applied to new pellet mills, (Visser et al., 2022), or to define the optimal biomass collection site for biochar production (Thengane et al., 2021).

Regardless of my approach to the tree's productivity shifts, the model is flexible enough to be modified into different levels of industrial productivity. For instance, this modification would aid existing literature and methodologies in evaluating industrial technological advancements. My contribution to the existing literature lies in the incorporation of climate change and LCC scenarios, the incorporation of FL problems into HS models, and providing evidence on potential development scenarios for the Brazilian EMS region, notably one of the world's most aggressive forestry markets.

In 2017, for example, only US TIMOs owned around 61.5% (or 675,000ha) of total TIMO-owned lands in Brazil (B. K. Da Silva et al., 2017). One of the reasons Brazil receives an impressive number of foreign investments is the comparative advantage the country has. Cubbage et al. (2020) highlighted it by comparing financial returns in Brazil and other selected wood baskets around the world. While, in Brazil, eucalyptus plantations could reach an Internal Rate of Return (IRR) up to 10.7% in 2017, in the US, the maximum achievable IRR was no greater than 7.9% for pine plantations.

My study emphasized the significance of incorporating climate fluctuations into strategic planning, thereby shedding light on the market's vulnerability to such variations. My model will assist managers, investors, and local governments, aiding them in their decision-making processes by reducing risk exposure and mitigating potential losses.

CHAPTER II

DRIVERS OF FORESTATION IN MIDWEST BRAZIL

Introduction

Land is among the most important factors of production for the forest industry. The access to it, however, is subject to intense competition with other activities such as agriculture, pasture, and urbanization (FAO, 2023b). In 2020, the global forest coverage was around 29% of the World's land, while woody crops were no more than 1.5%, and herbaceous crops represented around 12.9% of the total World's land, according to the Food and Agricultural Organization (FAO).

The demand for land is expected to accelerate as food and timber production reduces due to climate change and the global population grows (Molotoks et al., 2021). Also, as the population grows, the need for increased food supply will exert pressure on land competition worldwide. Furthermore, alterations in climate patterns have the potential to negatively impact crop productivity, making it necessary to explore strategies such as expanding agricultural coverage. For instance, an estimated 9% (3.7 million km^2 - 37% of US's total land area) of the world's current arable land may become non-harvestable or experience decreased productivity in the future (Zhang & Cai, 2011). In specific regions like Europe, the United States (US), and South America, the available arable land could potentially diminish by approximately -22% (0.68 million km^2), -1% (0.04 million km^2), and -23% (2.06 million km^2) respectively.

In the same vein, the demand for forest products is expected to increase around 2.2% per year for the next century (Tian et al., 2016). Wood fiber and paper demand, for example, is expected to rise by 13.7% worldwide (Statista, 2023). The current largest producers of wood pulp are the United States (US), Brazil, and Canada, producing 49.7 Million Tons (MT), 23.1 MT, and 14.9 MT of wood pulp respectivley in 2021. Regarding global trade, Brazil is the largest exporter of wood pulp (16 MT) followed by Canada (8.4 MT), and the US (7.6 MT) (FAO, 2023a).

Brazil's comparative advantage, competitive financial returns, and depreciated exchange rates are among the reasons explaining the country's relevance in the forest international market. Due to the attractive biological and financial environment, there was no other place in the world with such aggressive greenfield investment. According to the UN Environment Programme (2023), between 2000 and 2017, Brazil experienced a 49% expansion in its planted forest area, surpassing both South American economies (47%) and the global average (31%). This expansion was predominantly concentrated in the Midwest of Brazil, specifically along the eastern border of the Mato Grosso do Sul (MS) state.

The expansion of Eucalyptus plantations, a fast-growing pulpwood tree, in Brazil was historically situated in the country's South region. In the last decades, however, the pulp and paper industry began a migration to the Midwest, in the Eastern Mato Grosso do Sul (EMS). In 2009 and 2012, two of the country's largest pulp mills were installed in Três Lagoas, making the city the "Brazilian Pulpwood Capital" (World Rainforest Movement, 2011). Together, both mills consume around 17 million m^3 of pulpwood per year. A third mill is being installed and is expected to start operating in the second semester of 2024, increasing the pulpwood demand by 50% (Suzano S.A., 2021b). A fourth mill demanding around 2.5 million m^3 of pulpwood might be installed in the next decade in the EMS region (Valor International, 2022).

This market movement is followed by an intensive Land Cover Change (LCC) process. The main constraint for planting forest in that area, however, is the competition with pasture and agriculture (MapBiomas, 2023b). Currently, planted forests correspond to 940,000 ha (2.6% of total land), while pasture and agriculture correspond to 37.4% and 10.4%, respectively (MapBiomas, 2023b). Table 5 summarizes the most extensive land uses in Mato Grosso do Sul in 2021.

Table 5 Selected land cover classes coverage in Mato Grosso do Sul

Land cover class	Area (million ha)	% of total MS area
Pasture	13.35	37.4%
Forest	5.48	15.3%
Native	4.54	12.7%
Planted	0.94	2.6%
Agriculture	3.73	10.4%
Soybeans	3.15	8.8%
Sugar Cane	0.56	1.6%
Citrus	0.00	0.0%
Cotton	0.02	0.0%
Urban Infrastructure	0.08	0.2%

Source: (MapBiomas, 2023b)

An essential aspect of Brazil's forest market is its ownership model. Unlike the US, for example, there is no allocation of public land for commercial purposes. Public forests (97.9% of total forest coverage) are for preservation uses only (MapBiomas, 2023b). Another major difference from the US market is the high level of private properties' concentration in commercial forests. Due to forest market verticalization, individual landowners rarely engage in forest planting. The most common options are TIMOs and forest companies owning and managing their land. Unfortunately, due to lack of data, I cannot estimate the market share of each ownership type.

Conducting a study on LCC in a region where the forest industry is expanding, and where there exists competition for land with pasture and agriculture, is important for many reasons. Firstly, Brazil is the largest wood fiber exporter and the second-largest producer of pulpwood globally and understanding the drivers of LCC in such a context is crucial for sustainable management of forest resources.

Secondly, the competition for land among different land uses poses challenges for land use planning and decision-making. By investigating the factors influencing LCC in this region, policymakers, land managers, and stakeholders can gain insights into the socio-economic and environmental dynamics that are shaping the landscape. This knowledge can assist effective land use policies and strategies, balancing the economic benefits of the forest industry.

Furthermore, studying LCC in this context can contribute to my broader understanding of land use dynamics in Brazil and provide valuable insights for other regions grappling with similar challenges. By shedding light on the drivers of LCC and their implications, this research can support evidence-based decision-making, sustainable land management practices, and the preservation of valuable forest ecosystems in the face of growing competition for land resources.

I seek to answer the following research questions: (1) what are the most likely regions to experience LCC? (2) what is the effect of commodity prices in (e.g., soybean and cattle) the LCC process in the EMS region? (3) how does the economic environment affect the LCC process in the EMS region?

This study is divided into five sections: (1) introduction, which is this current one. (2) literature review, where I go through previous studies regarding LCC, the models' authors have used in the past, and results found. (3) methods and data, where I describe my variables and models used in this analysis. (4) results, where I describe the model's output, and (5) conclusion, where I discuss my findings compared to previous studies.

My results indicate that, on average, the LCC process is more common from pasture to agriculture, than into forests or other LC activities.

Literature Review

In this section I review the literature on LCC models, previous findings, and how I expand the discussion on LCC drivers in Brazil.

Empirical Findings on LC and LCC Drivers in the USA

Pioneering studies addressing the impacts of social and economic factors on LCC date back to the 1980s and 1990s (Iverson, 1988; LaGro & DeGloria, 1992; Ojima et al., 1994; Turner et al., 1996). Ojima et al. (1994) highlighted potential socioeconomic drivers of LCC and discussed how to incorporate them into LCC studies. Among the various factors, the authors argued on the ecological exposure that developing economies face, especially under favorable agricultural and market conditions.

In addition to Ojima's work, Turner et al. (1996) assessed the impact of social and economic variables, such as land ownership and agricultural prices, on the LCC process in the Olympic Peninsula and Appalachian Highlands. Their work was among the first studies that tackled the subject in the United States. Their findings suggested that steeper terrains could increase forestation in both study sites due to the difficulty in managing a crop in an uneven terrain. The authors also found that public lands (owned by the Department of Natural Resources – DNR) closer to markets were less likely to be forested. Even though the results contradicted the authors' expectations, they argued that forestation in public lands could be positively related to harvest probabilities rather than market distances.

A few years before, Iverson (1988) was already interested in understanding the drivers of landscape changes in Illinois. Among his many findings, he assessed a high propensity for agricultural coverage, especially in forest areas with higher soil productivity indexes. As a result, between 1820 and 1980, around 27.3% of timberland was converted into agriculture. Still on Iverson's work, only 19% of the forest area remained as forest by 1980. The intense LCC process was a result of factors such as fertile soil and increasing demand for agricultural products.

In the same vein, LaGro & DeGloria (1992) conducted a similar study to Iverson's (1988) in New York (NY). Similar to what was observed in Illinois, the forested area in NY decreased over time to make way for croplands and urban centers to develop. The remaining forests were primarily situated in steeper and rocky sites with lower-quality soils.

Studies on land use are not exclusive to the US; authors from around the world have also shown interest in understanding the patterns and drivers of LCC. As the demand for land continues to rise, competition escalates among forests, agriculture, urbanization, and economic growth. In the next section, I briefly review some of the work made outside the US.

Empirical Findings on LC and LCC Drivers Around the World

The economic literature often links economic development and growth to the exploitation of natural resources, which exposes developing countries to increased resource utilization. Many of these economies are in South America, particularly in the vicinity of the Amazon Rainforest.

In the Ecuadorian Amazon basin, Lopez (2014) assessed the drivers of agricultural LCC in a tribe-dominated area. The author employed a series of variables, such as soil quality, demographic pressure, distance to the nearest crop, and terrain slope, to measure the probability of LCC from forest to agriculture. He found that the demographic pressure was the primary driver of LCC in the area, arguing that the LCC process was a consequence of the increasing demand for food for the local population.

In Brazil, where the largest share of the Amazon is located, the phenomenon is not different. Between 1985 and 2020, the native forest coverage decreased around 12%, which represents around 52.2 million ha (MapBiomas, 2023b). Even though this trend is due to agricultural frontier expansion, there is also a parallel movement where forest crops are gaining relevance. And studies argue that they might be able to help recover the native flora.

In Brazil, the planted forest area increased almost sixfold, gaining around 7 million ha during the same period (MapBiomas, 2023b). As assessed by Silva et al. (2016), these planted forests can contribute to the restoration of native forests. Their study took place in Brazil's southeastern region, where they investigated the factors influencing rainforest recovery near *Eucalyptus* plantations. Proximity to existing forests, aspect, and slope were the primary drivers of reforestation. In a subsequent period, however, when the Brazilian pulpwood industry was established in the region, proximity to *Eucalyptus* forests emerged as the second most significant reforestation driving factor, only behind the proximity to existing forests.

Increased Land Surface Temperature (LST) is one of the results of the intense LCC in the country. In the Piracicaba region, southeastern Brazil, the LCC process that leveraged the agriculture dominance in the region, was responsible for almost doubling the average LST during the moist season (21.5°C to 41.3°C) (Sayão et al., 2020). During the dry season, the average LST growth was around 86%, increasing from 17.1°C to 31.7°C in 30 years.

The LCC pattern is also similar in Thailand. Over the last few decades, forested areas have been cleared for agriculture (Buya et al., 2020). In particular, the cultivation of rubber trees (*Hevea brasiliensis*) has seen a reduction in the planted area of around 39% between 2000 and 2018, while agriculture has grown by 66% during the same period. The authors argue that low natural rubber prices have discouraged rubber producers within the studied time frame.

These various authors I mentioned before have used multiple research methods to conduct their studies, ranging from theoretical reviews to multivariate multinomial regression, and more recently even complex machine learning algorithms. A commonly used tool in LCC studies are logistic and multinomial regressions. In the next section, I review these two latter methods, and how previous authors applied them into their research.

Model Selection

Logistic and multinomial regressions are two commonly used methods when dealing with categorical data, such as land cover types. While the former is designed for binary outputs, the latter can account for multiple categories (Agresti, 2002). These models have been widely applied in the LCC literature, enabling researchers to assess drivers of LCC (Buya et al., 2020; Chomitz & Gray, 1996; Hitayezu et al., 2016; Hu et al., 2014; Lopez, 2014; Mertens & Lambin, 2000; Turner et al., 1996; Van Dessel et al., 2011; Walker et al., 2002). In this section, I will begin by reviewing previous applications of the Logistic Regression Model (LRM), then will follow to previous application of the Multinomial Logistic Model (MNLM).

I summarize selected literature on LCC by their respective authors, year of publication, objective tackled, method, and studied location in Table 6 below.

Table 6 Methodological summary of selected Land Cover (LC) and Land Cover Change (LCC) papers

Author	Year	Dependent Variable	Model	Study Area
Iverson	1988	Land cover change	Regression and correlation analysis	USA
LaGro & DeGloria	1992	Urbanization	Least Squares	USA
Turner et al	1996	Land cover change	Multinomial	USA
Chomitz & Gray	1996	Commercial x subsistence agriculture	Multinomial	Belize
Wear & Bolstad	1998	Forest coverage	Poisson	USA
Mertens & Lambin	2000	Deforestation and LCC	Logistic	Cameroon
Schneider et al	2001	Deforestation	Logistic	USA
Walker et al	2002	Agriculture and pasture regimes	Multinomial	Amazon
Van Dessel	2011	Forest, Arable, and Vineyard	Logistic	Hungary
Hu et al	2014	Forest cover area	Logistic	China
Lopez	2014	Agriculture	Logistic	Ecuador
Hitazyezu	2015	Agricultural land cover change	Multinomial	South Africa
Silva et al	2016	Forest transition	Neural Network	Brazil
Silva et al	2020	Land cover change	Neural Network	Brazil
Buya et al	2020	Land cover	Logistic and Multinomial	Thailand

Logistic Regression Applications in LCC Studies

Although I focus this subsection on the LRM, I will not dedicate much time discussing it in the results section. The reason I included it in this study is to establish a benchmark and ensure consistency for the MNLM.

Pioneer LCC studies that employed an LRM were constrained by limited spatial data availability and rudimentary GIS tools. This was the case with Schneider & GilPontius (2001), who, due to data constraints, fitted a logistic regression using only slope, elevation, and distance to residential areas as independent variables to assess likely deforestation areas in Massachusetts, USA. Their findings indicated an inverse correlation between slope and distance to deforestation, and a positive correlation with elevation, suggesting that steeper and more distant lands from residential areas were less likely to be deforested.

The urban development in Cameroon was assessed by fitting two LRMs in different time periods, using distance to roads as a control variable (Mertens & Lambin, 2000). In the first period (1973 – 1986), there was no significant effect of proximity to roads on the likelihood of deforestation. However, in the second period (1986 – 1991), this variable became one of the most relevant factors explaining the phenomenon. According to the authors, during the first period, forest utilization was concentrated around existing towns, while in the second period, due to a migration process, forests near roads became more likely to be cleared.

LRMs are still in use today. Buya et al. (2020) employed multiple LRMs to assess the LCC process in Thailand for three different land cover types (agriculture, urban, and rubber tree forests). In their study, they considered only the previous land cover type as a control variable. While they were unable to measure the impact of other variables, they did observe a negative correlation between agriculture and rubber forests. Agriculture expanded by approximately 66% between 2009 and 2018, while rubber tree forests decreased by nearly 40%. Additionally, they used a MNLM with “undeveloped land” as the benchmark land cover class. The results from the MNLM and LRM showed similarity, indicating the robustness of the results.

Depending on the study framework and LC classes number, both models can be interchangeable and have similar results like the above mentioned. That is why later I will propose LRM with forestation as a binary output and an MNLM to better understand how the different activities in the EMS relate to each other.

Multinomial Logistic Regression Applications in LCC Studies

MNLM can be more complex, and sometimes more complete, than LRM. The difference between both is that instead of a binary output, I can now assume multiple categories assuming a benchmark one. Chomitz & Gray (1996) and Turner et al. (1996) were pioneers in applying the MNLM into LCC problems.

In the case of Belize, commercial agriculture is more sensitive to proximity to consumer markets than familiar agriculture (Chomitz & Gray, 1996). Even though both had a negative correlation to the control variable, land nearer to towns is more susceptible to be devoted to trade than to family consumption. Another interesting finding of Chomitz & Gray (1996) is that lands in forest reservations in Belize seemed to be less likely to be converted into any type of agriculture.

Turner et al. (1996) highlight how different ownerships tend to have distinct land cover distributions in the US. They assessed that private lands generally exhibit lower forest coverage, while public lands tend to have higher rates of forest coverage. They were also able to identify different spatial distributions, with the South having higher forest coverage than the Olympic Peninsula.

One of the most recent studies using multinomial models assessed urban LC changes in Philadelphia, PA (Locke et al., 2023). The authors classified 40 years of LC data into five LC classes: tree and shrub, herbaceous vegetation, other pervious, building, and other impervious. The time trend for the city showed that the LC tree and shrub coverage increased, while impervious declined over time. The growth of the Hispanic population stood as the sole influential factor providing a positive explanation for the observed increase in tree and shrub coverage. Conversely, population density and the presence of owner-occupied housing constrained the growth of tree and shrub coverage over recent decades.

Land Aspects and Distance to Market

After going through an extensive literature review, I identified some variables that are commonly used as controls to explain forest conversion. That is the case of terrain slope and elevation, for example (Hitayezu et al., 2016; Hu et al., 2014; R. F. B. daSilva et al., 2016; Turner et al., 1996; Van Dessel et al., 2011; Wear & Bolstad, 1998).

Steeper regions (higher terrain slope gradient) and more elevated ones tends to increase the likelihood of forest conversion due to landscaping cost minimization and accessibility (Mertens & Lambin, 2000; Turner et al., 1996; Van Dessel et al., 2011; Wear & Bolstad, 1998). Another commonly used variable is distance to markets, roads, and towns. The reason for that, especially in forestry, is because logistics is one of the industry’s largest cost components (Bjørndal et al., 2012). The literature has evidence that there is a negative relationship between distance to markets, roads, and towns in the forest LCC process (Turner et al., 1996).

Economic Variables

Besides logistics and land characteristics, agricultural commodity prices were used as controls to measure the substitution effect between forest and crops (Barson et al., 2004; Medrilzam et al., 2014). In Thailand, for example, attractive rice and rubber prices boosted the deforestation process (Medrilzam et al., 2014). A similar phenomenon was observed in Australia in the late 1990s, but regarding high beef prices leading to land clearing (Barson et al., 2004).

The Gross Domestic Product (GDP), also commonly used as the national income, has been previously used to assess the LCC process (Hu et al., 2014; Ketema et al., 2020; Uisso & Tanrıvermiş, 2021). Hu's (2014) investigation did not identify a significant relationship between GDP and forestation. Ketema's (2020) work, however, in East Africa revealed a positive association between GDP and LCC in terms of agroforestry and planted forestry. Furthermore, Uisso's (2021) study also demonstrated a positive relationship between GDP and arable land in Tanzania. These findings suggest that the impact of GDP on LCC may vary depending on the specific land use practices and geographic contexts considered.

To evaluate the influence of technological development on the process of LCC, a few studies have employed the number of tractors as a proxy for capital level (Bürgi & Turner, 2002; Jepsen et al., 2015; Uisso & Tanrıvermiş, 2021). Uisso's (2021) investigation, for example, uncovered a negative relationship between tractors and LCC. This finding suggests that the presence of tractors, indicative of capital accumulation, has played a significant role in making substantial changes to arable land coverage.

Contribution

My study contributes to three key topics. Firstly, I assess the impact of economic growth and capital levels on the LCC process. This analysis provides insights into the underlying factors that influence land use decisions, contributing to my understanding of sustainable land management practices. Secondly, I incorporate international market variables into my analysis, allowing us to explore the influence of global economic forces on local land use patterns. By considering the demand for forest-based products and the prices of internationally traded commodities, I provide a comprehensive perspective on the drivers of land use decisions. Lastly, I contribute to the understanding of land competition dynamics and the role of forests within it.

Through these contributions, my research offers valuable insights for policymakers and land managers, providing better quality data in decision-making processes and strategies for sustainable land use and management.

Methodology

This section provides an overview of the models employed and the data utilized in the analysis. I fitted two distinct formulations of regression models for categorical data, namely: (1) Logit, and (2) Multinomial logit models. My sample consists of registered rural properties within the EMS region. To perform my analysis, I collected data and arranged it in a balanced panel. My panel covers 2002 to 2020 and it was divided into trienniums. In my proposed time frame (2002 – 2020), pasture was shown to be historically dominant, overshadowing other LC classes such as agriculture and forests.

Study Area

My study area is the EMS market in Midwest Brazil. My observations are registered rural properties in 2020. The National Institute for Colonization and Agrarian Reform (Instituto Nacional de Colonização e Reforma Agrária – INCRA) is the Brazilian agency in charge of registering those properties. After filtering some of them due to inconsistency[11], I ended up with 13,348 observations. Figure 15 shows a map with each EMS property's location.

[11] Double count and overlaying properties.

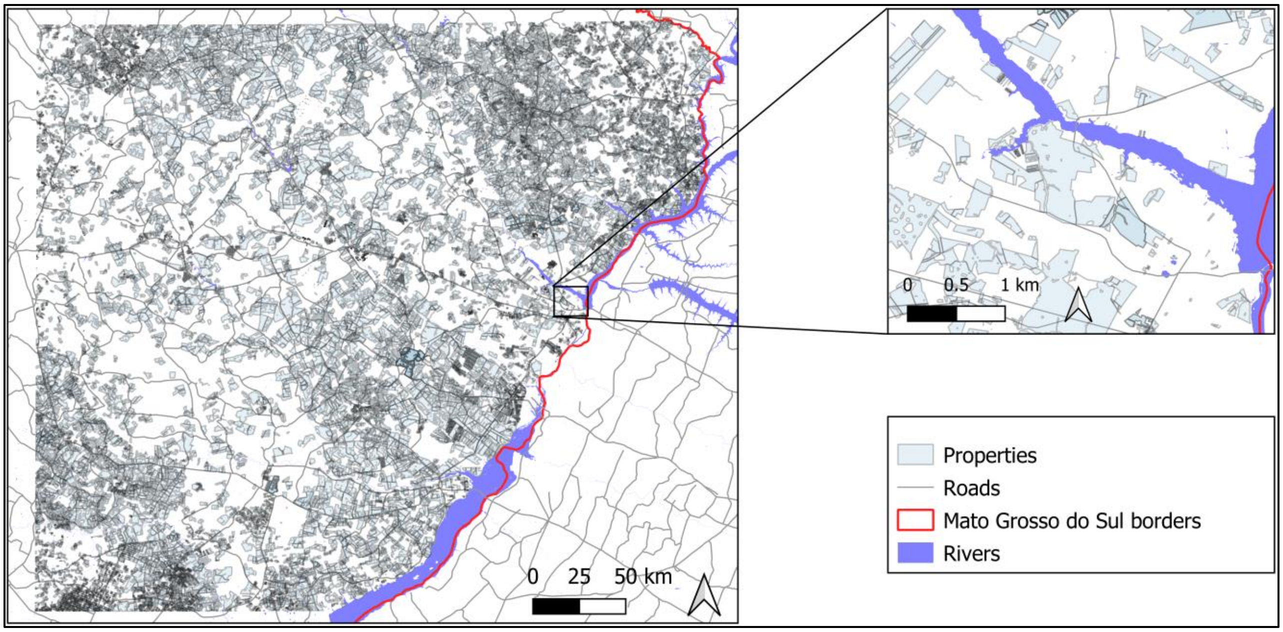

Figure 15 Study area – properties

Unfortunately, the rural property data available to us does not include any information regarding ownership or ownership type. As a result, I could not perform a more in-depth analysis of these aspects in the LCC dynamic. Here, I am only utilizing the properties as a sampling method.

Land Cover Classification and Dependent Variable Outline

Land cover class is my dependent variable, which represents the utilization of land for pasture, agriculture, or forest within a rural property in the EMS region. To assign the underlying LC of each observation, I calculated the relative area share that each land use had. If the coverage of an underlying LC was higher than 50%, that respective LC was assigned. In other words, if the area of the fictional property "A" was 50% covered by forest, 30% covered by agriculture, and 20% by other LCs, I assumed forest as that property's LC.

Figure 16 illustrates the MapBiomas data of the historical trend of LC in the EMS region, in the last trienniums. The Figure highlights the pasture dominance had over time and the extensive growth forests had alongside agriculture.

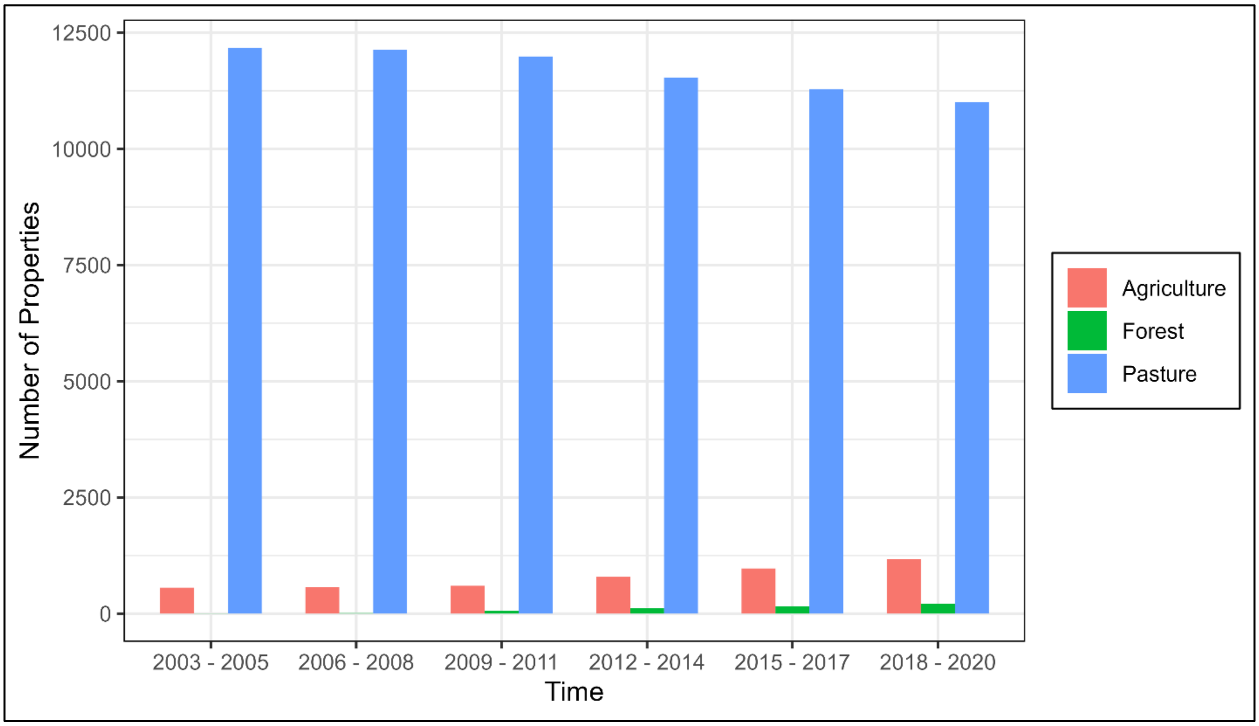

Figure 16 Number of properties per LC class over the last trienniums

After classifying the LCs, I fitted three different regression models with two different dependent variables. For the logit model, the dependent variable was the probability of an observation being primarily covered by forest. For the multinomial model, the dependent variable was the probability of an observation being covered by either forest, agriculture, or other categories instead of pasture. I used Stata 17.0 and R to fit the models, and for data geoprocessing, I employed QGIS.

Data Description

The variables selected are terrain elevation, terrain slope, distance to Eldorado's mill, distance to Suzano's mill, the Real Effective Exchange Rate (REER), cattle prices, soybean prices, municipal GDP growth, GDP per capita, and tractors per capita. All variables are statistically summarized in Table 7 below.

Table 7 Description of variables used in the models

Variables*	Source	Type	Mean	Standard Deviation	Min	Max
Elevation	INPE**	Constant	398.58	82.26	254	761.4
Slope		Constant	7.53	4.46	1	190.4
Distance to nearest mill	Company's report	Constant	254.68	114.7	2.75	479.4
REER	Comexstat and BCB***	Time series	13.18	4.31	6.9	18.4
Δ Cattle price	CEPEA+	Time series	5.24	28.55	-27.6	47.1
Δ Soybean price		Time series	-0.0004	24.66	-46.2	28.8
GDP growth	IBGE++	Panel	0.03	0.16	-0.94	0.54
ln GDP per capita		Panel	3.98	0.57	3.01	6.4
Tractors per capita		Panel	0.042	0.029	0.001	0.12

*Number of observations: 80,088; **Instituto Nacional de Pesquisas Espaciais (National Institute for Space Research); ***Brazilian Central Bank; +Centro de Estudos Avançados em Economia (Center for Advanced Studies on Applied Economics); ++Instituto Brasileiro de Geografia e Estatística (Brazilian Institute for Statistics and Geography)

My set of explanatory variables consists of data observations of different structures: (1) constant, where the data are different for every observation (i) but the same over time period (t); (2) time series, which the data are equal across observations (i), but different over time (t); and (3) panel, where the data vary among observations (i) and also over time (t). Each variable and its respective source and type are summarized in Table 7.

I collected the LC data in the MapBiomas platform. Terrain elevation and slope data were collected in the National Institute for Space Research (Instituto Nacional de Pesquisas Espaciais - INPE). I calculated the REER with data from the Brazilian Central Bank (BCB) and Comexstat. Daily soybean and cattle prices were collected from the Center for Advanced Studies on Applied Economics (Centro de Estudos Avancados em Economia – CEPEA). Data regarding population, GDP, GDP growth, and tractors were obtained in the IBGE census collection.

Econometric Model

Multiple statistical models have been employed over the years to study LCC. Pioneering studies relayed on conventional approaches such as binary classification, employing statistical techniques like logistic regression (Bhattacharya et al., 2021; Mertens & Lambin, 2000; Millington et al., 2007; Van Dessel et al., 2011). With that, the outcome variable (or dependent variable) would be the underlying LC classified as one and the rest as zero (Mertens & Lambin, 2000; Millington et al., 2007; Van Dessel et al., 2011; Wear & Bolstad, 1998). Gujarati & Porter (2008) define the univariate logistic regression model as:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_1 + u_i \tag{15}$$

where P_i is the probability of event i happening, or, in my case, the probability of an area/property being covered by the underlying LC i; $\beta_0$is the regression's y-intercept; β_1 is the slope of the explanatory variable X_1; and u_i the error term (Gujarati & Porter, 2008).

For the Multivariate Logistic Regression (MLR) case, I can derive Equation 15 as:

$$\ln\left(\frac{P_i}{1-P_i}\right) = Y_i = \beta_0 + \sum_{j=1}^{J} \beta_j X_j + u_i \tag{16}$$

where β_j is the slope of the j^{th} explanatory variable X_j. My logit model can then be defined as:

$$
\begin{aligned}
Y_{i,t} = \beta_0 + \beta_1 X_{1_i} + \beta_2 X_{2_i} + \beta_3 X_{3_i} + \beta_4 X_{4_i} + \beta_5 X_{5_{t-1}} + \beta_6 X_{6_{t-1}} + \beta_7 X_{7_{t-1}} \\
+ \beta_8 X_{8_{i,t-1}} + \beta_9 \ln\left(X_{9_{i,t-1}}\right) + \beta_{10} \ln\left(X_{10_{i,t-1}}\right) + \omega_{\mathrm{i,t}}
\end{aligned}
\tag{17}
$$

where $Y_{i,t} = \ln\left(\frac{P_{i,t}}{1-P_{i,t}}\right)$, which is the probability of the i^{th} property at triennium t being a forest as primary coverage. And for the i^{th} property, the terrain elevation and slope are represented by X_{1_i} and X_{2_i}, respectively. The distance to the nearest pulp mill from the ith property is denoted by X_{3_i}. The nation's lagged log of forest output is denoted by $\ln\left(X_{4_{t-1}}\right)$. The lagged deflated REER, cattle, and soybean prices are indicated by $X_{5_{t-1}}$, $X_{6_{t-1}}$, and $X_{7_{t-1}}$, respectively. The $X_{8_{i,t-1}}$, $\ln\left(X_{9_{i,t-1}}\right)$, and $\ln\left(X_{10_{i,t-1}}\right)$ indicate the lagged GDP per capita growth, lagged log of GDP per capita, and lagged logarithm of number of tractors in the municipality where the i^{th} property is situated.

For the MNLM, I can write it as follows:

$$
\ln\left[\frac{\Pr(y = m|X)}{\Pr(y = pasture|X)}\right] = \sum_{j}^{J} X_j \alpha_{j_{m|pasture}} \quad \forall\, m = \{forest, agriculture, others\} \tag{18}
$$

where $\ln\left[\frac{\Pr(y = m|X)}{\Pr(y = pasture|X)}\right]$ is the probability of a site being covered by the m^{th} LC as primary coverage instead of pasture, X_j is the explanatory variable vector, and $\alpha_{j_{m|pasture}}$ is α coefficients vector to be fitted for each m LC class over pasture. Although the structure is similar for all LCs, for brevity, I only wrote the entire equation for forest. Equation 18, can then be written as:

$$\ln\left[\frac{\Pr(y = forest|x)}{\Pr(y = pasture|x)}\right]$$
$$\begin{aligned} &= \alpha_{0_{forest|pasture}} + \alpha_{1_{forest|pasture}} X_{1_i} + \alpha_{2_{forest|pasture}} X_{2_i} \\ &+ \alpha_{3_{forest|pasture}} X_{3_i} + \alpha_{4_{forest|pasture}} X_{4_i} + \alpha_{5_{forest|pasture}} X_{5_{t-1}} \\ &+ \alpha_{6_{forest|pasture}} X_{6_{t-1}} + \alpha_{7_{forest|pasture}} X_{7_{t-1}} + \alpha_{8_{forest|pasture}} X_{8_{i,t-1}} \\ &+ \alpha_{9_{forest|pasture}} \ln\left(X_{9_{i,t-1}}\right) + \alpha_{10_{forest|pasture}} \ln\left(X_{10_{i,t-1}}\right) \\ &+ \alpha_{11_{forest|pasture}} D_1 + \alpha_{12_{forest|pasture}} D_2 \end{aligned} \tag{19}$$

In the LMM, I added two dummy variables to control for spatial and time effects. The regional dummy variable accounts for the eight microregions situated in the EMS and is denoted by D_1. The time dummy represents the six trienniums between 2002 and 2020. To avoid the "dummy trap", only seven and five dummies will be estimated for the regional and time effects, respectively.

Figure 17 illustrates how I conducted this study.

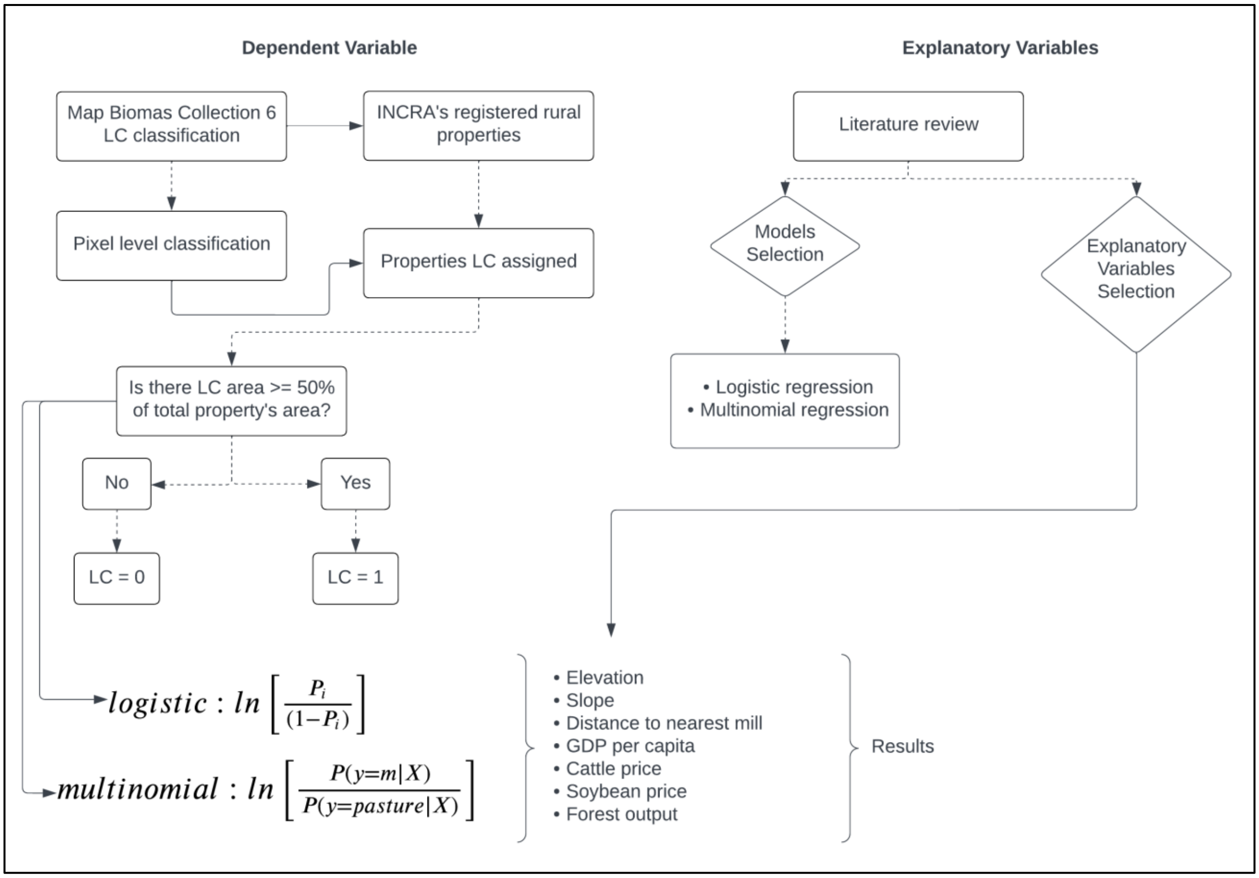

Figure 17 Model illustration

Variables Description

I chose my variables based on previous studies. Terrain elevation and slope, distance to markets (or mills in my case), income (denoted by the GDP per capita and GPD growth), and population were the variables I chose based on the LC and LCC literature (Hu et al., 2014; R. F. B. da Silva et al., 2016; Turner et al., 1996; Van Dessel et al., 2011; Wear & Bolstad, 1998). I incorporated REER, cattle and soybean prices, and tractors per capita to capture the effect of substitute LC classes and capital in forest coverage probability.

Elevation, Slope, and Distance to Pulp Mill

I do not expect elevation to have major influence given the major homogeneity of the region. However, I expect the terrain slope to have a positive sign for forestation due to the preference for flat land for agriculture and pasture.

I expect the same relationship for the variables that correspond to the distance to the mills. That is because the farther a property is to a mill, the less likely it will be covered by forest. That variable directly impacts the logistics cost of mills, which is one of the most expensive costs for pulp mills (Bjørndal et al., 2012). In the face of that, nearer lands are expected to be preferred.

Gross Domestic Product and Capital Level

I expect a positive coefficient sign for the GDP growth variable. The economics literature on growth calls attention to the fact that, due to relative proximity to the steady-state, poorer economies might grow at higher rates than richer ones (Barro & Sala-i-Martin, 1990). I then expect to observe a similar pattern in my data and results. So, properties located in poorer municipalities (in terms of GDP per capita) would be preferable to opt for forest instead of agriculture and pasture due to potential lower land prices, assuming that lower land prices would be more likely observed in poorer economies.

Real Effective Exchange Rate

To calculate the Real Effective Exchange Rate (REER), I first calculated the largest importers of Brazilian paper and pulp. Then, I calculated a weighted average of the exchange rate based on historical average imports share. I summarize the average imports share, relative weights, and exchange rate in Table 8 below.

Table 8 Average historical pulp imports from Brazil

Importer	Average imports share	Weight	Exchange rate ($/BRL)
China	43%	52%	2.69
USA	17%	21%	0.38
Italy	10%	12%	0.31*
Holand	9%	11%	
Japan	3%	4%	39.99
Total	82%	100%	-

*Given both countries are members of the European Union, therefore has Euro as their currency, I summed both when calculating the REER

Equation 20 shows the REER formula I used to calculate.

$$REER_t = 100 \prod_{n}^{N} x_{n,t} w_{n,t} \tag{20}$$

where $REER_t$ is the REER at time t. The exchange rate and weights of each import n is denoted by $x_{n,t}$ and $w_{n,t}$, respectively. I multiply the index by 100 for more practical interpretations. I expect the REER to have a positive sign for both forestation and agriculture, since that variable works as a proxy for international trade attractiveness for paper and pulp.

Commodity Prices

With that, I expect the substitute LC proxy prices (cattle and soybean prices) to have a negative relationship to the likelihood of a property being classified as a forest. The idea is that if cattle or soybeans become more financially attractive, there will be higher incentives for a site being covered by any of these two activities. For agriculture LCC, however, I am not sure about the sign given the correlation between soybean demand and the beef industry. I present the expected regression coefficient signs in Table 9 below.

Table 9 Expected regression coefficients sign

Variable	Expected sign	
	Forest	Agriculture
Elevation	NA	NA
Slope	(+)*	(-)**
Nearest mill	(-)	(+)
GDP growth	(+)	(?)***
REER	(+)	(+)
Cattle	(-)	(?)
Soybean	(-)	(+)
ln GDP per capita	(-)	(?)
Tractor	(?)	(?)

* the (+) sign denotes that a positive impact is expected; ** the (-) sign denotes that a negative impact is expected; *** the (?) sign denotes that the impact expected is uncertain

Time and Location Dummies

I included two dummy variables to capture the effects of time and location. The time dummy variable accounts for the temporal variation and is divided into six periods, each representing a triennium between 2002 and 2020. These periods allow us to examine changes over time in my analysis. To avoid the dummy variable trap, I include five dummy variables instead of six, with the first period serving as the reference level. Additionally, the location dummy captures the spatial variation by including eight dummy variables, one for each location. These variables help us understand the unique effects of each location, while also preventing multicollinearity by excluding the microregion 50003, since I used it as the reference region. Figure 18 shows the LC difference from 2002 to 2020 in the EMS region. In the Figure, the microregions' boundaries are also observable.

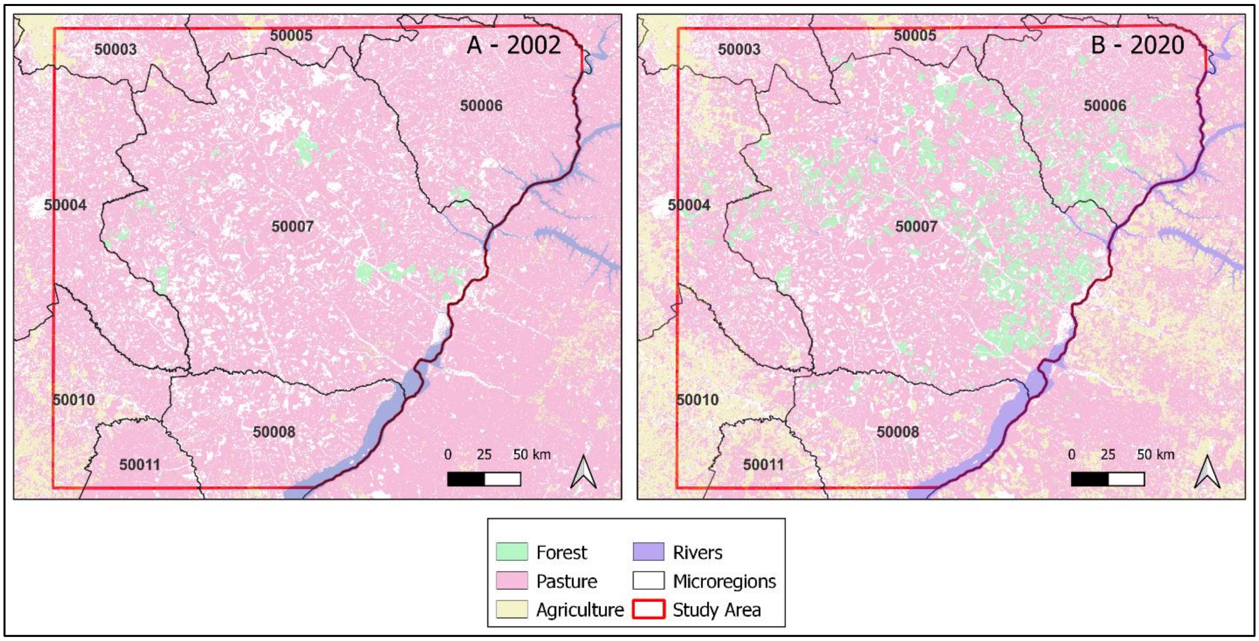

Figure 18 Land use and land cover in the EMS region

Results

In this section, I present the estimated coefficients. Table 10 summarizes the Logistic and Logistic Multinomial Models results. In columns 2 and 3 I have the logistic and multinomial regression coefficients, with significance level, and standard errors in parentheses. For both models the dependent variable is the probability of a property choosing forest as their main LC. In columns 3 to 5, I present the logistic multinomial regression coefficients. The reference LC for this model is pasture, so I am estimating the likelihood of a site being covered by forest, agriculture, or other LC over pasture.

Table 10 Fitted model coefficients

Variables	Estimated coefficients			
	Logistic	Logistic Multinomial (ref. = Pasture)		
	P(LC+ = Forest)	P(LC = Forest)	P(LC = Agriculture)	P(LC = Other)
(1)	(2)	(3)	(4)	(5)
Intercept	-	-0.171*** (0.002)	-0.195*** (0.002)	-0.445*** (0.002)
Elevation	0.007 (0.005)	0.002* (0.001)	-0.0003 (0)	-0.005*** (0)
Slope	0.055 (0.044)	0.056*** (0.011)	-0.129*** (0.008)	0.067*** (0.004)
Distance to nearest mill	-0.018*** (0.004)	-0.006*** (0.001)	0.013*** (0)	0.003*** (0)
Forest production	-0.06*** (0.006)	-0.899*** (0.033)	-0.654*** (0.021)	-0.644*** (0.015)
REER++	0.027 (0.041)	-0.06*** (0.014)	0.075*** (0.005)	0.326*** (0.004)
Δ Cattle	0.105*** (0.009)	0.039*** (0.002)	-0.001 (0.001)	-0.045*** (0.001)
Δ Soybean	-0.087*** (0.012)	-0.044*** (0.005)	0.021*** (0.001)	0.127*** (0.001)
GDP+++ growth rate	5.812*** (1.051)	-0.222*** (0.007)	-1.851*** (0.157)	-0.563*** (0.114)
ln GDP per capita	5.702*** (0.759)	1.097*** (0.074)	0.518*** (0.052)	0.633*** (0.035)
ln tractor per capita	-2.139*** (0.67)	-0.236*** (0.069)	-0.251** (0.03)	-0.049*** (0.021)

Standard errors in parenthesis; ***p-value<0.01; **p-value<0.05; *p-value<0.10; +Land Cover; ++Real Effective Exchange Rate; +++Gross Domestic Product

I fitted the logistic regression as a benchmark for the logistic multinomial model. Because of that, I decided to not include time and location dummies as fixed effects for them.

For the Logistic Multinomial Model (LMM), the coefficients are interpreted as the effect that the underlying explanatory variable has in the probability of a LC being chosen over pasture. For a better understanding, I computed the marginal effects for the LMM and summarized them in Table 11.

Table 11 Logistic multinomial regression explanatory variables' marginal effects*

Variables (1)	Forest (2)	Agriculture (3)	Others (4)
Elevation	-	-	-0.03%
Slope	0.03%	-0.59%	0.43%
Distance to nearest mill	-0.004%	0.05%	0.01%
Forest production	-0.56%	-2.39%	-2.98%
REER+	-0.05%	0.12%	1.69%
Δ Cattle	0.03%	-	-0.24%
Δ Soybean	-0.03%	0.01%	0.66%
GDP++ growth rate	-0.11%	-7.53%	-1.85%
ln GDP per capita	0.69%	1.81%	2.99%
ln tractor per capita	-0.15%	-1.04%	-0.09%

*Only 5% confidence level (or lower) statistically significant values were reported in the table; +Real Effective Exchange Rate; ++Gross Domestic Product

The values in Table 8 indicate the expected dependent variable percentage variation for every 1% variation in the underlying explanatory variable. If I analyze slope, for example, it says that if a terrain is 1% more elevated than the average, the underlying site would be 0.03%, -0.59%, and 0.43% more likely to be covered by forest, agriculture, or other LC over pasture, respectively. The negative effect on agriculture was expected given the hard access with machinery, like tractors, on steeper land.

Elevation and Distance to Nearest Mill

Elevation had only effects on the "others" LC. It means that, on average, elevation has no effect to determine LCC for forest or agriculture over pasture.

The distance to the nearest pulp mill had a negative influence on choosing forest over pasture and a positive effect for the remaining classes. It is well known that logistic costs are one of the most expensive cost components for the forest industry. Because of that, I expected a negative marginal effect for the forest. It means that a 1% farther property to the nearest mill would decrease 0.004% the chance of a site being covered by forest instead of pasture. For agriculture, this effect is positive, indicating that sites far from pulp mills would, on average, prefer agriculture over pasture by 0.05%. The same is valid for “others” LC, but in a lower magnitude (0.01).

Economic and Market Drivers

I expected the forest output in the previous period to have a positive sign and to be statistically different from zero. However, it had a negative sign for all LCs. I did not expect the national forest output to have any influence on agriculture or other LCs. I believe that I might have observed this negative marginal effect due to the importance that the Brazilian South wood basket still has.

Exchange Rate

The REER had a negative influence on the LCC process of forest over pasture, but positive for agriculture and the “other” LC. I must pay attention to the fact that the greater the REER number, the weaker the currency is. In other words, the greater the REER, the cheaper that Brazilian exported products will be. In the face of that, I expected to see a negative coefficient for forest given the underlying added value pulp and paper has compared to agricultural commodities, and global market distribution. In 2021, the domestic pulp and paper exports represented 69% of the total market’s output. For agriculture, around 19% of the total output production was exported (CEPEA, 2022; FAO, 2023a; IBGE, 2022).

Agricultural Commodity Prices

I expected the cattle price variation in the previous period to have a negative effect for all LCs given pasture is my reference LC. This assumption relies on the theory that agents are rational and will seek to maximize profits, so higher prices, or positive price variations would give them more incentive to opt for that underlying activity. For agriculture, I expected it to have a positive sign as well because of the relationship both sectors have. So positive cattle price variations would lead to higher supply of cattle (demanding more land), increasing the demand for cattle food.

I was able to capture this effect only for the "others" LC. The land coverage Substitution Effect (SE) for agriculture over pasture was not statistically different from zero. The effect for the forest was positive, which caught my attention in the first moment. Among the several reasons that this might have happened there is the relative long term that cattle investments demand, so only one lagged period would not be able to capture the forest SE.

For the soybean variation price, my expectations were similar to the ones for cattle price variation, except for the influence over agriculture. Even though domestic meat production is dependent on the agriculture output, the opposite is not strictly true. Because of that, I was uncertain about the coefficient of soybean price variation on pasture. What I observed was that positive price variations would create better incentives for a site being covered by agriculture and the "other" LC over pasture, while disincentivizing forestry as the primary LC. In other words, a 1% positive variation in the soybean prices in the previous period would, on average, decrease by 0.03% the probability of a site being covered by forest over pasture, and increase by 0.01% and 0.66% the probability of LCC from pasture to agriculture or the "other" LC, respectively.

GDP Level and Growth Rate

All LCs had a negative response to economic growth. In summary, when there is GDP growth, the likelihood of LCC from pasture to forest or agriculture is lower. It suggests that economic prosperity tends to incentivize cattle production.

The opposite is true for the GDP level. This suggests that historically wealthier areas are more likely to prefer forest, agriculture, or the “other” LC as their primary activity. Notice that GDP growth $\neq$ GDP level. There is a research field in economics that argues that higher GDP growth rates would indicate lower GDP levels because of relative distance to an economical steady state (Barro & Sala-i-Martin, 1990).

In my case, the marginal effects for the log of the GDP per capita increases the probability of LCC to agriculture (1.81%), forest (0.69%), or others (2.99%) over pasture as their main LC.

Number of Tractors

The number of tractors was used in this study as a proxy for the capital level. The marginal effect of this variable was negative for all LC classes. For every 1% growth in the log of the number of tractors, the probability of LCC to forest, agriculture, or other LC over pasture would be, on average, 0.15%, 1.04%, and 0.09% lower, respectively.

That highlights the fact that regions with higher capital investment would be more willing to choose pasture as their main LC.

Time Dummies

The time dummies, unlike the previous variables described, are compared to a benchmark period (2003 – 2005). In other words, I can assess in what time frame the probability of LCC was higher than the initial triennium. All the estimated coefficients were statistically significant at a 5% confidence level.

The probability of LCC into forest over pasture between 2012 – 2014 and 2018 – 2020 were 2.57% and 1.86% greater, respectively than they were in 2003 – 2005.

I believe that the installation of two pulp mills in the periods mentioned boosted the likelihood of forest as the main LC. The installation of both Suzano's (started operating in 2009) and Eldorado's (started operating in 2012) mills were the major driving factors between 2009 and 2014. Recently, a third mill was announced to be installed in the region to start operating in 2024 (Valor International, 2022).

For agriculture and others, the probability of LCC was higher than it was between 2003 and 2005 for all other periods. The high labor demand, liquidity, and price fluctuations are some of the potential explanations for that trend.

Discussion

The study assessed the drivers of LCC in the EMS region, controlling for economic aspects, commodity prices, and land characteristics. I was able to find insights into LCC decisions, specifically focusing on the preference for forest, agriculture, or other LCC class over pasture.

Previous studies have examined various factors that contribute to forest LCC, providing insights into the drivers of this process. Silva (2016) conducted a study in Brazil and identified several variables that could explain forestation. These variables included elevation, proximity to industry and commerce, proximity to eucalyptus, and slope. While the author did not specify the direction of the effects, they reported that these factors collectively accounted for up to 77% of the observed LCC.

In my study, I explored the influence of distance to market on forestation and found a negative correlation. This implies that as the distance to the market decreases, the likelihood of forestation increases. This result aligns with the findings of Silva (2016), where proximity to industry and commerce was identified as a significant driver of forest LCC.

Barson et al. (2004) and Medrilzam et al. (2014) observed a negative correlation between commodity prices and forestation. This suggests that, as agricultural commodity prices decrease, the likelihood of forestation increases. My study is in line with them as I found a negative correlation between soybean price variations, indicating that higher prices would incentivize temporary crops.

The influence of economic factors on forestation has also been explored in relation to GDP. Hu (2014) did not find a correlation between GDP and forestation, suggesting that income level does not significantly impact the conversion of land to forests in China. In contrast, Ketema (2020) found a positive correlation between GDP per capita and forestation in the East African Rift, indicating that higher incomes were associated with a greater likelihood of forest coverage. My research supports the latter finding, as I observed a positive correlation between GDP per capita and forestation. Additionally, I found a positive correlation between GDP per capita and agriculture, suggesting that economic development may drive both forestation and agricultural expansion.

Uisso (2021) found a positive correlation between GDP and arable land (agriculture) in Tanzania, which could imply a negative influence on forestation. My study did not specifically explore the process of arable land conversion, but I was able to assess drivers of LCC from pasture to agriculture. I found a positive correlation between GDP per capita and both forestation and agriculture. However, I also identified that GDP growth had a negative impact on the LCC process across all land cover classes. This suggests that while economic development may promote forestation and agricultural expansion to some extent, rapid economic growth might also contribute to other land cover changes, such as urbanization or industrial expansion, which can lead to overall negative impacts on forest coverage.

In summary, comparing my findings with previous studies reveals both similarities and differences in the drivers of forest LCC. Factors such as proximity to industry and commerce, distance to markets, commodity prices, slope, and GDP play complex roles in shaping forestation patterns. The variations observed could be attributed to diverse study locations, specific regional dynamics, or discrepancies in the time periods analyzed. Further research is needed to unravel the intricate relationships between these variables and their influence on forest LCC, enabling more targeted and effective conservation and land management strategies.

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