DOCTORAL DISSERTATION

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The Environmental Impacts caused by Agricultural Frontiers in Emerging Countries: The case of the MATOPIBA Region, Brazil

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“Não podemos pensar em desenvolvimento econômico, reduzir as desigualdades sociais, e em qualidade de vida sem discutirmos meio ambiente”.

-- Carlos Moraes Queiroz

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List of Abbreviations

AFI - Agroforestry Integration
API - Agropastoral Integration
ASPI - Agrosilvopastoral Integration
CCA - Canonical Correlation Analysis
CIMO - Context, Intervention, Mechanism, Outcome
CLFI - Crop-Livestock-Forestry Integration
CO_2 - Carbon Dioxide Emission
CO_2 GWP - Carbon Dioxide Emission in Global Warming Potential
EMBRAPA - Empresa Brasileira de Pesquisa Agropecuária
EU - European Union
FAO - The Food and Agriculture Organization
GDP - Gross Domestic Product
GHG - Greenhouse Gases
$GtCO_2$ - Gigatons of Equivalent Carbon Dioxide
Ha - Hectares
IBGE - Instituto Brasileiro de Geografia e Estatística
IPEA - Instituto de Pesquisa Econômica Aplicada do Brasil
Mha - Million Hectares
MHDI - Municipal Human Development Index
ML - Machine Learning
Mt CO2e - Metric Tons of Carbon Dioxide Equivalent
NGO - Non-Governmental Organization
PRISMA - Preferred Reporting Items for Systematic Reviews and Meta-Analyses
R$ - Brazilian Real
REDD - Reducing Emissions from Deforestation and Forest Degradation
RQ - Research question
RSPO - Roundtable on Sustainable Palm Oil
SD - System Dynamics
SDM - System Dynamics Modeling
SEEG - Sistema de Estimativa de Emissões de Gases de Efeito Estufa
SPI - Silvopastoral Integration
Sq. Cor - Squared Correlations
SVI - Social Vulnerability Index
T - Tons
Tg C- Teragrams of Carbon
VIF - Variance Inflation Factor

Abstract

The literature states that the advance of intensive agricultural production on the environment, known as the agricultural frontiers, is spreading mainly among emerging countries, due to lower production costs, flexible environmental regulations, soil fertility, and a favorable climate, among others. As a way of analyzing how environmental impacts are being generated and intensified, this dissertation presents a study of Brazil's newest agricultural frontier, Matopiba. The Matopiba region covers four states in the North and Northeast of Brazil and, although it comprises a large area of the Cerrado Biome, the region has gained considerable global importance due mainly to the production of soybeans and corn. Methodologically, this study used Descriptive Analysis, a Systematic Literature Review (SLR), and two empirical studies: Canonical Correlation Analysis (CCA) and System Dynamics Modeling (SDM). With the main objective of analyzing whether the Matopiba region of Brazil is a prominent topic in the world literature on agricultural frontiers and the environment in emerging countries, SLR showed that most of the world literature is concentrated in Brazil, but in the Amazon rainforest, indicating that studies on the Cerrado biome and the Matopiba region are still mainly concentrated among Brazilian researchers and are written in Portuguese. To analyze the environmental conditions generated by the agricultural frontier in Matopiba, CCA showed that there is a relationship between economic aggregates and environmental impacts in the region, with agricultural GDP having the highest canonical correlation with deforestation and one of the highest with CO_2 emissions. In addition, the CCA showed that agricultural production has a positive relationship with environmental impacts in Matopiba, with soybean and corn production, respectively, being the most polluting in the region. Intending to predict how long the available natural resources will sustain intensive agricultural production on Matopiba's agricultural frontier, the SDM showed that, as the agricultural area increases, native vegetation in areas with high and medium agricultural suitability is expected to be extinct within 20 years if no sustainable agricultural measures are implemented in the region. The results of these studies, among other findings, deepen the discussion on the environment and agricultural frontiers in emerging countries, contribute to the orientation of environmental public policies in Matopiba, and present a formulation of System Dynamics Modeling on agriculture and the environment that can serve as a basis for studies in other emerging countries.

Keywords: Agricultural Production. Environment. Brazilian Cerrado.

1. Chapter 1: Introduction

1.1. Research Problem and Questions

Agricultural frontiers, defined here as an expression indicating the advance of intensive agricultural production over the environment, are spreading mainly among emerging countries. This is due to factors such as flexible environmental regulations, lower production costs, growing global demand for agricultural products, and foreign investment, as well as social factors such as poverty and food dependency (Mariyam et al., 2023; Marengo et al., 2022; Dionizio et al., 2020; Spera et al., 2016; Horion et al., 2016; Gasparri & de Waroux, 2015; Mastrangelo and Gavin, 2012).

Current world grain production totals 3.3 billion tons, but this agricultural production is uneven, as it is concentrated in a few products and countries. Corn, rice, and soybeans (the three main commodities, respectively) account for two-thirds of world grain production and are grown mainly in emerging countries, where China, the United States, Brazil, and India account for 54% of all global production of these grains. In addition, with 124 million hectares under cultivation, Russia is the leading producer of barley, wheat, and sunflower; Indonesia and Malaysia are responsible for 95% of the world's palm oil production; Argentina, Paraguay, and Bolivia, alongside Brazil, are Latin America's main beef exporters (FAO, 2021).

The advance of agricultural frontiers is drastically aggravating environmental problems (Dos Reis et al., 2023; Usman et al., 2023; Ibrahim et al., 2022; Jahanger, Usman and Ahmad, 2023; Makhdum et al., 2022; Usman and Balsalobre-Lorente, 2022; Avagyan, 2018; Feintrenie, 2014; Villela et al., 2014; Gibbs et al., 2010). Problems such as increased emissions of polluting gases, increased rates of deforestation, water pollution, and loss of animal biodiversity, among others, are the result of unsustainable agricultural production in emerging countries (Avagyan, 2021, 2017 and 2010; Adegbeye et al., 2020). Another problem faced in these countries is the increased use of fertilizers and pesticides, observed mainly in Latin America and Southeast Asia (Avagyan, 2018; Schreinemachers and Tipraqsa, 2012).

The Matopiba region, the main focus of this study, is Brazil's most recent agricultural frontier. With an area of around 73 million hectares and a population of 6.2 million (IBGE, 2022), Matopiba covers four states in the north and northeast of Brazil (**Ma**ranhão, **To**cantins, **Pi**auí, and **Ba**hia), which comprise a large part of the Cerrado biome and a small part of Brazil's Caatinga biome.

The region is experiencing enormous economic growth, driven mainly by soybean and corn production (De Oliveira, Raposo, & Garcia 2024; Dos Reis et al., 2024; Loayza et. al, 2023; Nunes, Campelo Filho, & Benini, 2023). In 2021, soybean production was 16 million tons and corn production was 7.4 million tons in Matopiba, making the region responsible for almost 15% of total soybean production and almost 9% of total corn production in Brazil (IBGE, 2022). This has given Matopiba considerable global importance in grain production.

However, the advance of Matopiba's agricultural frontier has mainly been at the expense of the natural resources available in the region (Araújo et al., 2024; Evangelista & Pereira, 2024; De Sampaio Melo, Júnior, & de Espindola, 2024; Da Silva Arruda et al., 2024; Siqueira et al., 2024; Agostinho et al., 2023; De Oliveira Aparecido et al., 2023; De Souza et al., 2023; Ferreira, 2023; Santos et al., 2023). More than 12 million hectares of natural vegetation in the Brazilian Cerrado were converted into agricultural areas between 2000 and 2022 (MAPBiomas, 2023). In addition, in 2019 alone, almost 41 million tons of polluting gases (CO_2 GWP-AR5) were emitted from agriculture in the region (SEEG, 2020).

Because it covers two biomes of great importance for the world's biodiversity and the current importance of grain production at a global level, the first research question is **RQ1:** Is the Matopiba region in Brazil a hot topic in the global literature on agricultural frontiers and the environment in emerging countries? Furthermore, given the subjectivity of the term "environment" and the great environmental, socioeconomic, territorial, and cultural diversity of emerging countries, **RQ2:** How can we systematize the literature on agricultural frontiers and the environment in emerging countries? Answers to questions such as RQ1.1: Are some emerging countries/regions more prominent in studies on agricultural frontiers and the environment? RQ2.1: Are there any similarities between research on agricultural frontiers and the environment in emerging countries? will help to answer **RQ1** and **RQ2**, respectively.

To answer **RQ1** and **RQ2**, *Chapter 2* provides a Systematic Literature Review (SLR) of the main studies on the environmental impacts of agricultural frontiers in emerging countries over the last thirty years (1993 to 2022). The literary data for the development of *Chapter 2* comes mainly from my systematic review article entitled "Agricultural Frontiers and Environment: A Systematic Literature Review and Research Agenda for Emerging Countries", carried out in 2022 and published in the Journal "Environment, Development and Sustainability" in October 2023 (Sales, 2023). To develop Chapter 2, the analysis initially included 14,366 scientific articles from a wide range of subjects in the social and natural sciences, available in the Web of Science (Clarivate Analytics), Google Scholar, and ScienceDirect (Elsevier) databases.

SLR was the methodology chosen to formulate the theoretical basis for this dissertation because it is one of the most effective and robust ways of conducting a literature review today. This method evaluates, provides accurate and relevant information, and synthesizes evidence on a given subject.

The **Hypothesis** for **RQ1** is that: **H1**: Despite the growing number of studies on the Matopiba region in Brazil, it is still not as prominent in the global literature on agricultural frontiers and the environment, since most of this research is concentrated among Brazilian researchers, and is written in Portuguese.

The **Hypothesis** for **RQ2** is that: **H2**: Emerging countries are very diverse, but I believe there is some similarity between the research that emphasizes the relationship between agricultural frontiers and the environment in these countries. These studies essentially seek to measure the environmental impacts promoted by intensive agriculture, as well as to analyze more sustainable agricultural public policies and technologies.

Chapter 3, informative and descriptive, aims to present and contextualize the socio-economic and environmental characteristics of the Matopiba region in Brazil. This descriptive analysis is essential for understanding, organizing, and summarizing the data that will be used in the empirical studies in this thesis (chapters 4 and 5). *Chapter 3* is divided into two parts: the first section presents data that provides an overview of Matopiba's socio-economic situation; the second section analyzes the main environmental impacts that have been occurring in the region. As a reference, databases provided by the main Brazilian federal institutes and agencies were used.

Chapter 4, of an empirical nature, aims to analyze the environmental conditions generated by Matopiba's agricultural frontier using machine learning techniques. Concern about the environmental impacts of Matopiba's agricultural frontier is no coincidence and is gaining widespread repercussions. The first fact is that recovering the vegetation of the Cerrado Biome is not simple, as the biome is more than 45 million years old (in a quick comparison, the Amazon Biome is only 3,000 years old). Furthermore, although Cerrado is important for global agricultural production, it is also home to many species endemic to the planet and is one of the most important sources of fresh water in Latin America.

The idea behind *Chapter 4* is to develop two canonical correlation statistical models to verify the relationship and magnitude of dependence between economic variables (GDP aggregates) and environmental variables (deforestation, CO_2 emissions), as well as the relationship of dependence between the production of the region's main crops (soybeans, corn, sugar cane, rice, etc.) and the variables that represent environmental impacts.

This methodology was chosen because of the possibility that Canonical Correlation Analysis (CCA) offers of analyzing the degree of magnitude between sets of dependent and independent variables, as well as within each of these sets. CCA also makes it possible to use more than one dependent variable, as well as metric and non-metric variables.

The CCA analyses used the databases provided by the Gas Emission Estimation System (SEEG-Brazil), the Brazilian National Institute for Space Research, and the Brazilian Institute of Geography and Statistics (IBGE-Brazil) for the 31 micro-regions of the Matopiba region.

These two CCA statistical models serve as a basis to answer **Research Questions 3** and **4** and to prove **Hypotheses 3** and **4**, respectively.

RQ3. Is there any relationship between the economic aggregates and the environmental impacts generated on Matopiba's agricultural frontier?

RQ3.1. Which economic aggregate contributes the most to environmental impacts in the Matopiba region?

H3: There is a relationship between economic aggregates and environmental impacts in the Matopiba region, with the agricultural sector contributing the most to environmental degradation.

RQ4. Is agricultural production in Matopiba related to the environmental impacts generated in the region?

RQ4.1. Which crops contribute most to environmental impacts in Matopiba's agricultural frontier?

H4: Agricultural production has a relationship with environmental impacts in Matopiba, with soybean and corn production contributing the most to environmental issues in the region.

Chapter 5, also empirical, aims to use System Dynamic Modeling (SDM) to predict the future of the Matopiba region regarding available natural resources and intensive agricultural production. The methodological choice of SDM was due to the possibility of creating robust modeling and analysis of large-scale socio-economic systems for decision-making on complex issues, such as the clash between agricultural frontiers and the environment.

Matopiba is at a critical level of depletion of native vegetation and land suitable for agriculture, in which there are only 2.6 million hectares of undegraded pastures suitable for agriculture and an area of around 7.5 million hectares of native vegetation with high and medium agricultural suitability (BRASIL, 2021; Rudorff et al., 2015). In addition, more than 600,000 hectares of native vegetation are cleared every year in the region, converted mainly for agricultural cultivation (MapBiomas, 2023).

Thus, the following question arises: if current intensive agricultural production continues and no environmental intervention is implemented in the region, **RQ5**: how soon will the native vegetation be exhausted in the agriculturally suitable areas of Matopiba?

The **Hypothesis** for **RQ5** is that: **H5**: Matopiba's native vegetation is expected to be extinct in the agriculturally suitable areas within 20 years if current intensive agricultural production continues and no environmental intervention is implemented in the region.

In addition to trying to answer **RQ5**, *Chapter 5* also discusses measures (actions and/or public policies) to try to contain or slow down the process of environmental depletion in the Matopiba region.

Chapter 6, which is argumentative, presents the theses of the dissertation. The theses present my critical position on the subject discussed in this research, using original arguments and propositions evidenced by whether the study's hypotheses are met.

1.2 Research Motivations and Relevance

At first, I realized that, despite Matopiba's agricultural and environmental importance, this region has not yet “gained” worldwide repercussions when compared to the Amazon Region, for example. Therefore, the first motivation for this study is to verify whether the Matopiba region in Brazil is a prominent topic in the global literature on agricultural frontiers and the environment. This analysis will help to visualize a possible and important gap in the global literature on agricultural frontiers and the environment in emerging countries.

When relating agricultural production and the environment in Matopiba, I realized that there are no studies that verify which crops are considered the most polluting or least sustainable in the region. Therefore, my second motivation was to fill this gap and formulate, using machine learning techniques, an analysis of environmental conditioning between crops. It is believed that this information will serve as a basis for formulating or encouraging sustainable agricultural policies.

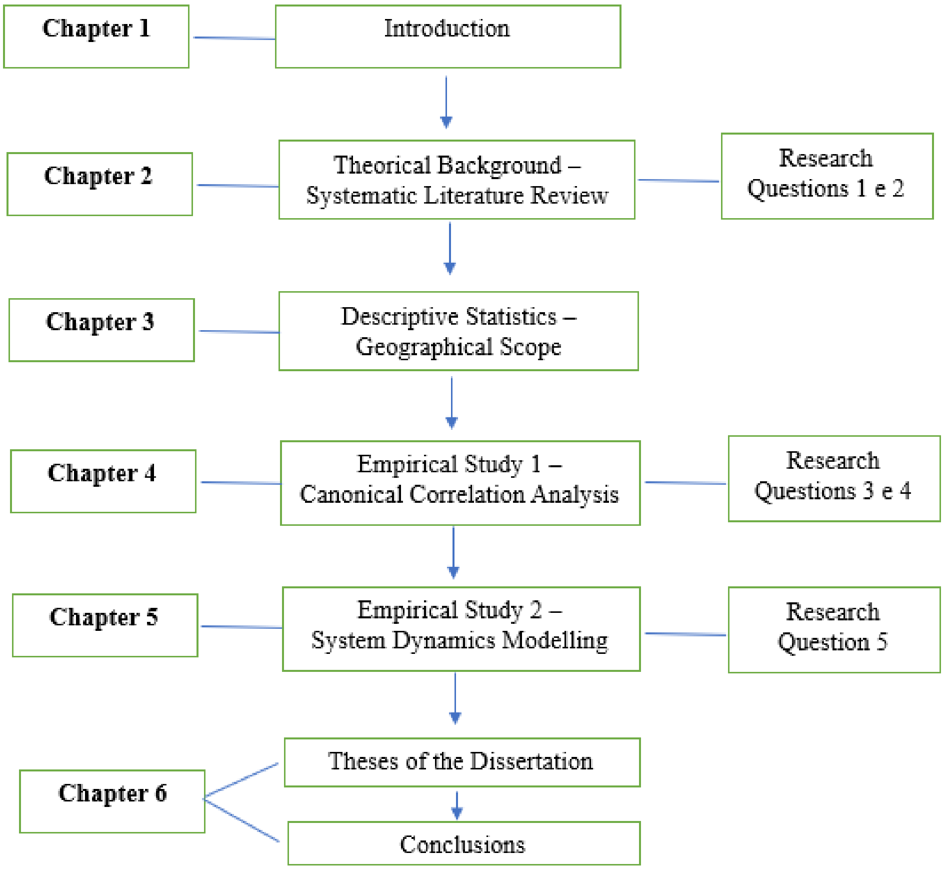
Another concern that motivated this study was to find out how much time “we have left” to try to reverse or minimize the process of extinction of the Cerrado Biome present in Matopiba. With the help of System Dynamics Modeling, the complexity of the dynamic relationship between the main crops and natural resources in Matopiba can be verified and, from there, measures can be proposed to help make agricultural production more sustainable.

The relevance of this study lies, among other factors, in the fact that it is one of the pioneers in deepening the discussion in the literature on the environment and agricultural frontiers in emerging countries; it contributes to the world literature on environmental issues in Brazil's Cerrado Biome; it presents and analyzes the environmental impacts promoted by intensive agricultural production in Matopiba to contribute to the orientation of environmental public policies in the region; it presents machine learning techniques to analyze environmental and economic variables for Matopiba; and it is a pioneer in the formulation of a System Dynamics Modeling on agricultural production and environmental impacts for the Brazilian Cerrado.

1.3. Structure of the Doctoral Dissertation

This dissertation is divided into six chapters, as shown in Figure 1. *Chapter 1* introduces the study, presenting the research problem and questions, and the justification for this work, as well as the structure of the dissertation. *Chapter 2* provides the theoretical background, through a Systematic Literature Review, with the main studies and theories on agricultural frontiers and the environment in Emerging Countries (this chapter serves as the basis for Research Questions 1 and 2).

Figure 1: Structure of the Doctoral Dissertation



Source: Own Elaboration.

Chapter 3 provides the descriptive statistics of this study, presenting the geographical scope and main characteristics of the Matopiba Region of Brazil. *Chapter 4*, the first empirical study in this dissertation, presents the Canonical Correlation Analyses to verify the conditioning factors of environmental impacts in Matopiba (this chapter serves as the basis for Research Questions 3 and 4).

Chapter 5, the second empirical study in this dissertation, presents System Dynamics Modeling applied to predicting the future of Matopiba's agricultural frontier (this chapter serves as the basis for Research Question 5). Finally, *Chapter 6* presents the theses of the dissertation, as well as the limitations of this study and contributions to future research.

2. Chapter 2: Literature Review: Agricultural Frontiers and Environment in Emerging Countries

Introduction

The Matopiba region in Brazil is currently considered a region of great importance for global soybean and corn production, as well as it comprehends a large part of the Cerrado biome and a small part of the Caatinga biome, both of which are of great importance for global biodiversity. Thus, the following research question arises: RQ1: Is the Matopiba region in Brazil a hot topic in the global literature on agricultural frontiers and the environment in emerging countries? RQ1.1: Are some emerging countries/regions more prominent in studies on agricultural frontiers and the environment?

Furthermore, to analyze and measure the environmental impacts of intensive agricultural production in emerging countries, it is necessary to consider the disparities and specificities of each region. Thus, RQ2: how can studies related to agricultural frontiers and the environment in emerging countries be synthesized? RQ2.1: Are there any similarities between research on agricultural frontiers and the environment in emerging countries?

To answer these questions, this chapter presents a Systematic Literature Review (SLR) of the main studies on the environmental impacts of agricultural frontiers in emerging countries from 1993 to 2022. The choice of the period of analysis was due to the curiosity of knowing whether literature "kept pace" with the environmental transformations promoted by the development of intensive agriculture in the mid-twentieth century. The choice to use SLR is because it is a systematic method for evaluating and synthesizing a given subject and, in this specific study, it will act as a gap to fill in the lack of in-depth discussion of studies on the environment and agricultural frontiers in emerging countries.

The first section of this chapter describes the methodological process involved in constructing the systematic literature review. Descriptive in nature, the second section presents the geographical distribution and the main terms found in the literature on agricultural frontiers and the environment. Section 3 discusses the main research carried out in emerging countries, emphasizing what the authors are concerned with studying in each country/region. Section 4 analyzes and presents how studies connect agricultural frontiers and the environment in emerging countries, subdividing this discussion into two focuses: the Expanded Industrial Agriculture Focus and the Socio-Economic-Ecological Focus. Section 5 presents the main suggestions and indications for future research.

2.1 The Systematic Literature Review Methodology

To analyze the main studies on agricultural frontiers and the environment in emerging countries, this chapter used a Systematic Literature Review (SLR) as a methodological process. A systematic review is conducted through a literature search, evaluation, and synthesis of evidence on a given subject, to provide accurate and relevant information (James et al., 2021).

In the initial phase of the SLR, the CIMO approach proposed by Denyer and Tranfield (2009) was used, which consists of planning the research questions and defining the scope of the study with emphasis on four points: the search for the scope and understanding of the context "C", the intervention "I", the mechanisms "M" and the results "O" that involve the research. After formulating and understanding the planning process, the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) were adopted to select the main studies. According to Moher et al. (2015), the PRISMA protocol helps to identify the main questions and problems addressed in the literature.

Thus, this SLR consists of 7 stages, with procedures 1 to 3 being part of the planning phase and procedures 4 to 7 being part of the PRISMA protocol, namely: 1 - search for possible studies following search queries selected based on expert recommendations; 2 - search for possible articles in other sources; 3 - implementation of inclusion and exclusion criteria; 4 - analysis and removal of duplicate articles; 5 - selection of articles for first reading (title, keywords, and abstract); 6 - selection of articles for full reading; 7 - analysis of the synthesis.

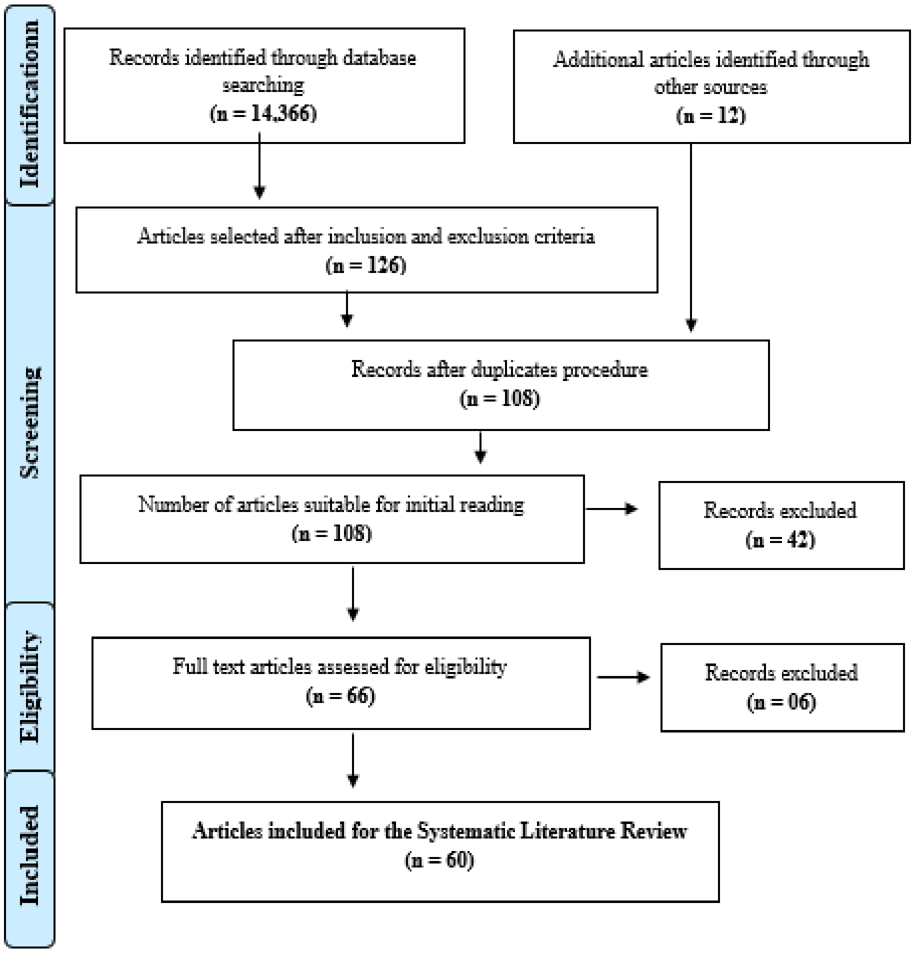
The Systematic Literature Review was carried out in 2022 with articles published between 1993 and 2022 (30 years). Initially, 14,366 scientific articles from the social and natural sciences disciplines were collected through search queries for the key terms "agricultur*[1] OR livestock OR farming AND frontier* AND environment*". This was done using electronic databases made available by ScienceDirect (Elsevier), Web of Science (Clarivate Analytics), and Google Scholar platforms.

[1] The use of asterisks next to keywords indicates that the exact spelling of the word was included in the search, for example, agricultur* includes agriculture, agricultural, etc.

In the second stage, articles were analyzed which, even if they were not in the searches of the three database platforms, were relevant, including recommended or well-known articles. From there, the inclusion and exclusion criteria were implemented, which consisted of selecting scientific articles ONLY written in English, published between 1993 and 2022, with a citation number[2] > 50 or with an average of 10 citations per year, and which had emerging countries[3] as their area of study.

Following the inclusion and exclusion criteria, as well as the recommendations, 138 articles were analyzed for possible duplicates using the EndNote reference management software. The summary of the process is illustrated in Figure 2.

Figure 2: Results of the Scoping Search



Source: Own Elaboration.

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[2] The number of citations was not an exclusion criterion for the additional relevant articles recommended by other sources.

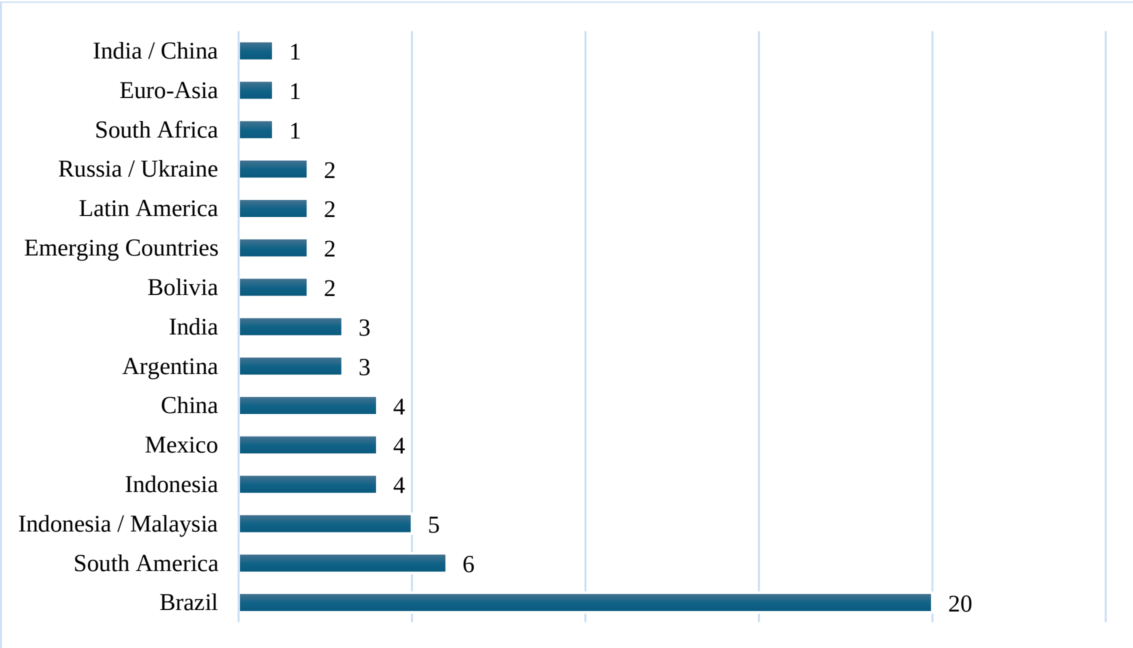
[3] The key terms for the analysis of emerging countries were: 'Developing countries OR Emerging countries OR Latin America OR Transition economies OR BRIC* OR Brazil OR India OR China OR Russia OR Indonesia OR Malaysia OR Argentina OR Turkey OR Mexico OR Hungary OR Poland OR Croatia OR South Africa OR Egypt OR Morocco'.

After eliminating the duplicate articles, the analysis was further refined, in which 108 articles were selected for an initial reading of the title, keywords, and abstract and, after cutting out 42 articles, 66 articles were read in full. Finally, after full reading, only 6 articles were excluded, and 60 articles categorized as "highly relevant" were ready for the literature review (*n = 60*).

2.2 Geographical Distribution and Key Terms of Studies

From the papers, 15 countries/regions are mentioned regarding the relationship between the agricultural frontier and the environment. Brazil was the most explored one with 20 papers (33,34% of the sample), followed by South America with 6 (10%), then the island region of Indonesia/Malaysia with 5 (8,35%), and Mexico, Indonesia (alone), and China with 4 articles each (6.66% each). Emerging countries were addressed by 2 papers only (3.33%). The selected papers' distribution is illustrated in Graph 1.

Graph 1: Distribution of articles studied by Country/Region



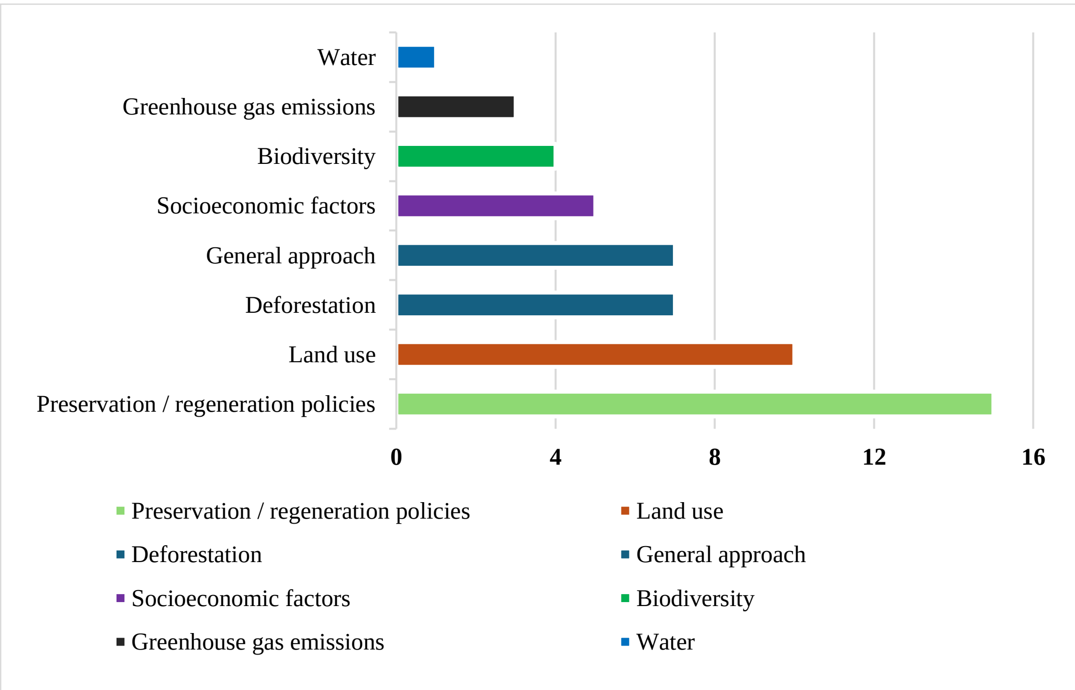
Source: Own Elaboration.

Following the methodology employed in the articles, it was noted that the influence of agricultural frontiers can encompass numerous factors and be evaluated through various methods. Regarding the methodological process characteristics, most of the studies were empirical (46), with only 14 adopting a theoretical approach. The empirical studies utilized a range of research models and methods, including satellite mapping analysis (15 articles), linear regression models (10 articles), simulation models (8 articles), logit models (6), analysis of variance (3), probabilistic models (2 articles), and both case studies and mathematical models (1 article each). Conversely, the theoretical articles mainly discussed the topic using the descriptive method (14 articles).

Although each article had specific goals, their primary aim was to analyze the impact of agricultural production on nature, assessing its effects on various environmental factors or examining the public policies and socioeconomic aspects involved. As shown in Graph 2, most authors focused on studying public policies for preservation or regeneration in agricultural frontiers (15 articles).

The second most researched topic was the environmental impact on land use (10 articles), followed by deforestation (7 articles). The interference of socioeconomic factors in the relationship between the environment and agricultural frontiers was studied in 5 articles. Additionally, there were studies on the environmental impact on animal biodiversity (4 articles), the measurement of greenhouse gas emissions (3 articles), and the impact on water (1 article).

Graph 2: Key topics for environmental impacts on agricultural frontiers



Source: Own Elaboration.

Furthermore, due to the broad and subjective nature of the term "environment," some articles (15 in total) did not focus on a single specific point but instead addressed multiple themes. For instance, one article analyzed the interference of agricultural frontiers on both land and water use, another looked at greenhouse gas emissions and land use, and another explored the interplay of socioeconomic factors and water use. Other studies examined deforestation alongside animal biodiversity, socioeconomic factors, or preservation and regeneration policies (1, 1, and 3 articles respectively). When an article had more than two main themes, it was classified as a general approach paper, with 7 such papers being studied.

2.3 Key Studies by Country/Region

Analyzing studies on agricultural frontiers in emerging countries provides a comprehensive context due to the unique characteristics of each country. Whether considering population size, topography, climate, or political landscape, research in these nations encompasses a diverse array of aspects and issues. This section offers an overview of significant research conducted in emerging countries, highlighting the primary concerns of the authors in each region.

Brazil, known as a global biodiversity hotspot, has been a focal point for studies on the environmental impacts of intensive agricultural production, especially in the Amazon Rainforest (Nepstad et al., 2001, 2006, 2008; Mertens et al., 2002; Soares-Filho et al., 2002, 2004; Rodrigues et al., 2009; Pacheco, 2009; Macedo et al., 2012; Schiesari et al., 2013; Verburg et al., 2014; Ochoa-Quintero et al., 2015; Nobre et al., 2016). Research topics in the Brazilian Amazon are diverse, covering loss of animal biodiversity, deforestation measurement, land use, and forest preservation policy analysis.

For instance, Nepstad et al. (2001) and Soares-Filho et al. (2004) investigated the impacts of road paving on deforestation, while Rodrigues et al. (2009) studied how human development levels influence deforestation. Mertens et al. (2002) focused on deforestation due to cattle ranching, and Ochoa-Quintero et al. (2015) on the loss of native species from environmental degradation.

Studies on public policy effectiveness include Nepstad et al. (2006), who compared inhabited and uninhabited reserves, and Pacheco (2009), who examined land reform impacts on deforestation. Nepstad et al. (2008) analyzed economic, forest, and climate trends in the Amazon, while Verburg et al. (2014) looked at balancing conservation policies with commodity prices. Nobre et al. (2016) proposed a new sustainable development paradigm for land use and climate change.

In addition to studies on the Amazon, a few articles analyzed other Brazilian biomes of global importance, such as the Cerrado and the Atlantic Forest. One fact worth highlighting is that, with the implementation of the inclusion and exclusion criteria for this SLR (scientific articles ONLY written in English, published between 1993 and 2022, and with citation number greater than 50), only 3 articles dealt with the Brazilian Cerrado or the Matopiba region in Brazil. However, before the English language exclusion criterion was implemented, 98 articles considered to have a high impact factor dealt with the issue of the agricultural frontier and the environment in the Matopiba region. This shows that research on the Brazilian Cerrado or the Matopiba region in Brazil is still at a local level, i.e. it is mainly concentrated among Brazilian researchers and is written in Portuguese.

Research on the Cerrado has focused on land use and water reuse (Spera et al., 2016), soybean production expansion (Rausch et al., 2019), and optimizing agricultural profit while maintaining freshwater quality and biodiversity (Kennedy et al., 2016). In the Atlantic Forest, Umetsu and Pardini (2007) examined habitat changes for small mammals due to human activity. Broader studies include Barretto et al. (2013) on agricultural intensification and land use patterns, Picoli et al. (2018) on crop expansion and land changes from pasture intensification, and Da Silva Junior et al. (2020) on persistent fires and compliance with the 2015 Paris Agreement.

The literature on agricultural frontiers and the environment is not confined to Brazil. Indonesia and Malaysia also feature prominently due to significant agricultural expansion driven by palm oil production (Koh and Wilcove, 2008; McCarthy and Cramb, 2009; Koh et al., 2011; Wicke et al., 2011; Carlson et al., 2012, 2013, 2018; Miettinen et al., 2012; Busch et al., 2015).

Additionally, articles addressing multiple emerging countries discuss the environmental impact of commodity production and exports (Henders, Persson, and Kastner, 2015) and smallholder farmers' deforestation decisions (Babigumira et al., 2014). Studies focusing on South America examine agricultural intensification in the Chaco region (Baumann et al., 2017; Fehlenberg et al., 2017; Le Polain de Waroux et al., 2018) and the Río de la Plata area (Baeza and Paruelo, 2020).

Research in China has centered on land use variations (Lin and Ho, 2003; Chen et al., 2014), agricultural production efficiency (Deng and Gibson, 2019), and water use (Wang et al., 2019). Mexican studies often explore trade-offs, such as between ecological reserves and archeological-ecotourist zones (Turner Ii et al., 2001), economic benefits of irrigation versus groundwater effects (Raquel et al., 2007), and community-based forest management versus protected areas (Ellis and Porter-Bolland, 2008).

Argentine research has mainly focused on the Chaco, investigating agricultural expansion's effects on deforestation (Gasparri and Grau, 2009) and animal biodiversity (Mastrangelo and Gavin, 2012), as well as the controlling factors of this expansion (Volante et al., 2016). Indian studies have examined the environmental consequences of the Green Revolution (Singh, 2000), the impacts of human interference in watersheds (Rao and Pant, 2001), and the presence of big cats in agricultural areas (Athreya et al., 2013).

Studies indicate that agricultural frontiers impact the environment in emerging countries through intensive production, with the extent varying based on natural resources affected and country-specific factors such as public policies, regulations, and incentives. To provide updated insights and support the discussion in the next section, Table 1 presents literature on agricultural frontiers and the environment in emerging countries published from 2013 to 2022.

Table 1: Reputable articles on Agricultural Frontiers and the Environment from 2013 to 2022

Reference	Study area	Approach / Issue	Contributions
Volante et al. (2016)	Argentina	Preservation or regeneration policies	The "Native Forest Law" was enacted to regulate the deforestation process; nonetheless, it proved insufficient to prevent the land from changing due to deforestation.
Nobre et al. (2016)	Brazil	Preservation or regeneration policies	The creation of high-value goods, services, and platforms using digital, biological, and sophisticated materials technology is made possible by the Amazon Rainforest. It is recognized as a worldwide audience of biological assets as a result.
Spera et al. (2016)	Brazil	Land use / Water	Between 2003 and 2013, there was a yearly decline in the amount of water recycled into the atmosphere through evapotranspiration because of the agricultural area expanding from 1.2 to 2.5 million hectares, with native Cerrado vegetation accounting for 74% of this newly cultivated land.
Barretto et al. (2013)	Brazil	Land use	In agriculturally consolidated areas, land use intensification occurred in tandem with the shrinkage of cultivated and pasture lands, in contrast to agricultural frontier areas where land use intensification occurred in tandem with the extension of agricultural land.
Ochoa-Quintero et al. (2015)	Brazil	Deforestation / Biodiversity	Mammal and bird species are less common in environments where between 30 and 40 percent of the land is covered by forests. By 2030, just 22% of landscapes would probably be able to support at least 75% of these species due to deforestation, according to predictions.
Kennedy et al. (2016)	Brazil	Land use	Better outcomes arise when the focus of land use is biodiversity and ecosystem services. In comparison to the way land is now used, the Cerrado can potentially increase agricultural revenue and provide significant benefits in biodiversity and water quality.
Picoli et al. (2018)	Brazil	Land use	To preserve land for agricultural use, one solution is the dual production system.
Schiesari et al. (2013)	Brazil	Preservation or regeneration policies	Small farmers who receive no technical assistance and little knowledge have increased their use of pesticides. Large manufacturers, on the other hand, adhere to scientific advice more and even replace the most hazardous substances willingly since they have access to higher technical knowledge and resources.
Verburg et al. (2014)	Brazil	Preservation or regeneration policies	The importance of conservation policies is demonstrated by the fact that, depending on the commodity price scenario, a fall in the average policy aim of the Forest Code from 80% to 60% results in an additional 41 to 57% deforestation.
Rausch et al. (2019)	Brazil	General Approach	Between 2003 and 2014, the increase of soy contributed 22% to the conversion of the Cerrado biome, despite the industry's incentives to move production to previously deforested areas.

Da Silva Junior et al. (2020)	Brazil	Preservation or regeneration policies	Brazil needs to utilize public policies, private sector initiatives, and societal changes to curb deforestation brought on by the enlargement of the agricultural frontier in the Amazon and Cerrado biomes. If not, national GHG reduction targets will be jeopardized because the total emissions from fires in the six Brazilian biomes will surpass 5.7 $GtCO_2$.
Chen et al. (2014)	China	Land use	There are two "lessons" to be learned from China's policies for rural development: non-migrants should be encouraged to modify their farms during the emigration process in rural areas, and their interests should also be protected by the government; land zoning and other ecological protection policies should restrict border deforestation.
Deng and Gibson (2019)	China	Socioeconomic Factors	While eco-efficiency is better in developed city areas, land productivity is concentrated in cities located far from the provincial or economic center. Thus, sustainable agricultural output requires timely management of trade-offs between agricultural productivity and urbanization.
Wang et al. (2019)	China	Socio-economic factors / Water	Between 2000 and 2017, China's efficient use of water in agriculture was attributed to the increasing percentage of secondary or higher education and the per capita income of rural families.
Henders, Persson and Kastner (2015)	Emerging countries	Greenhouse gas emissions / Land use	Between 2000 and 2011, the primary embodied flows of land use change in emerging countries were attributed to the export of soybeans and beef from Latin America to China, Europe, North Africa, and the Middle East. Conversely, the primary embodied flows of carbon emissions were attributed to the export of wood products and palm oil from Indonesia and Thailand to Europe and Asia, primarily to China and India.
Babigumira et al. (2014)	Emerging countries	Socio-economic factors / Deforestation	Poorer and more isolated households in Emerging Countries were less likely to destroy forests than households with medium to high assets and a stronger market orientation.
Horion et al. (2016)	Eurasia	General Approach	The collapse of the Soviet Union, the abandonment of farmland, and human influences (more salinization, increased grazing intensity, and altered irrigation techniques) have all contributed to a decline in rainfall efficiency.
Athreya et al. (2013)	India	Biodiversity	Although a wide range of wild carnivores can be found on human-dominated agricultural land, the absence of other wild animals and wild herbivore prey suggests that agriculture has caused human intervention in native ecosystems.
Carlson et al. (2013)	Indonesia	Greenhouse gas emissions	Between 2000 and 2010, the country's 47% intact forest destruction was fueled by intensive palm oil development. According to projections, the growth of plantations in Kalimantan alone would be responsible for about 20% of Indonesia's CO_2 emissions in 2020 if this course was continued.
Carlson et al. (2018)	Indonesia	Preservation or regeneration policies	Deforestation in the nation has decreased by 33% because of palm oil plantations accredited by the Roundtable on Sustainable Palm Oil (RSPO). Nonetheless, most approved plantations had minimal residual forest, indicating that certification is ineffective.

Busch et al. (2015)	Indonesia	Preservation or regeneration policies	The nation's rates of deforestation have increased as a result of concessions for oil palm plantations and logging operations in recently approved regions. The implementation of a carbon pricing program or broadening the moratorium to include not just existing concessions but also regions outside of concessions and protected areas would have prevented this.
Graesser et al. (2015)	Latin America	Land use	In Latin America, between 2001 and 2013, new agriculture and grassland displaced forests by 17% and 57%, respectively.
Meyfroidt et al. (2016)	Russia and Ukraine	Preservation or regeneration policies	After 2000, areas with a younger workforce and a growing rural population saw greater recultivation and less abandonment of crops. Just 8.5 million hectares (Mha) of the 47.3 million Mha of farmed land that was abandoned in 2009 may be used for agriculture with no cost to the environment and few socioeconomic limitations.
Jewitt et al. (2015)	South Africa	General Approach	Between 2005 and 2011, the primary factors contributing to the loss of 7.6% of KwaZulu-Natal's natural habitat were mining, dams, agriculture, and forestry plantations. Additionally, the residual biodiversity in these places or those nearby is negatively impacted by the anthropogenically altered land covers, including secondary vegetation.
Baumann et al. (2017)	South America	Greenhouse gas emissions	Between 1985 and 2013, crops and pastures replaced 20% of the whole Chaco Forest, resulting in massive carbon emissions of 824 Tg C overall and 46.2 Tg C in 2013 alone.
Fehlenberg et al. (2017)	South America	Deforestation	Livestock in Argentina, Bolivia, and Paraguay was strongly linked to deforestation. However, soy farming in Argentina may have contributed indirectly to deforestation in Bolivia and Paraguay, as it was the only direct cause of deforestation in the Argentine Chaco.
Gasparri and De Waroux (2015)	South America	Preservation or regeneration policies	Coupled agricultural frontiers make more actor-centered approaches to conservation policy and research necessary. These methods must be grounded in practical models that consider the growing coupling between productive sectors and geographic areas.
Le Polain de Waroux et al. (2018)	South America	Socioeconomic Factors	Frontier expansion in the Chaco was fueled by revenue generated by new agricultural technologies, infrastructure, and increased producer prices. However, the existence of anomalous economic rents and the presence of a small number of individuals with the ability to affect the entire process impact the dynamics of these borders.
Baeza and Paruelo (2020)	South America	Land use	The Campos do Rio da Prata are experiencing a significant shift in land use, mostly as a result of the agricultural frontier's advancement (which increased by 23% between 2000 and 2014) and the disappearance of field areas on both sides of the Uruguay River and in the western part of the Pampa Interior.
Nolte et al. (2017)	South America	Preservation or regeneration policies	It is likely more difficult to encourage governmental and commercial players to implement effective policies to counteract deforestation in the Brazilian Amazon than it is in the Cerrado, Chaco, and Chiquitano.

Source: Own Elaboration.

2.4 The Connections between Agricultural Frontiers and the Environment

The literature review has concentrated on measuring the effects of intensive farming on remaining natural resources, along with analyzing more sustainable agricultural public policies and methodology. Consequently, the interaction between agricultural expansion and the environment in Emerging Countries will be explored in two distinct approaches: the Extended Industrial Agriculture Focus, which involves the literature's emphasis on measuring, analyzing, and interpreting the impacts on natural resources (including water, soil, air, wildlife, and plants) caused by the growth of agricultural activities; and the Socio-Economic-Ecological Focus, which examines how local socioeconomic factors and public policies influence population behaviors in the context of environmental and agricultural frontier interactions.

2.4.1 Extended Industrial Agriculture Focus

Several studies have shown significant environmental impacts resulting from the expansion of agricultural frontiers in emerging countries. Research with Extended Industrial Agriculture Focus has examined these impacts on a wide range of natural resources, including land, fauna, flora, air, and water. To do this, the researchers used argumentative/narrative text, satellite-based maps, and linear, probabilistic and simulation models as the main methodologies.

The term "environment" is broad and subjective, leading some researchers to address multiple natural resources in a single study. Data revealed that studies analyzing two natural resources primarily focus on the environmental impact of agricultural production on land use or flora (deforestation) along with another resource. For example, Ochoa-Quintero et al. (2015) found that deforestation in the Brazilian Amazon reduced mammal and bird populations in areas with 30 to 40% forest cover. Predictions for 2030 indicated that under the same deforestation scenario, only 22% of Amazonian landscapes would support at least 75% of these species.

Henders, Persson, and Kastner (2015) identified that changes in land use and carbon fluxes from 2000 to 2011 were primarily driven by exports of beef, palm oil, and soybean in Emerging Countries. Spera et al. (2016) found that agricultural expansion in the Brazilian Cerrado from 2003 to 2013 decreased the amount of water recycled into the atmosphere.

Articles that analyze multiple natural resources provide a broader view of regional impacts. For instance, Rao and Pant (2001) concluded that agricultural and extractive activities, coupled with population growth, led to a vegetation cover decline in the central Himalayan region of India between 1963 and 1996, which in turn stimulated soil and water loss in the Sadiyagad watershed region.

In Malaysia and Indonesia, Koh et al. (2011) reported that 6% of tropical peatlands were used for palm oil production, causing the emission of over 4.5 million Mg of carbon per year and the loss of 140 million g of biomass carbon, along with significant biodiversity destruction. Similarly, Carlson et al. (2012) noted a 4% reduction in forest cover in Indonesia from 1989 to 2008 due to intensive palm oil production, with projections indicating further deforestation on regional and community lands.

Studies covering Eurasia, Africa, and Brazil also highlight diverse environmental impacts. Horion et al. (2016) observed that rainfall use efficiency in the region from Western Ukraine to Eastern China and from Southern Russia to Turkmenistan decreased following the Soviet Union's collapse in 1991, alongside anthropogenic effects like grazing intensity, increased salinization, and irrigation changes.

Jewitt et al. (2015) found that from 2005 to 2011, over 7% of the natural habitat in South Africa's KwaZulu-Natal was devastated due to intensified agriculture, mining, and dam construction, transforming land use and causing biodiversity loss. In Brazil, Rausch et al. (2019) attributed 22% of the Cerrado Biome's deforestation from 2003 to 2014 to soybean production, suggesting that private sector policies restricting deforestation could reduce degradation.

Land Use

The review then focuses on studies analyzing the impact of agricultural frontiers on individual natural resources, beginning with land use. Barretto et al. (2013) used the OLS model to show that intensified land use decreased pastures and crops in established agricultural regions while increasing agricultural land on the frontiers. Baeza and Paruelo (2020) found that agricultural expansion in the Río de la Plata[4] region decreased pastures, particularly along the Uruguay River and western Pampa Interior.

Graesser et al. (2015) emphasized the importance of distinguishing between pastures and crops in land use efficiency studies in Latin America, as they have different soil impacts. Wicke et al. (2011) concluded that palm oil production significantly impacted land use in Indonesia and

[4] The South American countries of Uruguay and Argentina have natural border between them, formed by Rio de la Plata.

Thailand, leading to substantial forest cover loss. Lin and Ho (2003) reported significant agricultural land loss in China due to urbanization, rural industrialization, and agricultural restructuring. Chen et al. (2014) highlighted the need to consider rural out-migration when studying land use changes in China.

To mitigate the environmental impact of agricultural production on land use, Picoli et al. (2018) suggested that double cropping systems in Mato Grosso, Brazil, saved land used for agriculture. Kennedy et al. (2016) indicated that optimal land use outcomes balance agricultural needs with environmental preservation. Smith et al. (2007) found that soil organic carbon loss due to climate change in Russia and Ukraine could be minimized by prioritizing environmental considerations.

Flora

Flora in Emerging Countries is heavily impacted by agricultural production, with significant deforestation attributed to soy and livestock. Fehlenberg et al. (2017) found that soybean cultivation drove deforestation in the Argentine Chaco, while cattle ranching increased deforestation in Argentina, Bolivia, and Paraguay. Mertens et al. (2002) linked cattle production in the Brazilian Amazon to increased deforestation and fire outbreaks. Müller et al. (2012) noted that intensive agriculture and cattle ranching drove deforestation in Bolivia.

Gasparri and Grau (2009) reported that global soy demand led to the clearance of 1.4 million hectares of dry forest in the Argentinean Chaco from 1972 to 2007. Macedo et al. (2012) suggested that soybean production could inversely relate to deforestation with effective land use policies.

Other factors also drive deforestation. Nepstad et al. (2001) observed that road construction increased deforestation rates in the Amazon Rainforest. Pacheco (2006) found that deforestation in Bolivia intensified when the economic model shifted to a more liberal one.

Fauna

The literature also addresses the loss of animal biodiversity due to advancing agricultural frontiers. Koh and Wilcove (2008) found that oil palm cultivation reduced bird and butterfly populations in Malaysia and Indonesia. Mastrangelo and Gavin (2012) reported fewer bird species in cattle production areas of the Argentinian Chaco compared to intact forests.

Some studies documented animal migrations due to agricultural expansion. Umetsu and Pardini (2007) found that native vegetation destruction in Brazil's Atlantic Forest increased invasive species. Athreya et al. (2013) noted that intensive agriculture in India led to large wild carnivores moving into human-inhabited areas.

Air

To assess atmospheric impacts, researchers quantified pollutant emissions from intensive agriculture and simulated pollution scenarios. Baumann et al. (2017) found that agricultural intensification decimated 20% of the Chaco Forest between 1985 and 2013, causing significant carbon emissions. Miettinen et al. (2012) reported that peatland devastation for oil palm cultivation in Malaysia and Indonesia emitted 230310 Mt CO_2e. Carlson et al. (2013) projected that oil palm production in Kalimantan, Indonesia, would contribute to 20% of the country's CO_2 emissions by 2020.

Water

Only one study discussed the impact of agricultural frontiers on water. Raquel et al. (2007) used Game Theory to analyze optimal decisions between increasing agricultural production using irrigation and minimizing environmental impacts on groundwater in Mexico's Alto Rio Lerma Irrigation District. They concluded that irrigation significantly decreases groundwater, and optimal decisions depend on the relative importance of irrigation and overall water use. For environmental sustainability, the Pareto optimum would extract about 370 million cubic meters of water per year.

2.4.2 Socio-Economic-Ecological Focus

To analyze the literature with a Socio-Economic-Ecological focus, the authors presented data on the environmental impacts caused by agricultural frontiers, with an emphasis on listing possible solutions for preservation and regeneration, in addition to examining how socioeconomic factors can influence environmental degradation. The discussion first addresses potential solutions to environmental issues and then considers the impact of socioeconomic aspects.

In their study on Mexico, Ellis and Porter-Bolland (2008) highlighted the importance of protected areas for forest preservation, noting that deforestation was more prevalent in regions with community-based forest management compared to protected areas. Similarly, Volante et al. (2016) examined the Argentine Chaco, revealing that forest laws like the "Native Forest Law" were insufficient to curb deforestation and regional transformation. They suggested that changes in law enforcement strategies or the introduction of alternative incentives, such as the EU's biofuel import standards, might help reverse this trend.

Understanding regional heterogeneity is crucial for adopting environmental protection measures in emerging countries. Pacheco et al. (2010) noted that while Reducing Emissions from Deforestation and Forest Degradation (REDD) is vital for conserving tropical forests in Latin America, socioeconomic and land use heterogeneity complicates policy implementation. Nolte et al. (2017) discussed South American biomes, stating that the Cerrado, Chaco, and Chiquitano regions, despite having lower carbon stocks and biodiversity, are agriculturally significant with numerous private properties and better compliance with forestry regulations than the Amazon. Policies to combat deforestation must consider the specific characteristics of each agricultural frontier. Gasparri and De Waroux (2015) emphasized the need for models that analyze the coupling of geographic locations and productive sectors due to the significant role of soybean and cattle production in driving deforestation in South America.

In Brazil, much of the literature focuses on the Amazon Rainforest. Suggested solutions for forest preservation and regeneration include creating ecological parks, preserving indigenous reserves (Nepstad et al., 2006), enforcing the Forest Code to prevent deforestation (Verburg et al., 2014), regulating the use of fire by landowners, enhancing environmental performance in commodity markets, and incentivizing carbon markets (Nepstad et al., 2008). Additionally, Nobre et al. (2016) recommended promoting sustainable land use and climate change mitigation through biological, digital, and material technologies.

Studies in Southeast Asia (Indonesia and Malaysia) identified the main drivers of palm oil cultivation and proposed solutions to mitigate the resulting environmental issues. McCarthy and Cramb (2009) found that the shift to neoliberalism facilitated forest devastation by agricultural frontiers, replacing subsistence farming with mechanized agriculture. Busch et al. (2015) argued that reducing agricultural concessions and promoting carbon emission reduction policies are crucial to reversing environmental degradation in Indonesia.

Carlson et al. (2018) added that RSPO certification, while not a panacea, significantly reduced deforestation in Indonesia from 2001 to 2015. Wilcove and Koh (2010) discussed Southeast Asia, concluding that "boycott" policies are ineffective for this region, and that promoting competitiveness through incentives like REDD would be more successful. Singh (2000) found that the Green Revolution's intensive agricultural production in India led to soil degradation and water pollution, suggesting that increasing and diversifying biomass productivity, moisture conservation, nutrient management, and land use planning are essential for restoring degraded areas.

Regarding the influence of socioeconomic factors, several studies have shown that environmental degradation rates in emerging countries decrease with socioeconomic development, whether intellectual or financial. For instance, Rodrigues et al. (2009) demonstrated that literacy, life expectancy, and living standards inversely correlate with environmental degradation, supporting the Environmental Kuznets Curve hypothesis. Schiesari et al. (2013) found that small-scale farmers with higher education and technical support tend to use fewer pesticides and less harmful resources.

Deng and Gibson (2019) studied China's Shandong region, finding that land productivity is concentrated in cities far from economic centers, but eco-efficiency is higher in developed cities and eco-tourism areas. Conversely, Babigumira et al. (2014) concluded that wealthier farmers in 24 emerging countries tend to deforest more than poorer smallholder farmers lacking market knowledge.

Beyond the direct link between environmental degradation and socioeconomic levels, other studies highlight different ways socioeconomic factors affect the relationship between agricultural frontiers and the environment. Meyfroidt et al. (2016) argued that young labor and an increasing rural population are essential for recultivating abandoned agricultural land in Russia and Ukraine, stimulating new agricultural frontiers. Le Polain de Waroux et al. (2018) found that the expansion of agricultural frontiers in the South American Chaco responds well to new technologies, infrastructure, and rising prices. However, these frontiers' dynamics are shaped by abnormal economic rents and a limited number of actors (commodity producers, speculators, rentiers) influencing the process.

2.5 Research Agenda

Brazil is considered the "home country" for discussions on the relationship between intensive agricultural production and the environment, with literature primarily focusing on the Amazon rainforest. These studies have noted that several measures to combat environmental degradation, such as expanding protected areas, implementing national and foreign financial incentives, and enacting national public policies, have been in place for some time.

However, there is a lack of studies measuring the effectiveness of these measures, either individually or collectively, or their impact across the vast expanse of the Amazon, which spans nine Brazilian states and six other countries. Furthermore, other crucial Brazilian biomes, like the Cerrado, Atlantic Forest, Caatinga, Pampas, and Pantanal, have been largely overlooked. The Cerrado, for instance, is Brazil's most recent agricultural frontier (Matopiba) and warrants special attention due to its high deforestation rates, unique biodiversity, and significant natural aquifers.

Research on Indonesia and Malaysia has highlighted the numerous environmental impacts of intensive palm oil production, with studies already measuring the effectiveness of certification schemes like the RSPO. Despite these efforts and the ongoing destruction of tropical forests, palm oil production and associated degradation continue unabated. Pirker et al. (2016) noted that only 17% of the world's suitable area remains for palm oil expansion, and these areas are increasingly inaccessible. Future research should identify these areas and assess whether soil degradation and deforestation trends align with palm oil expansion. There is also a need to investigate potential desertification processes in Indonesia and Malaysia and explore reversal strategies if such trends are identified.

In populous countries like India and China, the impacts of agricultural frontiers on the environment are closely linked to potential land and food scarcity. Balancing cultivation and food production needs with space for growing populations is critical. Research should focus on meeting current food demands with minimal environmental impact, emphasizing soil management and the restoration of degraded areas. Additionally, studies should explore whether intensive production and degraded areas drive migration, investigating how changes in soil and deforestation stimulate population movements in these countries.

Emerging countries are heterogeneous but share a strong political-structural dependence, influenced by internal and external stimuli. Agricultural production and environmental policies are often driven by markets and governments. Research should examine how different forms of government in emerging countries impact the relationship between agricultural frontiers and the environment. Is there a consensus on these measures? Are they spatially dependent or merely tied to local governments? Moreover, the influence of foreign markets on agricultural production and preservation policies in emerging countries remains underexplored. Are these influences driven by internal markets or external forces? Do they lean towards an Extended Industrial Agriculture bias or a Socio-Economic-Ecological Focus?

While promoting agricultural production is essential for economic growth in emerging countries, it is equally important to understand and mitigate the environmental impacts of agricultural frontier expansion. Can sustainable development be achieved in countries where agricultural production is the main economic driver? To what extent can the environment sustain this expansion? These are critical questions to address, requiring a balance between agricultural production and environmental impact, potentially through multi-component forecasting models like System Dynamics Modeling. This approach could help develop measures to balance intensive agricultural production with environmental sustainability more effectively.

Summary

This chapter used a Systematic Literature Review to analyze key research on the impact of agricultural frontiers on the environment in emerging countries, discussing theories on environmental and agricultural transformations over the past thirty years (1993-2022).

Although the literature on agricultural frontiers and the environment in emerging countries adopts diverse theories and methodologies, most studies focus on measuring the impact of agriculture on natural resources, which I call the Expanded Industrial Agriculture Approach, and on examining how local socioeconomic factors and public policies influence the population's relationship with agricultural frontiers and the environment, defined as the Socioeconomic-Ecological Approach. These two definitions of approaches are currently the best way to systematize the literature on agricultural frontiers and the environment in emerging countries.

In studies with an Expanded Industrial Agriculture Focus, intensive agriculture is shown to degrade various natural resources. However, discussions primarily address environmental impacts on flora (deforestation rates), air (pollutant gas measurements), and land use changes, indicating a need for more research on the impacts of agricultural production on water resources. Articles with a Socio-Economic-Ecological Focus propose solutions to environmental problems in emerging countries, such as creating ecological parks, expanding forest protection areas, implementing region-specific public policies, enforcing stricter environmental laws, and promoting biological, digital, and material technologies. Research also shows that socioeconomic aspects like literacy, life expectancy, and high living standards tend to reduce environmental degradation rates.

The data also revealed that most studies on the agricultural frontier and the environment are concentrated in Brazil, followed by studies on South America and the island regions of Indonesia and Malaysia. It was then observed that there is a lack of research on European economies in transition, emerging African countries, and Russia, as well as on the agri-environmental impact of the high demand for food in populous countries such as India and China.

Studies on Brazil have focused mainly on the Amazon Rainforest, leaving a significant gap in the literature on other important Brazilian biomes, such as the Cerrado, the Atlantic Forest, the Caatinga, the Pampas, and the Pantanal. It was observed that research on the Brazilian Cerrado or the Matopiba region in Brazil is still mainly concentrated among Brazilian researchers and is written in Portuguese, since, with the adoption of the English language exclusion criterion, these studies had few samples.

Future research on agricultural frontiers and the environment should not only propose solutions but also measure the effectiveness of these proposals in reducing/reversing degradation in emerging countries, considering market influences, government types, and regional heterogeneity. Research should adopt dynamic forecasting models to balance intensive agricultural production with environmental impacts. Furthermore, studies should address recent topics like agricultural digitalization, migration of agro-industrial poles, nanotechnology, and the circular economy.

3. Chapter 3: Matopiba: Brazil's Newest Agricultural Frontier

Introduction

This chapter is descriptive and informative and aims to summarize the socio-economic and environmental characteristics of the Matopiba region in Brazil. The analysis was based on data provided by Brazilian institutes and projects, namely: Empresa Brasileira de Pesquisa Agropecuária (EMBRAPA)[5], Instituto Brasileiro de Geografia e Estatística (IBGE)[6], Instituto de Pesquisa Econômica Aplicada do Brasil (IPEA)[7], Sistema de Estimativa de Emissões de Gases de Efeito Estufa (SEEG)[8] and MAPBiomas[9] Brazil.

The first section gives an overview of the socio-economic situation of Matopiba, mainly presenting the delimitation of the region and the evolution of GDP, agricultural production, and land cover. The second section characterizes the environmental aspects of the region (climate, relief, geology, hydrography), as well as presents an overview of the main environmental impacts suffered in recent years.

3.1 Developmental Aspects

With an area of around 73 million hectares and a population of 6.2 million (IBGE, 2022), Matopiba is a region in the north and northeast of Brazil that encompasses four states: Maranhão (33% of the total area of this region), Tocantins (38%), Piauí (11%) and Bahia (18%). In the geographical delimitation proposed by EMBRAPA (used by the country's main institutes), the region comprises 337 municipalities divided into 31 geographical micro-regions[10].

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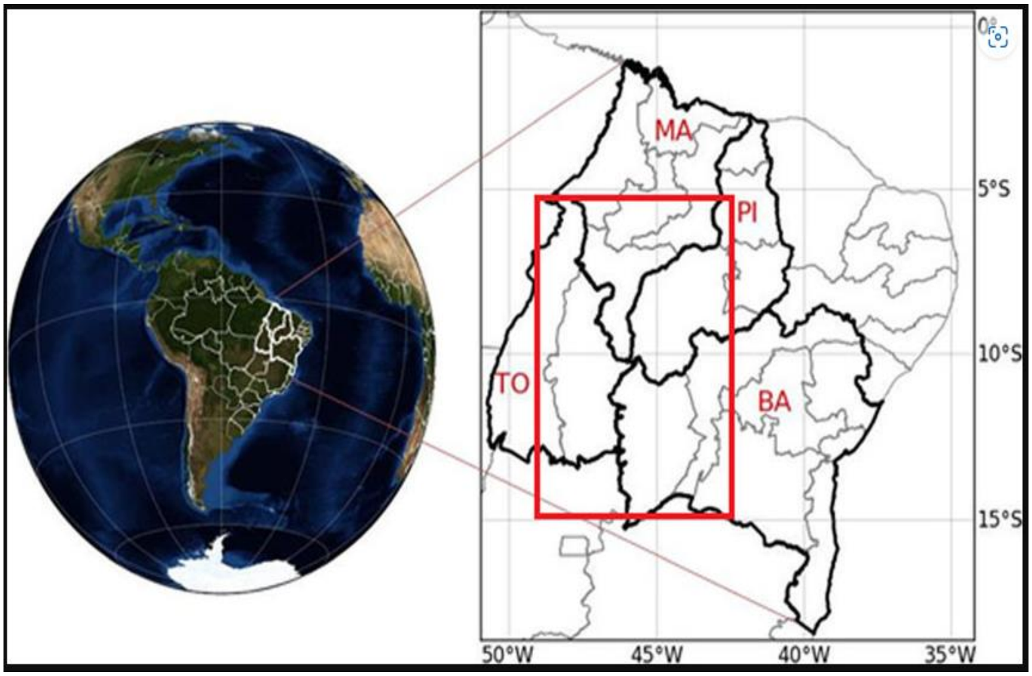
[5] Public research company linked to the Brazilian Ministry of Agriculture, Livestock and Supply.
[6] A public institute of the Brazilian federal administration. Created in 1934, it is the main provider of geographical and statistical information in Brazil.
[7] A federal public foundation linked to Brazil's Ministry of Planning and Budget. It promotes advanced economic research in the country.
[8] Online platform developed by the Observatório do Clima initiative that provides data on GHG emissions throughout Brazil.
[9] The project is an initiative of Brazilian civil society Observatório do Clima, co-created and developed by a multi-institutional network involving universities, NGOs and technology companies with the aim of mapping land use and land cover in Brazil every year and monitoring changes in the territory.
[10] The list of the 337 municipalities and 31 geographic microregions of Matopiba can be found in Table A1 at Appendix A.

Figure 3: Geographical Location Matopiba Region - Brazil



Source: Salvador (2014).

The region encompasses around 324,326 agricultural establishments occupying an area of approximately 36 million ha, as well as 781 agrarian reform settlements and quilombola areas (approximately 14 million ha), 46 ecological conservation units (8.4 million ha), and 35 indigenous lands (4.2 million ha) (Miranda, 2015).

According to the Regional, Urban and Environmental Bulletin developed by IPEA (Pereira, Porcionato, & Castro, 2018), Matopiba has been undergoing socio-economic transformations because of the expansion of intensive agriculture, in which social indicators, such as the Municipal Human Development Index (MHDI) and the Social Vulnerability Index (SVI), have shown trends of social improvement in Matopiba since the 2000s. This progress is directly related to improvements in educational indicators (a reduction in the illiteracy rate, an increase in the high school attendance rate, and an increase in the average number of years of study in the region), as well as associated with improvements in urban infrastructure (an increase in water supply networks, garbage collection, and sewage services).

Data from the Report on the Personal Distribution of Income and Wealth of the Brazilian Population (BRASIL, 2016) shows that there was a decrease in the Gini index in Matopiba in 2010 compared to 2000. The reduction in income inequality was observed in 250 municipalities (74%

of the region). This improvement is due to the implementation of public policies aimed at redistributing income, such as the Bolsa Família Program[11] and the Continuous Cash Benefit[12] (Pereira, Porcionato, & Castro, 2018).

Gross Domestic Product (GDP)

Between 2000 and 2021, the Matopiba region had a gross GDP growth rate of 1,419%, going from 10.6 billion reais in 2000 to 150.9 billion reais in 2021. Taking taxes into account, this growth is 1460%, from a current GDP of 11.3 billion in 2000 to 166 billion reais in 2021. The region's great economic growth has been driven mainly by agriculture and the goods and services sector.

Data from IBGE (2022) show that, although the state of Tocantins has the largest number of municipalities in Matopiba, the state of Maranhão had the largest share of the region's total GDP in 2021, followed by Tocantins and Bahia. Piauí, which has the fewest municipalities, is also the smallest in terms of its share of the region's GDP.

Based on the general GDP data for Matopiba, it is also worth analyzing the gross value added by sectors of the economy: agriculture, industry, services, and administration (defense, public education, health, and social security). Data from IBGE (2022) also shows that the agricultural sector contributed 31% of the total added value in 2021 in the region, while industry contributed 14%, the services sector 33%, and the administration sector 22%.

Although the agricultural sector will account for 31% of the total value added in 2021, it is important to consider that the services sector has various activities related to agriculture, such as transportation, storage, logistics, trade, and technical assistance, among others, which justifies the significant value of the services sector (Pereira, Porcionato, & Castro, 2018).

In addition, the relative share of the agricultural sector was the highest among the economic sectors compared to 2000 (an increase of 1716%). This increase was greater than the growth rate

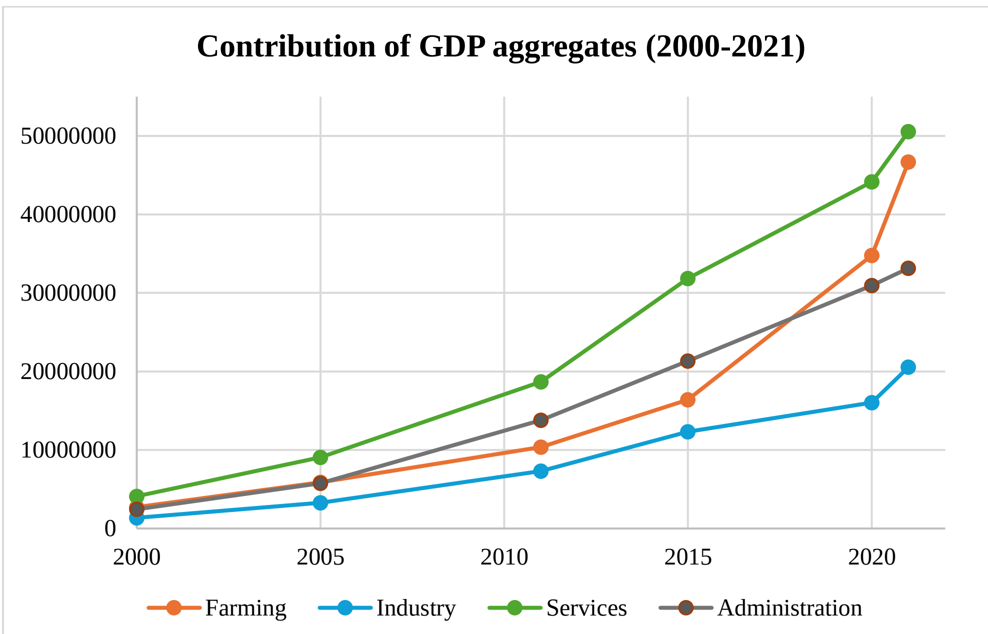
[11] It is a cash transfer program run by the Brazilian federal government and linked to the Ministry of Development and Social Assistance, Family and Fight against Hunger. As well as guaranteeing income to families living in poverty, the PBF seeks to integrate public policies, strengthening families' access to basic rights such as health, education and social assistance.

[12] It is a social assistance benefit in Brazil, provided by the National Social Security Institute, which guarantees a minimum monthly wage to people with disabilities who can prove that they do not have the means to provide for themselves or their family.

of total GDP over the same period. As illustrated in Graph 3, agricultural GDP rose from 2.7 billion in 2000 (26% of the total aggregate) to 46.7 billion reais in 2021 (31% of the total aggregate).

Considered the country's most recent agricultural frontier, the literature corroborates these figures and lists the agricultural sector as the main factor in Matopiba's economic development (De Oliveira, Raposo, & Garcia 2024; Dos Reis et al., 2024; Loayza et al., 2023; Nunes, Campelo Filho, & Benini, 2023; Batista et al., 2022; De Oliveira, Dörner, & Schneider, 2020; Ribeiro et al., 2020; Widmarck, 2020; De Araújo et al., 2019; Bragança, 2018; Pereira, Castro, & Porcionato, 2018).

Graph 3: Contribution of Economic Sectors to the GDP of the Matopiba Region (R$)



Source: Own Elaboration, with data from IBGE (2022).

The GDP of services grew from 4.1 billion in 2000 to 50.5 billion in 2021. Despite a growth of 1230%, there was a decrease in the contribution of the services GDP to the total value added, from a contribution of 39% in 2000 to 33% in 2021.

The industrial sector showed the lowest growth rate compared to 2000 (755%), which meant that the industrial sector's relative share of the total value added grew by just 1%, from 13% in 2000 to 14% in 2021. These figures indicate that the industrial sector is losing ground in Matopiba.

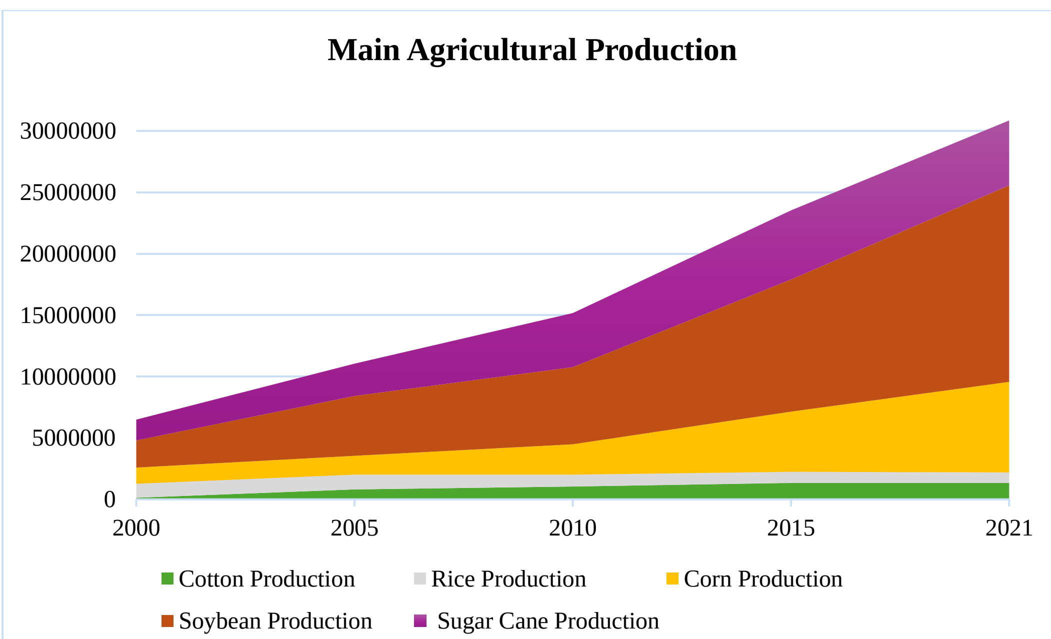
There was also an increase in GDP from administration, from 2.4 billion in 2000 to 33.1 billion in 2021. Despite a small decrease in the contribution to total value added (from 23% in 2000 to 22% in 2021), the figures represent a growth of 1356% in public investment and social security in the region.

Agricultural Production

Until the first half of the 20th century, the Matopiba region was covered by pastures and native vegetation (Cerrado and Caatinga) and, as a result, agriculture was considered unproductive. However, since 2005, there has been an expansion of agricultural activity in the region, with the emergence of large monoculture farms that use mechanized technologies for large-scale production, mainly for the export of soy, corn, and cotton (BRASIL, 2021). This expansion was due to the region's flat topography and the low cost of land compared to the consolidated areas of central-southern Brazil.

Agricultural production in Matopiba grew by 387% between 2000 and 2021, from 8.4 million tons in 2000 to 32.5 million tons in 2021. As Graph 4 shows, this high growth was mainly due to soybean and corn production.

Graph 4: Agricultural Production in Matopiba Region (t)



Source: Own Elaboration, with data from IBGE (2022).

With an increase of 725%, soybean production went from 2.2 million tons in 2000 to 16 million tons in 2021. This growth has made soybean the main agricultural crop in Matopiba, accounting for almost 50% of all agricultural production in the region. In addition, Matopiba is already responsible for almost 15% of Brazil's total soybean production.

Corn production increased from 1.3 million tons in 2000 to 7.4 million tons in 2021 (an increase of 560%). Currently, corn production represents 22% of Matopiba's total production and, together with soybeans, is the region's main agricultural crop (71% of total agricultural production).

Sugarcane production is the third largest in Matopiba. It went from 1.7 million tons produced in 2000 to almost 5.3 million tons in 2021, which represents an increase of 310% over the period. This increase makes sugarcane production responsible for 16% of the region's total agricultural production.

Cotton production grew the most between 2000 and 2021 in Matopiba (1072%). Production went from 124,000 tons in 2000 to 1.3 million (t) in 2021. However, despite this enormous growth, cotton represents only 4% of the region's total production.

Considered one of Matopiba's main crops, rice production has been declining since 2000. It went from 1.4 million tons in 2000 to 912,000 in 2010 and 851,000 in 2021. This decline is mainly associated with the replacement of rice production by soybeans and corn.

In addition to large-scale grain production, the region also has room for livestock and fruit, roots, and tubers, the main ones being cassava, beans, sugar cane, watermelon, and pineapple.

The Brazilian Ministry of Agriculture says that a large part of this increase in grain productivity (mainly soybean) is due to the technologies currently used in Matopiba, such as the use of hybrids and cultivars adapted to the soil and climate conditions, conservation management systems (no-till farming and Crop-Livestock-Forest Integration), as well as the efficient use of pesticides, correctives, and fertilizers.

The states of Bahia and Tocantins are currently the largest agricultural producers in the region. Production in Bahia was more than 10.2 million tons, with the micro-regions of Barreiras and Santa Maria da Vitória being the most important. A noteworthy fact is that the municipalities of the Barreiras micro-region alone produced around 7.9 million tons, 5.5 million tons of which were soybeans, making this micro-region the largest agricultural producer in Matopiba.

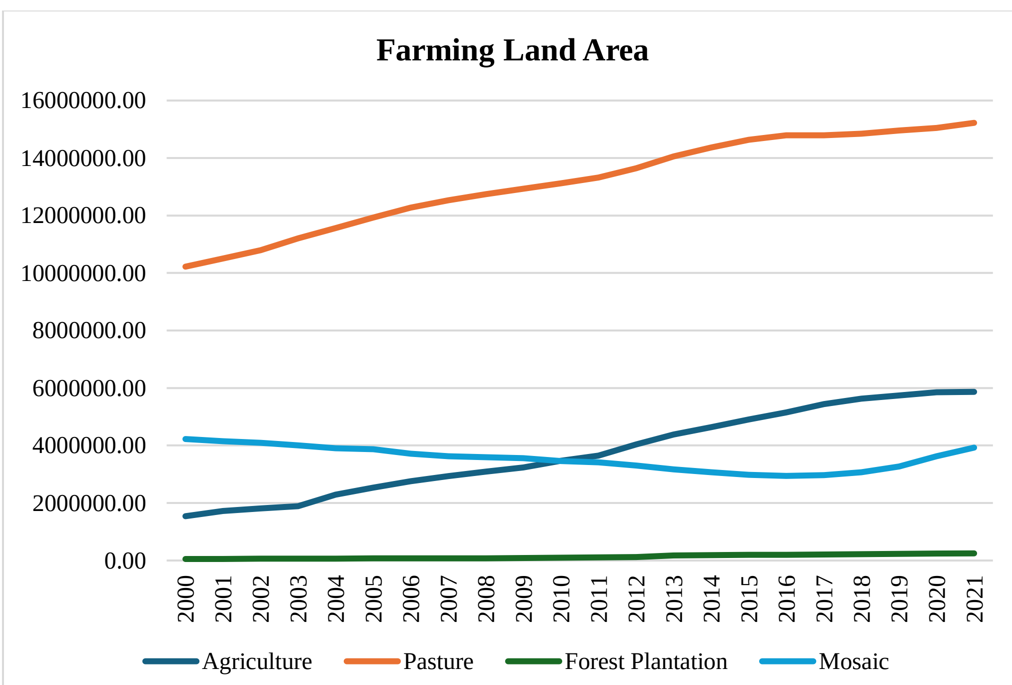
The state of Tocantins produced just over 9.1 million tons in 2021, with the micro-regions of Miracema do Tocantins, Rio Formoso and Porto Nacional standing out. The soybean crop was also the largest producer in Tocantins (3.7 million tons), followed by corn production (approximately 2 million tons).

The municipalities of Maranhão produced around 8.6 million tons in 2021, with the micro-regions of Balsas Gerais and Chapadas das Mangabeiras being the biggest producers, with soybeans and corn also standing out. Finally, the state of Piauí produced 4.6 million tons, mainly driven by the municipalities in the Alto Parnaíba Piauiense and Alto Médio Gurguéia micro-regions.

Land Cover and Use

The progress of farming in Matopiba can also be seen when looking at the history of land cover in the region. Farming areas jumped from 16 million hectares in 2000 to 25.2 million in 2021. As illustrated in Graph 5, this increase was due to the intensive growth of pasture and agricultural areas.

Graph 5: Distribution of Farming Land Use in Matopiba Region (ha)



Source: Own Elaboration, with data from IBGE (2022).

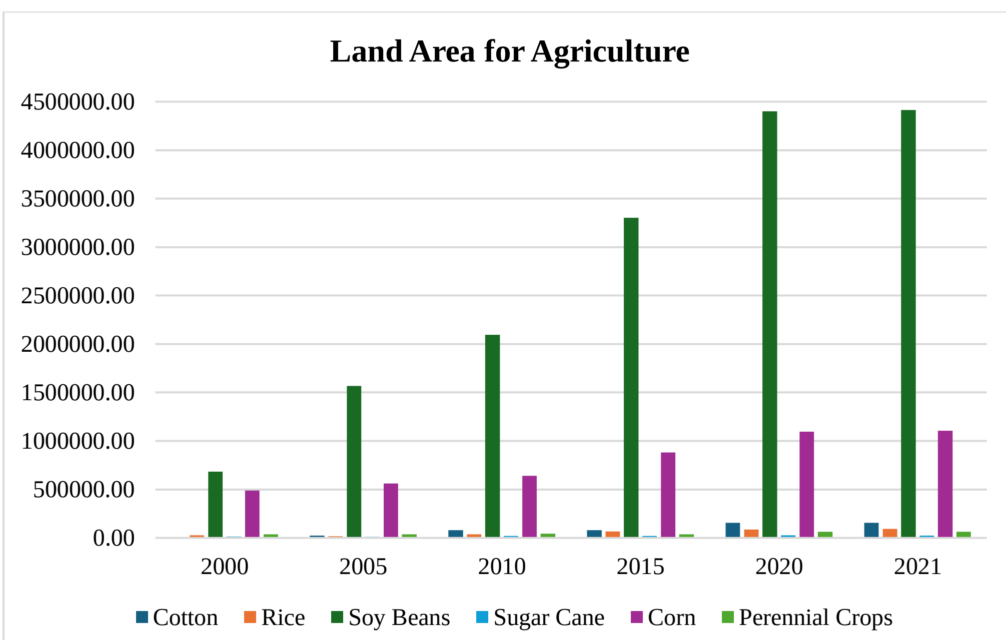
Pastureland increased by another 5 million hectares between 2000 and 2021 in Matopiba. It went from an area of 10.2 million hectares in 2000 to 15.2 million hectares in 2021, which represents an increase of 149%. The area devoted to agriculture grew by 381% in the same period, from 1.5 million hectares in 2000 to over 5.8 million in 2021, mainly due to the large production of soybeans and corn in the region (this will be discussed later in this session).

Despite a 473% increase between 2000 and 2021, forest plantation areas occupied only 2.5 million hectares in 2021. Also known as silviculture, these areas grow tree species to produce wood, resins, and essences, among other things.

Looking at the annual average, from 2010 to 2021, the area for farming grew by an average of 478.3 thousand hectares per year, with 203 thousand hectares on average for agriculture, 184 thousand for pasture, 79 thousand for mosaic areas, and 12.1 thousand hectares on average per year for forest plantations.

Due to the wide variety of crops grown in Matopiba and the fact that it currently demands the most land, a more in-depth analysis of the distribution of agricultural land use in the region was deemed necessary. With an area of 4.4 million hectares, soybeans would occupy 75% of all agricultural land in Matopiba by 2021, but this wasn't always the case.

Graph 6: Distribution of Agricultural Land Use in Matopiba Region (ha)



Source: Own Elaboration, with data from IBGE (2022).

In 2000, soybean production occupied an area of just over 68,000 hectares. However, due to public policies and intense technological modernization, soy has become the most widely grown grain in Matopiba and, by 2010, it has already occupied an area of more than 2 million hectares. Between 2000 and 2021, there was a 646% increase in soybean area in the region.

The area planted with corn grew by 226% in the same period, from 48,8027 hectares in 2000 to 1.1 million in 2021. As a result, corn production occupies 19% of the agricultural area.

The increase in agricultural area can also be seen in other temporary crops (cotton, rice, sugar cane, among others), but they only represent 5% of the total area. Finally, the area of permanent crops (coffee, apples, pears, grapes, mangoes, oranges, among others) grew by 180% between 2000 and 2021 but represents only 1% of the total agricultural area in the region.

3.2 Environmental Aspects

Characterization

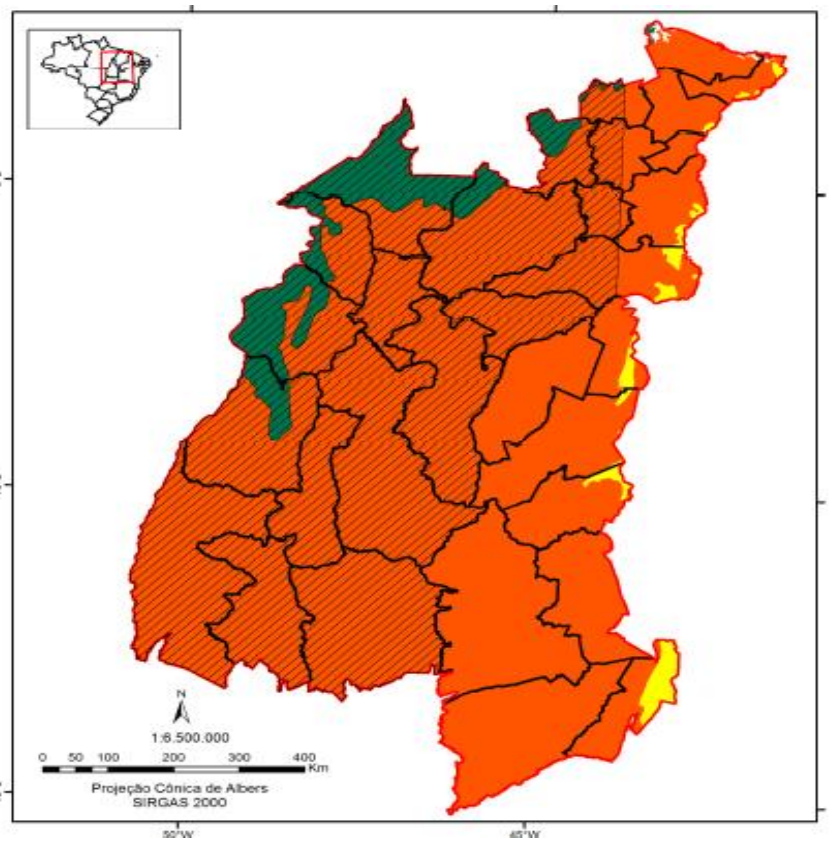
One of the criteria used in Matopiba's territorial delimitation was the area of the region's existing biomes. The Cerrado is the predominant biome, representing around 67 million hectares (91% of the territory). The region also has around 5.4 million hectares of the Amazon Biome (7.3%) and 1.2 million hectares of the Caatinga Biome (1.7%).

Due to the predominance of the Cerrado Biome, Matopiba has ecosystems with forest (predominantly tree species), savannah, and grassland formations. Savannahs represent 61% of Matopiba's natural formations, forests comprise around 32%, and grassland formations around 7%. (Oliveira, 2007). Figure 4 shows the territorial delimitation of Matopiba by biome area, in which the Cerrado is represented by orange, the Amazon Biome by green, and the Caatinga by yellow.

The relief of the region is very diverse, with 19 major morphological groups. In the larger area, broad, gentle hills predominate, which are areas characterized by degradation processes in any lithology. The domain of plateaus and plateaus (the second largest in the area) is characterized by relief of degradation in sedimentary rocks. However, the region also has flattened surfaces, river plains, valleys, hills, and low mountains, among other features.

Diversity is also seen in the soil classes in Matopiba, where there are 12 different classes, with latosols, neosols, and plinthosols being the dominant classes. Latosols, the predominant soil in the region, cover an area of around 28 million hectares and are characterized by intense weathering, but with good permeability and high porosity, i.e. favorable physical characteristics for agricultural use.

Figure 4: Territorial Delimitation of Matopiba by Biome Areas



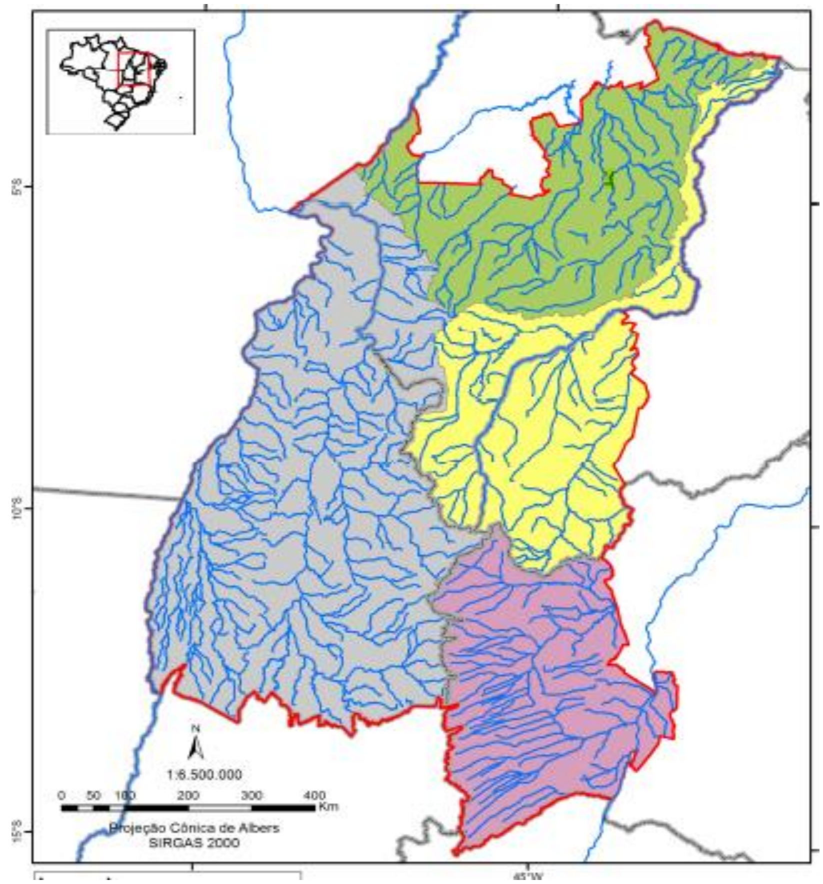
Source: EMBRAPA (Miranda et al. 2014).

Matopiba's climate is characterized by Tropical Central Brazil (53%), Tropical Equatorial Zone (44%), and Equatorial (3%) climate zones. Due to the region's large territorial extension, the semi-humid tropical climate predominates in the central extension of the territory, with average temperatures above 18°C throughout the year and dry spells of between 4 and 5 months; while the semi-arid climate predominates on the eastern edge of the region, with high temperatures and low humidity and rainfall (6 dry months) (Oliveira, 2007).

In addition to the favorable climate and soils for agricultural production, Matopiba is a region with an extreme abundance of fresh water, in which four of Brazil's main hydrographic basins are found, namely: The Tocantins-Araguaia River Basin, the Parnaíba River Basin, the Atlantic Basin in its North-Northeast stretch, and the São Francisco River Basin.

Figure 5 shows the territorial distribution of Matopiba's river basins. The Tocantins-Araguaia River basin is shown in blue, the Parnaíba River basin in yellow, the Atlantic basin in green, and the São Francisco River basin in purple.

Figure 5: Distribution of Matopiba's River Basins



Source: EMBRAPA (Miranda et al. 2014).

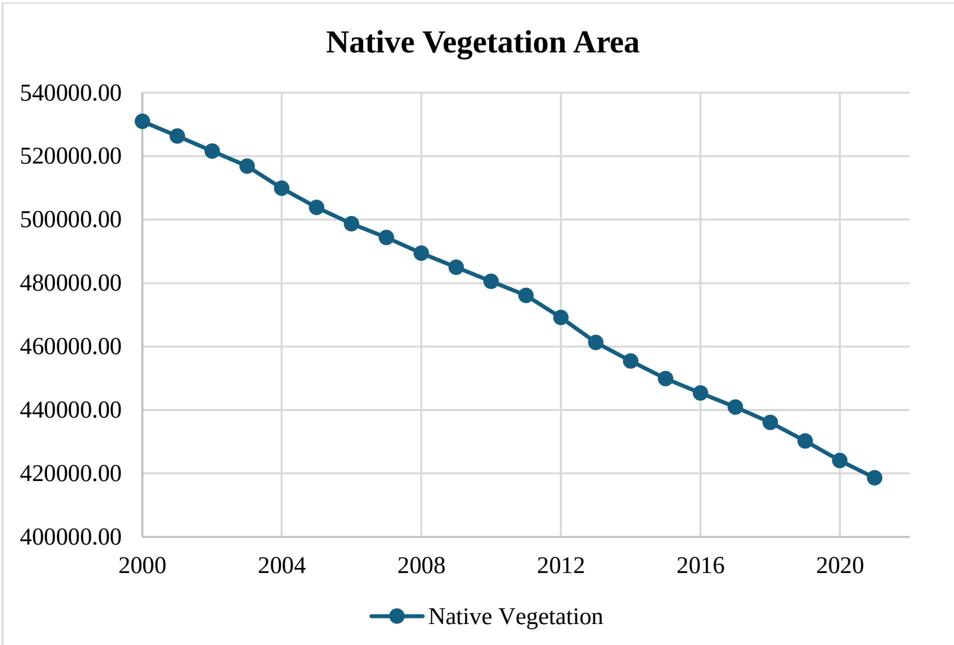
The basins of the Tocantins rivers, the Atlantic Basin in its North-Northeast section, and the São Francisco are home to the main rivers in the region and some of the most important in Brazil: Araguaia, Gurupi, Itapicuru, Mearim, Parnaíba, Pindaré, São Francisco and Tocantins.

Environmental Impacts

In addition to an enormous animal biodiversity, Matopiba encompasses a diversity of endemic plants of global importance. However, around 12 million hectares of native vegetation were lost between 2000 and 2022.

As illustrated in Graph 7, native vegetation covered an area of around 53 million hectares in 2000 in Matopiba, while in 2022 this area was 41 million. Around 502,000 hectares of native vegetation are cleared every year in the region.

Graph 7: Native Vegetation Area in Matopiba Region (ha)



Source: Own Elaboration, with data from MapBiomas (2023).

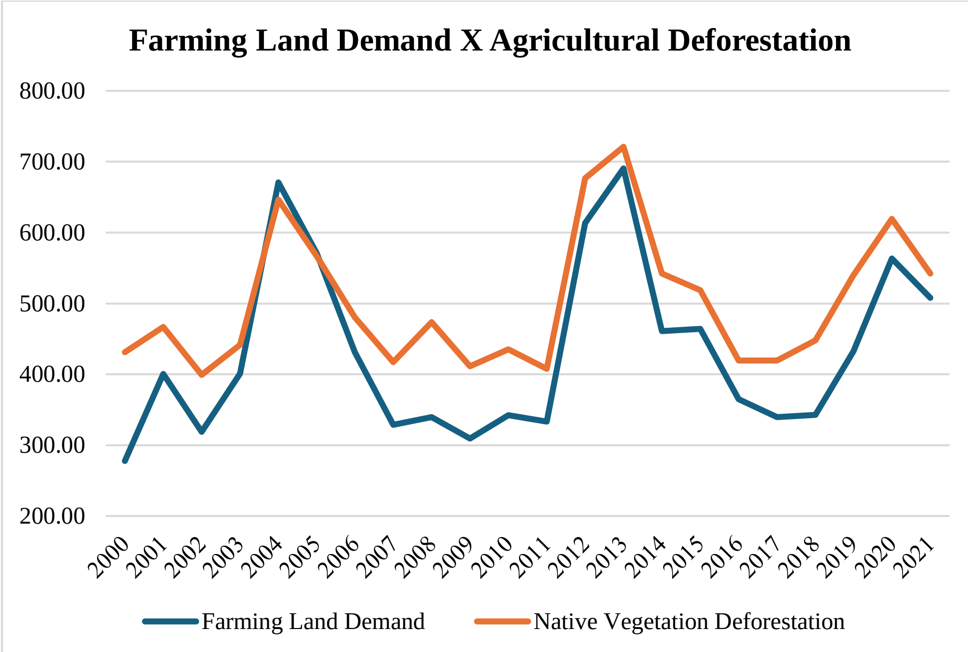
Data from MapBiomas (2023) shows that farming was responsible for 99.5% of the conversion of native vegetation between 2000 and 2022. Other factors, such as mining, urbanized areas, and aquaculture, had little influence, together accounting for just 0.5%.

The conversion of vegetation into pasture amounted to 5.5 million hectares, which represents 50% of all vegetation converted in Matopiba between 2000 and 2022. Agriculture comes next, with a converted area of 3.45 million (31% of the total conversion).

The conversion of vegetation to agriculture and pasture may be even greater, due to the mosaic areas. The conversion of native vegetation to mosaic areas amounted to around 2 million hectares (18% of the total conversion). Finally, the conversion of vegetation to forestry, also called Forest Plantation, amounted to just 150,000 hectares (1%) between 2000 and 2022.

As shown in Graph 8, the annual increase in the area under farming (farming land demand) shows practically the same trend as deforestation in Matopiba, which once again demonstrates that agriculture may be the main cause of the suppression of native vegetation in the region.

Graph 8: Annual Trends in Farming Land Demand and Deforestation in Matopiba (ha)



Source: Own Elaboration, with data from MapBiomas (2023).

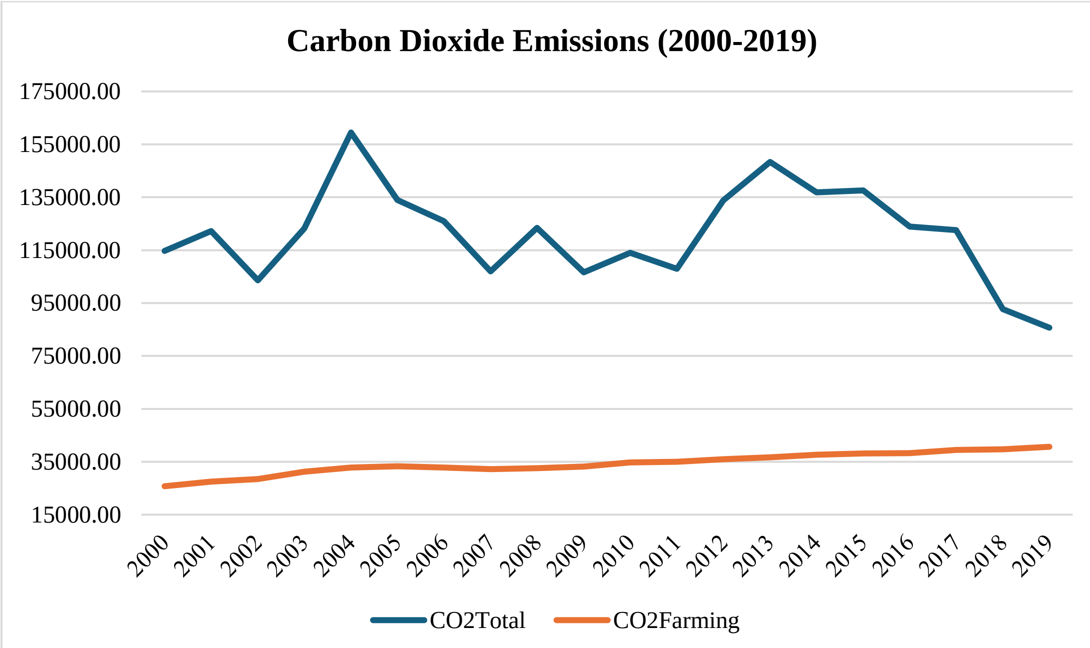
The small excess deforestation to the farming land demand, according to a report by the Climate Observatory (2024), is due to the current accuracy of deforestation detection systems, as well as the fact that deforestation in Matopiba is spreading to Legal Reserves and Permanent Protection Areas (places that couldn't even be touched).

In addition to the deforestation of native vegetation, the rates of carbon dioxide emissions from farming have also been increasing in Matopiba. Although the total rate of CO_2 emissions is inconstant and decreased between 2013 and 2019, data from the Gas Emission Estimation System - Brazil (SEEG, 2020) shows that CO_2 emissions from farming increased by around 15 million tons (GWP-AR5) between 2000 and 2019.

As seen in Graph 9, CO_2 emissions from farming increased from 25.7 million tons in 2000 to 40.6 million in 2019. Total CO_2 emissions in 2019 were just over 85.7 million tons, which means that farming is responsible for 47% of total CO_2 emissions in the region.

In addition, the average annual CO_2 emissions from farming have been growing. For the period from 2000 to 2019, the average was 34.3 million tons per year. On the other hand, considering a more recent period (2015 to 2019), farming emits more than 39.2 million tons per year in the region.

Graph 9: Carbon Dioxide Emissions in Matopiba Region (tons GWP-AR5)



Source: Own Elaboration, with data from SEEG (2020).

The literature corroborates these figures and shows that the expansion of agribusiness in Matopiba is causing major environmental impacts in the region (Araújo et al., 2024; De Sampaio Melo, Júnior, & de Espindola, 2024; Da Silva Arruda et al., 2024; Siqueira et al., 2024; Agostinho et al., 2023; De Oliveira Aparecido et al., 2023; De Souza et al., 2023; Ferreira, 2023; Santos et al., 2023; Ferreira-Paiva et al., 2022; Nepomoceno, & Carniatto, 2022; Polizel et al., 2021; Schneider, Biedzicki de Marques, & Peres, 2021; Dos Reis et al., 2020; De Barros, & Stege, 2019; Barbirato, & Souza, 2018; Matricardi et al., 2018; Salvador, & de Brito, 2018).

Summary

This chapter has described the socioeconomic and environmental characteristics of the Matopiba region, using available academic literature and data provided by Brazilian institutes and projects.

In addition to outlining the region, the first part of this chapter analyzed the evolution of GDP, agricultural production, and land cover. A comparative analysis showed that Matopiba has been undergoing socio-economic transformations due to the expansion of intensive farming. The region's GDP had a gross GDP growth rate of 1.419% between 2000 and 2021, driven mainly by agriculture and the goods and services sector. Agricultural production rose from 8.4 million tons in 2000 to 32.5 million tons in 2021, mainly due to the production of soybeans (50% of total agricultural production) and corn (21% of total agricultural production). Farming areas jumped from 16 million hectares in 2000 to 25.2 million in 2021.

The second section characterized the environmental aspects of the region, showing that Matopiba has an abundance of fresh water and a favorable climate and soils for agricultural production. This section also presented the main environmental impacts suffered in recent years in the region, where around 12 million hectares of native vegetation were lost between 2000 and 2022 (with agriculture being responsible for 99.5% of this conversion), as well as CO_2 emissions from agriculture increasing by around 15 million tons between 2000 and 2019.

4. Chapter 4: Verification of Environmental Conditions in Matopiba

Introduction

The descriptive statistics presented in Chapter 3 showed that Matopiba's agricultural production and GDP are growing intensely, while at the same time, there is an increase in the deforestation of native vegetation and agricultural CO_2 rates in the region. Therefore, this chapter aims to use machine learning techniques to develop two statistical models to analyze the environmental conditions generated by the agricultural frontier in the region.

Canonical Correlation Analysis (CCA) was used to verify the relationship and magnitude of dependence between environmental impacts, economic growth, and agricultural production in Matopiba. This statistical technique of the machine learning approach was chosen because of the possibility of finding a linear combination in each set of variables that maximizes the relationship between one or more dependent and independent variables.

The first section of this chapter describes the machine learning approach, and the entire methodological process involved in the analyses (model specification, results interpretation schedule). Section 2 presents the results of the canonical analysis, which first discusses the relationship between environmental impacts and economic growth and then the relationship between environmental impacts and agricultural production.

4.1 The Machine Learning Method

Machine Learning (ML) is a subfield of artificial intelligence that focuses on creating systems that learn or improve data performance based on the very data they consume. ML uses techniques that are an advance on traditional multivariate statistical methods, as it offers insights that are essential for creating predictive models using many artificial intelligence algorithms (Silveira et al., 2023).

The field of ML is broad and encompasses various statistical and computational techniques used to analyze and interpret database patterns, especially in multivariate data analysis and probabilistic inference. Techniques that aim to analyze the degree of relationship between variables by grouping and/or discriminating profiles, such as MANOVA, canonical correlation analysis, and factor analysis, are integral parts of the ML toolkit (Murphy, 2012).

ML techniques have been used in studies that address environmental impacts (Liu, Wang and Fang, 2024; Shoushtari, Zadeh and Daghighi, 2024; Prioux et al., 2023; Rao et al., 2023; Abu El-Magd, Maged and Farhat, 2022; Asha et al., 2022; Gao and Mavris, 2022; Yang et al., 2022; Algren, Fisher and Landis, 2021; Brownlee et al., 2021; Harding and Lamarche, 2021; Abdella et al., 2020; Colla et al., 2020; Garre, Ruiz and Hontoria, 2020; Storm, Baylis and Heckelei, 2020; D'Amico et al., 2019; Lacoste et al., 2019; Cordier et al., 2018) and agricultural production (Attri, Awasthi and Sharma, 2024; Liu et al., 2024; Rane et al., 2024; Amini and Rahmani, 2023; Pallathadka et al., 2023; Akhter and Sofi, 2022; Cravero et al., 2022; Wani et al., 2022; Benos et al., 2021; Meshram et al., 2021; Pant et al., 2021; Hamrani, Akbarzadeh and Madramootoo, 2020; Reddy et al., 2020; Sharma et al., 2020; Storm, Baylis and Heckelei, 2020; Rehman et al., 2019; Balducci, Impedovo and Pirlo, 2018; Liakos et al., 2018).

This chapter will use canonical correlation analysis (CCA) with a machine learning approach. CCA is the general multivariate analysis model that uses metric and non-metric variables as dependent and independent variables. While multiple regression analysis involves one metric dependent variable and several independent variables, canonical correlation analysis relates a set of several dependent variables Y (metric and non-metric) to a set of several independent variables X (metric and non-metric) (Hair et al., 2009).

$$Y_1 + Y_2 + \cdots + Y_p = X_1 + X_2 + \cdots + X_k$$

CCA finds a linear combination in each set of variables that maximizes the relationship between the dependent and independent variables. Each linear combination is called a canonical statistical variable (latent variable), which represents the weighted sum of the variables that make up the respective set of variables. Thus, the two linear combinations must produce the maximum possible correlation between the latent variables (hence the name Canonical Correlation) (Ho, 2013; Sherry and Henson, 2005).

The general CCA model is described in the equation:

$$\propto_1 Y_1 + \propto_2 Y_2 + \cdots + \propto_p Y_p = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Where:
$Y_1, Y_2, \ldots Y_p$ are the canonical dependent variables,
$X_1, X_2, \ldots X_n$ are the canonical independent variables,
$\propto$ are the correlation coefficients for each canonical dependent variable of the model,
β are the correlation coefficients for each canonical independent variable of the model.
.

Models Specification

In this chapter, CCA is used to analyze the two proposed models. Model 1 consists of analyzing the canonical correlation between environmental and economic growth variables. The analysis will be carried out in two stages:

1. The relationship of dependence between environmental issues and the economic aggregates of GDP is initially verified.
2. If there is a significant correlation, an attempt is made to identify the relative contribution of the economic aggregates to explaining environmental impacts in Matopiba.

Model 1 is described in the equation:

$$\propto_1 Y_1 + \propto_2 Y_2 = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

Where:
Y_1 represents CO_2 Total Emissions,
Y_2 is the Deforestation of Native Vegetation in the region,
X_1 represents Gross Value Added in Agriculture,
X_2 is the Gross Value Added in Industry,
X_3 is the Gross Value Added of Services and Administration,
$\propto$ are the correlation coefficients for each canonical dependent variable of Model 1,
β are the correlation coefficients for each canonical independent variable of Model 1.

Model 1 serves as the basis for proving Hypothesis 3 of this study and provides empirical support to answer the following questions: Is there any relationship between the economic aggregates and the environmental impacts generated on Matopiba's agricultural frontier? Which economic aggregate contributes the most to environmental impacts in the Matopiba region?

Model 2, in turn, aims to analyze the canonical correlation between environmental and agricultural production variables. The analysis is also carried out in two stages:

1. Initially, the dependency relationship between environmental variables and the production of the main crops in Matopiba is verified.
2. The aim here is to identify the contribution of each agricultural crop to environmental impacts in the region.

Model 2 is described in the equation:

$$\propto_1 Y_1 + \propto_2 Y_2 = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

Where:

Y_1 represents CO_2 Agricultural Emissions,

Y_2 is the Deforestation of Native Vegetation in the region,

X_1 represents the Quantity Produced of sugar cane,

X_2 is the Quantity Produced of corn,

X_3 is the Quantity Produced of soybeans,

X_4 represents the Quantity Produced of rice,

$\propto$ are the correlation coefficients for each canonical dependent variable of Model 2,

β are the correlation coefficients for each canonical independent variable of Model 2.

Model 2 serves as the basis for proving Hypothesis 4 and provides empirical support to answer RQ4: Is agricultural production in Matopiba related to the environmental impacts generated in the region? Which crops contribute most to environmental impacts in Matopiba's agricultural frontier?

Table 2 describes the variables that make up Models 1 and 2 of the CCA. The analyses of both models used the 31 micro-regions of Matopiba as a sample, shown in Appendix 1 of this study.

Table 2: Variables that make up Models 1 and 2 of the CCA

Variables Description			Source
Dependent Variables of Model 1 (Environmental Impacts)			
Y_1	CO_2 Emissions	CO_2 Total Emissions	Gas Emission Estimation System, Brazil.
Y_2	Deforestation	Area of Deforestation of Native Vegetation (Km^2)	National Institute for Space Research, Brazil.
Dependent Variables of Model 2 (Environmental Impacts)			
Y_1	CO_2 Emissions	CO_2 Agricultural Emissions	Gas Emission Estimation System, Brazil.
Y_2	Deforestation	Area of Deforestation of Native Vegetation (Km^2)	National Institute for Space Research, Brazil.
Independent Variables of Model 1 (GDP Economic Aggregates)			
X_1	Agricultural GDP	Gross Value Added in Agriculture (thousand reais)	CENSUS - Brazilian Institute of Geography and Statistics (IBGE)
X_2	Industrial GDP	Gross Value Added in Industry (thousand reais)	CENSUS - Brazilian Institute of Geography and Statistics (IBGE)
X_3	Services and Administration GDP	Gross Value Added of Administration and Services (thousand reais)	CENSUS - Brazilian Institute of Geography and Statistics (IBGE)
Independent Variables of Model 2 (Agricultural Production)			
X_1	Sugar Cane	Quantity Produced of sugar cane (tons)	PAM - Brazilian Institute of Geography and Statistics.
X_2	Corn	Quantity Produced of corn (tons)	PAM - Brazilian Institute of Geography and Statistics.
X_3	Soybeans	Quantity Produced of soybeans (tons)	PAM - Brazilian Institute of Geography and Statistics.
X_4	Rice	Quantity Produced of rice (tons)	PAM - Brazilian Institute of Geography and Statistics.

Source: Own Elaboration.

In addition to the availability of databases, the environmental variables in Model 1 (deforestation of native vegetation and total CO_2 emissions) were chosen because these are the main environmental problems faced in the Matopiba region in recent years. For Model 2, CO_2 emissions exclusive to the agricultural sector were used to determine which of the region's main crops (sugar cane, corn, soy, and rice) are the most polluting. The choice of all the variables that make up CCA Models 1 and 2 was based on the data and information presented in Chapter 3.

Verification of Assumptions

CCA requires that the assumptions of linearity, normality, and absence of multicollinearity are met. These assumptions will be verified for the variables in the two study models.

Linearity: canonical correlation is the linear relationship between two or more statistical variables. Thus, when statistical variables are related in a non-linear way, this relationship is not captured by the CCA. The Scatter Plot will be used to check the linearity of the variables.

Normality: although the CCA may have non-metric variables, it is advisable to check the normality of the metric variables. This assumption has been met by the Central Limit Theory (Ellenberg, 2015; Salsburg, 2009).

Multicollinearity: since multicollinearity affects the technique's ability to isolate the impact of the independent variable on the dependent variable, its absence must also be considered in the CCA. The absence of multicollinearity will be analyzed using the value of the Variance Inflation Factor (VIF).

Results Interpretation Schedule

The results will be analyzed in two stages. Firstly, the fit of the model will be checked, and whether there is a possible correlation between the variables. This process will be carried out using significance tests, size effects, and dimension reduction analysis.

Significance tests: four multivariate significance tests will be analyzed: Pillai's criterion, Hoteling's label, Wilks' Lambda, and Roy's GCR. Among these tests, Wilks' lambda (λ) is the most widely used due to its more general applicability (Sherry and Henson, 2005).

Size effects: the results of significance tests can be affected by the size of the sample, i.e. when the sample is too small, they may not be observed, while when the sample is too large, there may be an overestimation of the relationships. It is therefore also important to interpret the effect size indices, which are determined by subtracting Wilks' λ value from 1. The effect sizes for testing the significance of the correlation coefficient, r, are 0.10, 0.30, and 0.50, for small, medium, and large, respectively (Cohen, 1988). The effect sizes in the CCA have the same function as the R^2 in the regression analysis.

Dimension reduction analysis: another limitation of significance tests is that they do not test each canonical function separately, i.e. there is a hierarchy. Therefore, a dimension reduction analysis with the complete model (all the roots of the canonical function) is recommended (Sherry and Henson, 2005).

Once the fit of the model and the possible significance of the variables in the model have been verified, the canonical analysis is carried out. This step will be carried out using the variance explained in each canonical function, as well as interpreting the standardized coefficients (canonical weights) and structural correlations (canonical loadings).

Variance explained in each function: initially, we check how many canonical functions will be analyzed in the CCA using the eigenvalues. Eigenvalues are used to evaluate each function in isolation, where only functions that explain a reasonable amount of variation between the two sets of canonical statistical variables (Sq. Cor > 0.10) should be interpreted. The results of the Squared Canonical Correlation (Sq. Cor) should be noted.

Standardized Coefficients (canonical weights) and Structural Correlations (canonical loadings): the magnitude of the standardized coefficients represents their relative contribution to the canonical function. However, due to the instability of standardized coefficients, especially in the presence of multicollinearity, the interpretation of structural canonical correlations is considered more appropriate (Ho, 2013; Sherry and Henson, 2005). Canonical weights and canonical loadings will be analyzed together.

4.2 Results of the Canonical Correlation Analysis

This section presents the results of the Canonical Correlation Analysis between Environmental Impacts and Economic Growth (Model 1), as well as between Environmental Impacts and Agricultural Production (Model 2). For both models, the assumptions of Normality, Linearity, and Multicollinearity were checked and met. The verification of the assumptions can be found in Appendix C of this dissertation.

4.2.1 CCA Between Environmental Impacts and Economic Growth

The four significance tests showed statistically significant results at a level of 0.05 for Model 1, with Wilks' $\lambda = 0.21237$ ($F = 10.13962$; $p < 0.01$). Thus, the null hypothesis that there is no relationship between the two sets of latent variables can be rejected, i.e. there is probably a relationship between the economic aggregates of GDP and environmental impacts in Matopiba.

The effect size of the model was 0.78763, i.e. the proportion of variance shared between the two sets of variables in the two canonical functions is 78.76%. Taken together, the results (so far) indicate that the entire model is statistically significant and can be considered to have a large effect size (> 0.70).

The results of the dimension reduction analysis also show that the complete model 1 (all the roots of the canonical function) is statistically significant (Wilks' $\lambda = 0.21237$, $F = 10.13962$, $p < 0.01$). As a result, the three analyses show that there is a large and significant canonical relationship between environmental impacts and the economic aggregates of GDP in the Matopiba region.

The next step was to identify the relative contribution/effect of each GDP aggregate on environmental impacts. Analysis of the eigenvalues showed that the relationship between the variables is captured by the first and second functions in the canonical model. According to the results of the Squared Canonical Correlations (Sq. Cor) presented in Table 3, the first function explained 63.91% of the variation within its function (Sq. Cor = 0.63912), and the second function explained 41.15% (Sq. Cor = 0.41152) of the variation within its function, which means that they should be retained for interpretation.

Table 3: Eigenvalues and Canonical Correlations of Model 1

Roots	Eigenvalues	Percentage	Cumulative Percentage	Canonical Correlations	**Squared Canonical correlations (Sq. Cor)**
1	1.77098	71.691	71.691	0.79945	**0.63912**
2	0.69930	28.308	100	0.64150	**0.41152**

Source: Own Elaboration.

The magnitude of the Standardized Canonical Coefficients represents their relative contribution to the two canonical functions, but this is particularly unstable in the presence of multicollinearity. Although the assumption of the absence of multicollinearity has been met in both models, it is safer to interpret the Structural Canonical Correlations (Ho, 2013).

Looking at the coefficients of the Structural Canonical Correlations in Table 4, deforestation was the most significant dependent variable (0.71493) for the first canonical function and is directly associated with the Gross Value Added of Agriculture (0.54243). This means that an increase in Agricultural GDP positively affects deforestation in the Matopiba region.

Table 4: CCA between Environmental Impacts and Economic Growth

		Standardized Canonical Coefficients		**Structural Canonical Correlations**	
Dependent Variables (Environmental Impacts)		1º	2º	1º	2º
Y_1	CO_2 Total Emissions	- 0.73943	**0.75608**	- 0.42851	**0.90354**
Y_2	Deforestation	**0.95554**	0.45317	**0.71493**	0.69919
Independent Variables (GDP Economic Aggregates)					
X_1	Agricultural GDP	0.87158	0.61500	**0.54243**	**0.83996**
X_2	Industrial GDP	**- 1.11867**	**0.69941**	-0.40234	**0.85548**
X_3	Services and Administration GDP	0.27471	- 0.14035	-0.12641	0.81871

Source: Own Elaboration.

The second canonical function has CO_2 emissions as the most powerful dependent variable, with 0.90354. Analyzing the coefficients of the structural canonical correlations, it was observed that the Gross Value Added of Industry (0.85548) and Agriculture (0.83996) have greater canonical weights (positive relationship) for CO_2 emissions in Matopiba.

The results of the structural canonical correlations in Model 1 indicate that there is a canonical relationship between environmental impacts and the economic aggregates of GDP in Matopiba, with agricultural GDP being the largest contributor to deforestation and one of the largest to the CO_2 emissions in the region.

These results corroborate the descriptive statistics and current literature on environmental problems and economic growth in Matopiba, presented in Chapter 3 of this study (De Oliveira, Raposo, & Garcia 2024; Dos Reis et al., 2024; Loayza et. al, 2023; Nunes, Campelo Filho, & Benini, 2023; Batista et.al, 2022; De Oliveira, Dörner, & Schneider, 2020; Ribeiro et.al, 2020; Widmarck, 2020; De Araújo et.al, 2019; Bragança, 2018; Pereira, Castro, & Porcionato, 2018).

Matopiba's GDP has registered a growth rate of over 1,400% in recent years, driven mainly by agriculture and the goods and services sector. At the same time, the region has lost more than 12 million hectares of native vegetation and increased CO_2 emissions from agriculture by around 15 million tons. This indicates that this sharp economic growth in the region has come at the expense of Cerrado Biome's environmental resources.

4.2.2 CCA Between Environmental Impacts and Agricultural Production

The four significance tests and the results of the dimensional reduction analysis were also statistically significant for Model 2 (significance level = 0.05). With Wilks' $\lambda = 0.14909$ ($F = 21.95816$; $p < 0.01$), the null hypothesis that there is no relationship between the two sets of latent variables can be rejected.

The effect size of model 2 was also high, with a proportion of shared variance in the canonical functions of 85.09% (0.85091). This indicates that there is a relationship (strong) between agricultural production and environmental impacts in Matopiba.

According to the results of the eigenvalues and squared canonical correlations presented in Table 5, two canonical functions will also be interpreted in Model 2. The first canonical function explained 92.76% of the variation within its function (Sq. Cor = 0.92768), and the second function explained 32.12% (Sq. Cor = 0.32121).

Table 5: Eigenvalues and Canonical Correlations of Model 2

Roots	Eigenvalues	Percentage	Cumulative Percentage	Canonical Correlations	**Squared Canonical correlations (Sq. Cor)**
1	12.82682	96.44199	96.44199	0.96316	**0.92768**
2	0.47322	3.55801	100	0.56676	**0.32121**

Source: Own Elaboration.

As shown in Table 6, the first canonical function has CO_2 agricultural emissions as the strongest dependent variable (0.99078), with the greatest contribution from soybean and corn productions (0.65165 and 0.46621, respectively).

Deforestation was the strongest dependent variable in the second canonical function, indicating that soybean (0.78706) and corn (0.75353) productions are also the most responsible (among the crops studied) for deforestation in the region.

Table 6: CCA Between Environmental Impacts and Agricultural Production

		Standardized Canonical Coefficients		**Structural Canonical Correlations**	
Dependent Variables (Environmental Impacts)		1º	2º	1º	2º
Y_1	CO_2 Agricultural Emissions	**1.11374**	- 0.76397	**0.99078**	0.13545
Y_2	Deforestation	- 0.18294	**1.33814**	0.56566	**0.82464**
Independent Variables (Agricultural Production)					
X_1	Sugar Cane	0.33859	- 0.42799	0.28445	- 0.38664
X_2	Corn	0.08057	0.39142	**0.46621**	**0.75353**
X_3	Soybeans	**0.55343**	**0.43643**	**0.65165**	**0.78706**
X_4	Rice	**0.76432**	**- 0.44181**	0.41204	- 0.46357

Source: Own Elaboration.

The results of the canonical analysis showed that soy is the crop that generates the most deforestation and CO_2 emissions in Matopiba, closely followed by corn production, in other words, soybean and corn production are the main contributors to environmental impacts in the region. These results are also consistent with the descriptive analysis presented in Chapter 3.

At the same time as there has been intense environmental degradation in Matopiba, agricultural production has increased by another 24 million tons in recent years, driven mainly by soybean and corn cultivation. Today, soy accounts for 50% of total agricultural production and occupies 75% of all agricultural land in the region. Many studies place soy as the main agricultural crop in the region and one of the most damaging to the environment (Loayza et. al, 2023; Nunes, Campelo Filho, & Benini, 2023; Batista et. al, 2022; Lopes, Lima, & Dos Reis, 2021; De Oliveira, Dörner, & Schneider, 2020; Santos, 2020; Silva et al, 2020; Spyrides, 2020; Nepstad et al, 2019; Bragança, 2018; De Freitas & Buosi, 2018; Carneiro Filho & Costa, 2016).

Despite a lower production rate than soybeans, corn accounts for 21% of total agricultural production and occupies 19% of Matopiba's agricultural area. In addition to the soy-specific literature above showing that corn production is increasing and has a major environmental impact on the region, other studies also confirm soy and corn as the most polluting crops in Matopiba (Araújo et al., 2024; Evangelista & Pereira, 2024; Polizel et al., 2021; Almeida de Souza et al. 2020; Pires, 2020; Widmarck, 2020; Buzato et al., 2018; Bolfe et al., 2016; Borghi et al., 2014).

Summary

This chapter developed two statistical models to verify the relationship and magnitude of dependence between environmental impacts, economic growth, and agricultural production in Matopiba. To do this, machine learning techniques such as Canonical Correlation Analysis (CCA) were used.

Model 1 provided empirical support to prove that there is a relationship between economic aggregates and environmental impacts in the Matopiba region, with agricultural GDP having the highest canonical correlation with deforestation and one of the highest with CO_2 emissions in the region.

With the main objective of analyzing which crops are less sustainable in Matopiba, Model 2 proved that agricultural production has a relationship with environmental impacts in Matopiba, with soybean production being the most polluting in the region, having the highest canonical correlation with deforestation and CO_2 agricultural emissions, closely followed by corn production. This result corroborates with the current literature and the descriptive analyses presented in Chapter 3.

5. Chapter 5: System Dynamics Modeling applied to predict the future of Matopiba

Introduction

The descriptive statistics presented in Chapter 3 and the results of the canonical correlation analysis presented in Chapter 4 show and prove that agricultural production is the main factor in the conversion of native vegetation into pasture and agricultural areas in Matopiba. However, Matopiba is at a critical level of natural resource depletion for this agricultural production, with only 2.6 million hectares of non-degraded pasture suitable for agriculture (BRASIL, 2021) and an area of around 7.5 million hectares of native vegetation with high and medium agricultural suitability (Rudorff et al., 2015).

Thus, this chapter aims to use System Dynamics Modeling (SDM) to predict the future of Matopiba regarding available natural resources (land suitable for agriculture and native vegetation) and intensive agricultural production. From there, measures will be discussed to try to contain or slow down the process of environmental depletion in the region.

System Dynamics (SD) is a scientific framework that addresses systems based on the theory of non-linear dynamics and feedback control. As a methodology, SD is based on quanti-qualitative techniques, emphasizing stakeholder involvement and encouraging researchers themselves to adopt a non-linear mental model approach (Sterman, 2000). A detailed description of the methodology and rationale behind SD is presented by Sterman (2000) and Bossel (2007).

This chapter is structured in two sections. The first section describes System Dynamics Modeling, and the entire methodological process involved, such as the SDM application process and the results interpretation schedule. Section 2 presents the results of the SDM for Matopiba, in which the conceptual development and simulation of the model will be presented and discussed, as well as proposing some solutions to the research problem.

5.1 The System Dynamics Modeling Methodology

In summary, System Dynamics Modeling (SDM) focuses on integrating physical processes, information flows, and management policies with the dynamics of the variables of interest. The totality of these relationships constitutes the “structure” of the system, in which “dynamic behaviors” are generated over time. The main objective of the SDM is to understand the creation of the dynamics of interest (how and why) to seek out and propose management policies for the situation analyzed (Saysel, Barlas, and Yenigün, 2002).

SDM is designed to be a robust modeling and analysis of large-scale socio-economic systems, based on psychology, economics, and other social sciences to incorporate decision-making in the face of complex issues. Issues such as environmental management, logistics, regional sustainable development, urban economic growth, and ecological modeling use this methodology as a way of solving highly complex problems (Kiss and Kiss, 2021).

Studies on environmental management (Luo, Liu and Zhao, 2023; Prinsloo, Schmitz and Lombard, 2023; Francis and Thomas 2022; Hu et al., 2021; Mobaseri, Mousavi and Mousavi Haghighi, 2021; Naderi et al., 2021; Prouty, Mohebbi & Zhang, 2020; Liu, Liu & Wang, 2020; Tan et al., 2018; Abdelkafi & Täuscher, 2016; Dace et al., 2014; Guan et al., 2011; Qi & Chang 2011; Stave 2010 & 2002; Fong, Matsumoto & Lun 2009; Jifeng, Huapu & Hu, 2008; Leal Neto et al., 2006) and Agricultural Production (Esteso et al., 2023; Shamsuddoha, Nasir and Hossain, 2023; Wang et al., 2022; Aboah et al., 2021; Muflikh, Smith and Aziz, 2021; Taghikhah et al., 2021; Fernandez-Mena et al., 2020; Bastan et al., 2018; Rich, Rich and Dizyee, 2018; Jeong and Adamowski, 2016; Kotir et al., 2016; Von Loeper et al., 2016; Walters et al., 2016; Dace et al., 2015; Yu et al., 2013; Li, Dong and Li, 2012; Shen et al., 2009; Shi and Gill, 2005; Saysel, Barlas and Yenigün, 2002) also used the SDM methodology.

The SDM is built with the relevant help of simulation tools/software such as Vensim, Stella, and AnyLogic, among others. As it is one of the most advanced tools for dynamics simulation methodologies, this chapter uses AnyLogic[13] 8.8 for the SDM for the Matopiba region.

SDM Application Process and Results Interpretation Schedule

With some similarity to other modeling approaches, the SDM application process consists of developing the model concept and developing the simulation model (Figure 6). This application process will be the schedule for interpreting the results of this study.

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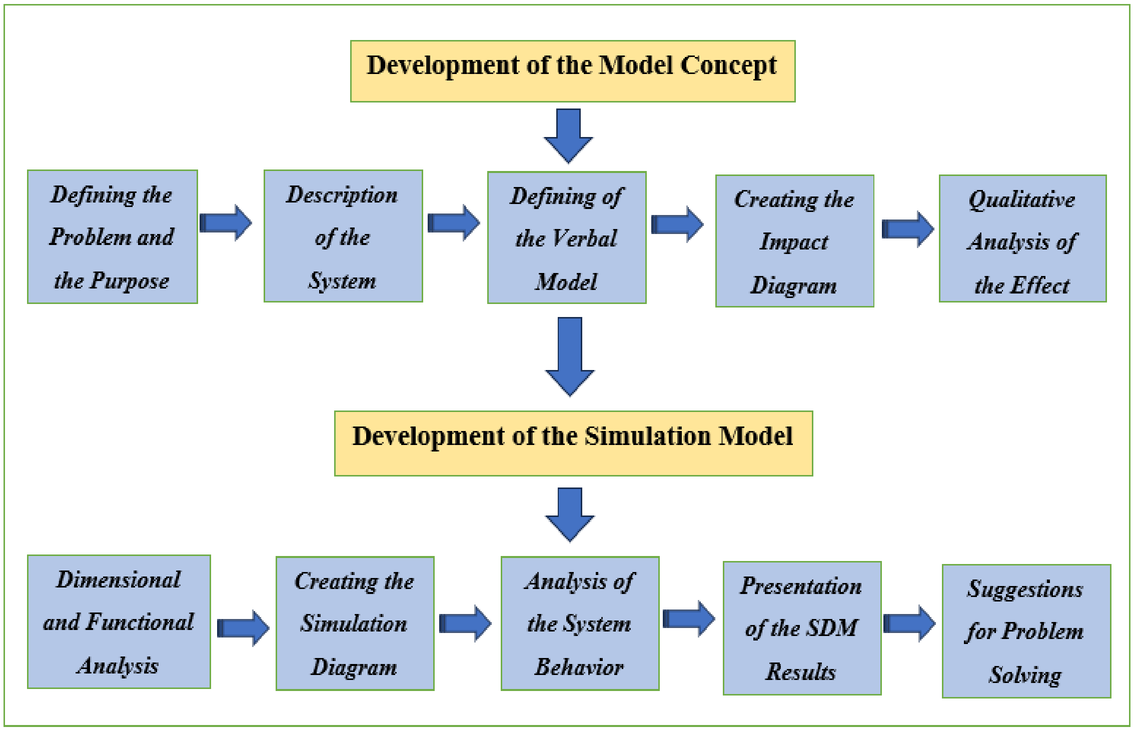
[13] AnyLogic: Simulation Modeling Software Tools & Solutions for Business

Figure 6: The Process of the System Dynamics Modeling Building



Source: Own Elaboration, based on Banks et al. (2013).

The development of the model concept has the following stages: (1) definition of the problem and justification for the model; (2) description of the system components; (3) definition of the verbal simulation model; (4) creation of the model's Impact Diagram; and (5) qualitative analysis of the impact structure.

The first stage of the model concept describes and summarizes the problem and justification for the study model, using the available literature and relevant data on the subject as a reference. The second stage aims to describe the components of the system, conceptualizing the main agents of interest that make up the model. The third stage involves defining the verbal simulation model, i.e. defining the possible direct relationships between the agents in the model, considering that each influence relationship is examined separately, with the others remaining unchanged (ceteris paribus). These relationships between the agents will lead to the creation of the influence or impact diagram (step 4), in which the directions between the variables studied will be presented. Stage 5 brings the qualitative analysis of the impact structure, i.e. the structure and validity of the model's application are discussed.

For the development of the simulation model, five other stages are articulated: (1) development of the dimensional and functional analysis of the model; (2) creation of the Simulation Diagram; (3) analysis of the system's behavior (modeling tests); (4) presentation of the results of the System Dynamics Modeling; and (5) suggestions for problem-solving.

In Stage 1 of the simulation model, dimensional analysis, functional relationships, quantification, the basic elements of the model (program instructions), and the computable model are developed. Later, the Simulation Diagram is built in Stage 2, focusing on analyzing the structure of the model, as well as its validity (development of sub-models, stock flow, feedback, relationships between elements), i.e. this structure must correspond to the original structure of the system and the objectives of the study model. The third stage is the analysis of the dynamic system's behavior, in which the execution parameters, initial and final values, and trajectory curves in the model's phase space are observed, as well as the empirical validity, sensitivity, and behavior (mainly oscillation) of the SDM. Step 4 consists of presenting the SDM results using the graphical options offered by the modeling framework program (trajectory curve diagram, for example), as well as discussing how the SDM results contributed to achieving the research objectives. Finally, in Step 5, the main suggestions for solving the study problem are presented and discussed.

5.2 Development of the SDM Concept for Matopiba

The development of the model concept is preliminary to the simulation and starts with a careful analysis of the problem, the justification, and the objectives to be met by the model. This stage also presents the components of the dynamic system being studied, the verbal simulation model, the Impact Diagram, and the qualitative analysis of the model's structure.

Definition of the Problem and Justification for the Model

Data from Brazil's main research institutes, presented in Chapter 3 of this study, show that approximately 12 million hectares of native vegetation have been lost between 2000 and 2022 in Matopiba, with farming accounting for 99.5% of this conversion.

Farming grew by 158% between 2000 and 2021, mainly due to the increase in pasture areas and soybean and corn production in the region. Consequently, the annual demand for land is also increasing, with more than 475,000 hectares of new land needed annually for farming in Matopiba, where approximately 203,000 hectares are required for agriculture, 184,000 for pastures, 79,000 for mosaic areas and 12,100 hectares on average per year for forest plantations.

However, the Solidaridad Brasil study (Brasil, 2021) showed that Matopiba has only 6.6 million hectares of pasture suitable for agriculture, of which 4 million hectares are degraded pasture. In addition, the relative area of native vegetation with high and medium agricultural suitability and no slope restriction is around 7.5 million hectares (Rudorff et al., 2015). Therefore, the major challenge facing Matopiba's agricultural frontier today is to balance intensive agricultural production with the environment, in other words, to maintain production using the minimum area of native vegetation.

The following questions then arise: how long will the available natural resources (suitable land and native vegetation) support intensive agricultural production in Matopiba? What measures can be taken to try to contain or slow down the process of environmental depletion in the region? To answer these questions, the main objective of this chapter is to develop system dynamics modeling to predict the future of Brazil's newest agricultural frontier (Matopiba). To do this, we will look at the "lifetime" of the region's environmental resources without any action being taken to intensive agricultural production and, from there, propose (appropriate) solutions to this problem.

The justification for the SDM is based on the importance of environmental and agricultural production of Matopiba for the world, while at the same time serving as a base model for other studies that address the environmental impacts of agricultural frontiers, especially in emerging countries.

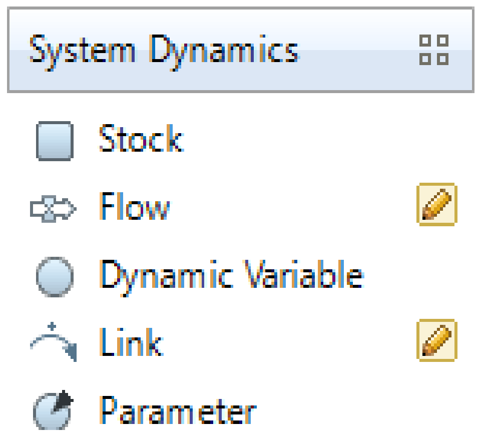
Description of the System Components

The SDM for Matopiba consists of two *Stocks*: Native Vegetation Availability and Virgin Land Demand Availability. These subsystems are the main components of the model and have their values defined by input and output *Flows*. These two stocks were chosen due to the data and analyses presented in Chapters 3 and 4 of this dissertation, which show the direct relationship between agricultural production, increased demand for land, and environmental impacts (mainly deforestation of native vegetation).

Stocks are state variables that change their value continuously over time and define a static part of the system. *Flows*, on the other hand, define how stock values change over time and are linked to the rest of the model through intermediate elements such as *Dynamic Variables* and *Parameters*. Figure 7 shows the format of the System Dynamic components displayed in Anylogic.

Dynamic Variables are usually functions of constants and stocks that represent a state of the model and can assign themselves the result of a calculation or operation. This model has 24 dynamic variables, 21 of which are used to analyze the demand for farming land in Matopiba, 1 variable represents agricultural deforestation, 1 to analyze the impact of land demand on agricultural deforestation, and 1 dynamic variable to analyze other impacts on agricultural deforestation.

Figure 7: The format of the components of System Dynamics



Source: Anylogic.

The *Parameters* represent some characteristics of the modeled object statically, i.e. it is a constant in a single simulation and is changed only when it is necessary to adjust the model's behavior. There are 23 parameters in the SDM for Matopiba, 20 of which are used as constants in the analysis of farming land demand, 1 represents the (constant) change in the forest plantation area, 1 constant to measure the impact of land demand on agricultural deforestation, and 1 parameter to represent non-agricultural deforestation.

It should be noted that soybeans and corn were the only crops used to construct parameters and dynamic variables for the demand for agricultural land since these are the most polluting and influential crops on Matopiba's agricultural frontier (discussed in Chapter 3 and presented in Table 6 of Chapter 4).

The relationship between the variables that make up the model will be discussed in the following section: "*Definition of the Verbal Simulation Model*".

Definition of the Verbal Simulation Model

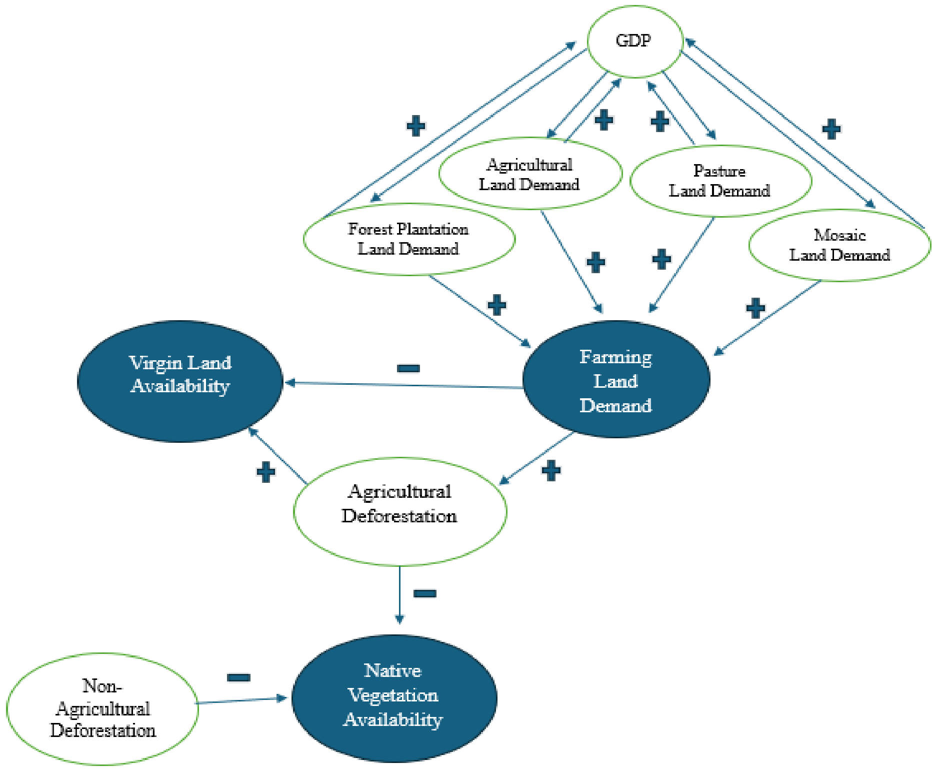
The relationships formed from SDM for Matopiba are as follows:

- Native Vegetation Availability is reduced by Agricultural Deforestation.
- Native Vegetation Availability is reduced by Non-Agricultural Deforestation.
- Agricultural Deforestation is driven by Farming Land Demand.
- Agricultural Deforestation is driven by Other Agricultural Factors.
- Virgin Land Availability is driven by Agricultural Deforestation.
- Virgin Land Availability is reduced by Farming Land Demand.
- Farming Land Demand is driven by Agricultural Land Demand.
- Farming Land Demand is driven by Pasture Land Demand.
- Farming Land Demand is driven by Mosaic Land Demand.
- Farming Land Demand is driven by Forest Plantation Land Demand.
- Agricultural Land Demand is driven by GDP.
- Pasture Land Demand is driven by GDP.
- Mosaic Land Demand is driven by GDP.
- GDP is driven by Agricultural Land Demand.
- GDP is driven by Pasture Land Demand.
- GDP is stimulated by Mosaic Land Demand.

Creation of the Model's Impact Diagram

As the basis of the simulation model, Figure 8 shows the Impact Diagram of the variables that make up the SDM for Matopiba.

Figure 8: The Impact Diagram of the SDM for Matopiba



Source: Own Elaboration.

Qualitative Analysis of the Impact Structure

As seen in the SDM Impact Diagram for Matopiba (Figure 8), the region's native vegetation is reduced by agricultural deforestation which, in turn, increases the area of land used mainly for agriculture. The use of land for agriculture leads to economic growth in the region (represented here by GDP) and this economic growth increasingly encourages demand for land, resulting in agricultural deforestation and, consequently, the reduction of native vegetation.

This is the agricultural-environmental cycle that has been taking place in Matopiba in recent years. As discussed in Chapters 3 and 4, recent literature and official Brazilian government data show that the creation of Matopiba's agricultural frontier has led to high economic growth in the region, but this has come at the expense of Cerrado's native vegetation.

This Impact Diagram is the basis for Matopiba's SDM, which will analyze the agricultural and, above all, environmental future of the region if there is no intervention.

5.3 Results of the System Dynamics Modeling for the Matopiba Region

The simulation model provides the computable part of the SDM for Matopiba, in which the main results of the structural and dimensional analysis of the model will be presented, as well as the empirical validity, sensitivity, and behavior of the variables. From there, suggestions will be made for the study's problems, as well as the model's limitations.

Development of the dimensional and functional analysis of the model

As described in the "Description of the System Components" section, SDM for Matopiba has 2 stocks, 24 dynamic variables, and 23 parameters. Therefore, this section aims to describe each of these elements, presenting their initial values or the corresponding functions that were used in the simulation process.

Table 7 summarizes the initial values or functions that make up the stocks and parameters. The references for these values were the available literature, as well as official data from the Brazilian government for the year 2020. To estimate some internal parameters (fraction), Bivariate Regression Analyses were carried out. The results of these analyses, as well as compliance with the assumptions, are presented in Appendix D of this dissertation.

The “NativeVegetationAvailability” stock represents the area of native vegetation with high and medium agricultural suitability which, according to (Rudorff et al., 2015), was approximately 7.5 million hectares. A statistical estimate was used to arrive at the value of 7.16 million hectares for 2020 (the initial value of this stock in thousands of hectares).

The initial value of the “VirginLandAvailability” stock is 2.6 million hectares. The reference for this value was the study developed by Solidaridad Brasil (Brasil, 2021), which showed that Matopiba has only 2.6 million hectares of undegraded pasture suitable for agriculture.

The value of the external parameter “NonAgriculturalDeforestation” is 26.78 thousand hectares and represents the average non-agricultural deforestation in Matopiba over the last three years of the analysis (2018-2020).

The “OtherAgriImpactsRate” parameter represents the factors external to farming land demand that can impact agricultural deforestation in the region. To arrive at this value, a weighted average was made between the impact of farming land demand on agricultural deforestation and the real value of this deforestation, i.e. this parameter indicates the value of agricultural deforestation not stimulated by farming land demand.

Table 7: Initial Values of Model Elements (stocks and parameters)

	Initial Value	Unit of Measurement	Source
Stocks			
NativeVegetationAvailability	7167.25	Thousand Hectares	MAPBiomas, Brazil.
VirginLandAvailability	2630.38	Thousand Hectares	MAPBiomas, Brazil.
External System Parameters (Constants)			
NonAgriculturalDeforestation	26.78	Thousand Hectares	MAPBiomas, Brazil.
OtherAgriImpactsRate	132.00	Thousand Hectares	MAPBiomas, Brazil.
ForestPlantationChange	14.51	Thousand Hectares	MAPBiomas, Brazil.
Internal System Parameters			
LandDemandToAgriDeforestationRatio	0.815	Fraction	Own parameter estimation[14].
CornLandToGDPRatio	152.738	Fraction	Own parameter estimation.
SoyLandToGDPRatio	30.968	Fraction	Own parameter estimation.
PastureLandToGDPRatio	22.284	Fraction	Own parameter estimation.
MosaicLandToGDPRatio	57.565	Fraction	Own parameter estimation.
GDPToCornLandRatio	0.00637	Fraction	Own parameter estimation.
GDPToSoyLandRatio	0.03237	Fraction	Own parameter estimation.
GDPToPastureLandRatio	0.04491	Fraction	Own parameter estimation.
GDPToMosaicLandRatio	0.01528	Fraction	Own parameter estimation.
CornLandIncreaseByGDP_Init	20.89	Thousand Hectares	MAPBiomas, Brazil.
SoyLandIncreaseByGDP_Init	196.25	Thousand Hectares	MAPBiomas, Brazil.
PastureLandIncreaseByGDP_Init	245.19	Thousand Hectares	MAPBiomas, Brazil.
MosaicLandIncreaseByGDP_Init	3.11	Thousand Hectares	MAPBiomas, Brazil.

Source: Own Elaboration.

[14] To estimate the “own parameters”, databases provided by MAPBiomas, Brazil and IBGE, Brazil were used.

The value of the “ForestPlantationChange” parameter represents the average land demand (increase or decrease in area from one year to the next) of Forest Plantations in the Matopiba region in the last few years of the analysis.

Moving on to describe the internal parameters, “LandDemandToAgriDeforestationRatio” represents the impact of farming land demand on agricultural deforestation in Matopiba. A bivariate regression analysis was carried out to verify the relationship between these two variables.

Bivariate regression analysis was also used to see the relationship between land demand for corn, soybean, pasture, and mosaic and GDP (“CornLandToGDPRatio”, “SoyLandToGDPRatio”, “PastureLandToGDPRatio”, ‘MosaicLandToGDPRatio’), as well as the relationship between GDP and the demand for land for these crops (GDPToCornLandRatio, ‘GDPToSoyLandRatio’, ‘GDPToPastureLandRatio’, “GDPToMosaicLandRatio").

The parameters “CornLandIncreaseByGDP_Init”, “SoyLandIncreaseByGDP_Init”, “PastureLandIncreaseByGDP_Init” and “MosaicLandIncreaseByGDP_Init” represent, respectively, the annual land demand for corn, soy, pasture, and mosaic used in the model. This was done by adding the real average demand for land in recent years with the impact of GDP on demand (GDPToLandRatio) and with the impact of land demand on GDP (LandToGDPRatio) afterward.

Dynamic variables, as already defined, are usually functions of stocks and constants used to store the results of the model simulation, i.e. they do not have initial “values”, but functions.

The variable "AgriculturalDeforestation", for example, represents agricultural deforestation in the region. To create it, two other dynamic variables were used that represent the impact of farming land demand and other external agricultural impacts on agricultural deforestation. Thus:

"AgriculturalDeforestation" = "ImpactLandDemandOnAgriDeforestation" + "OtherImpactsOnAgriDeforestation"

The variable "ImpactLandDemandOnAgriDeforestation" is formed by the relationship between the demand for land for farming and agricultural degradation in Matopiba, that is:

"ImpactLandDemandOnAgriDeforestation" = "FarmingLandDemand" * "LandDemandToAgriDeforestationRatio"

"FarmingLandDemand" is the combination of the land demand for forest plantation, mosaic areas, pasture, and agriculture.

"FarmingLandDemand" =
"ForestPlantationLandDemand" + "MosaicLandDemand" + "PastureLandDemand" + "AgriculturalLandDemand"

The variable "ForestPlantationLandDemand" corresponds to the parameter "ForestPlantationChange", which represents a fixed value that represents the increase in demand for forest plantations from one year to the next.

"ForestPlantationLandDemand" = "ForestPlantationChange"

“MosaicLandDemand” corresponds to another dynamic variable “MosaicLandChange”, which represents the increase in demand for mosaic land from one year to the next. To create “MosaicLandChange”, the initial demand for land for mosaic areas due to GDP (constant) was added to the increase in demand for land caused by the impact of GDP and other factors in year +1. Thus:

“MosaicLandChange” = time()<=1? MosaicLandIncreaseByGDP_Init:(“MosaicLandIncreaseByGDP”+ MosaicLandIncrease_Others_Init)

The increase in demand for mosaic areas stimulated by GDP is measured by multiplying the change in GDP in the region from year to year and its impact on mosaic demand, i.e.:

“MosaicLandIncreaseByGDP” = ‘GDPChange’ * GDPToMosaicLandRatio

This change in GDP is achieved by adding the increase in GDP from mosaic land and other factors:

“GDPChange” = ‘GDPIncreaseByMosaicLand’ + GDPIncrease_Others_Init

Finally, the increase in GDP from mosaic land is the result of multiplying the increase in demand for mosaic land from one year to the next (-1) and its impact on GDP:

"GDPIncreaseByMosaicLand" = delay("MosaicLandChange",1) * MosaicLandToGDPRatio

This same process was done for the "PastureLandDemand" variable. Like this:

"PastureLandDemand" = ""PastureLandChange"

"PastureLandChange" = time()<=1? PastureLandIncreaseByGDP_Init:("PastureLandIncreaseByGDP"+ PastureLandIncrease_Others_Init)

"PastureLandIncreaseByGDP" = "GDPChange" * GDPToPastureLandRatio

"GDPChange" = "GDPIncreaseByPastureLand" + GDPIncrease_Others_Init

"GDPIncreaseByPastureLand" = delay("PastureLandChange",1) * PastureLandToGDPRatio

The variable "AgricultralLandDemand" corresponds to the sum of two other dynamic variables "CornLandChange" and "SoyLandChange". From there, the same process was applied to both variables.

For "CornLandChange" we have:

"CornLandChange" = time()<=1? CornLandIncreaseByGDP_Init:("CornLandIncreaseByGDP"+ CornLandIncrease_Others_Init)

"CornLandIncreaseByGDP" = "GDPChange" * GDPToCornLandRatio

"GDPChange" = "GDPIncreaseByCornLand" + GDPIncrease_Others_Init

"GDPIncreaseByCornLand" = delay("CornLandChange",1) * CornLandToGDPRatio

For the dynamic variable "SoyLandChange" we have:

"SoyLandChange" = time()<=1? SoyLandIncreaseByGDP_Init:("SoyLandIncreaseByGDP"+ SoyLandIncrease_Others_Init)

"SoyLandIncreaseByGDP" = "GDPChange" * GDPToSoyLandRatio

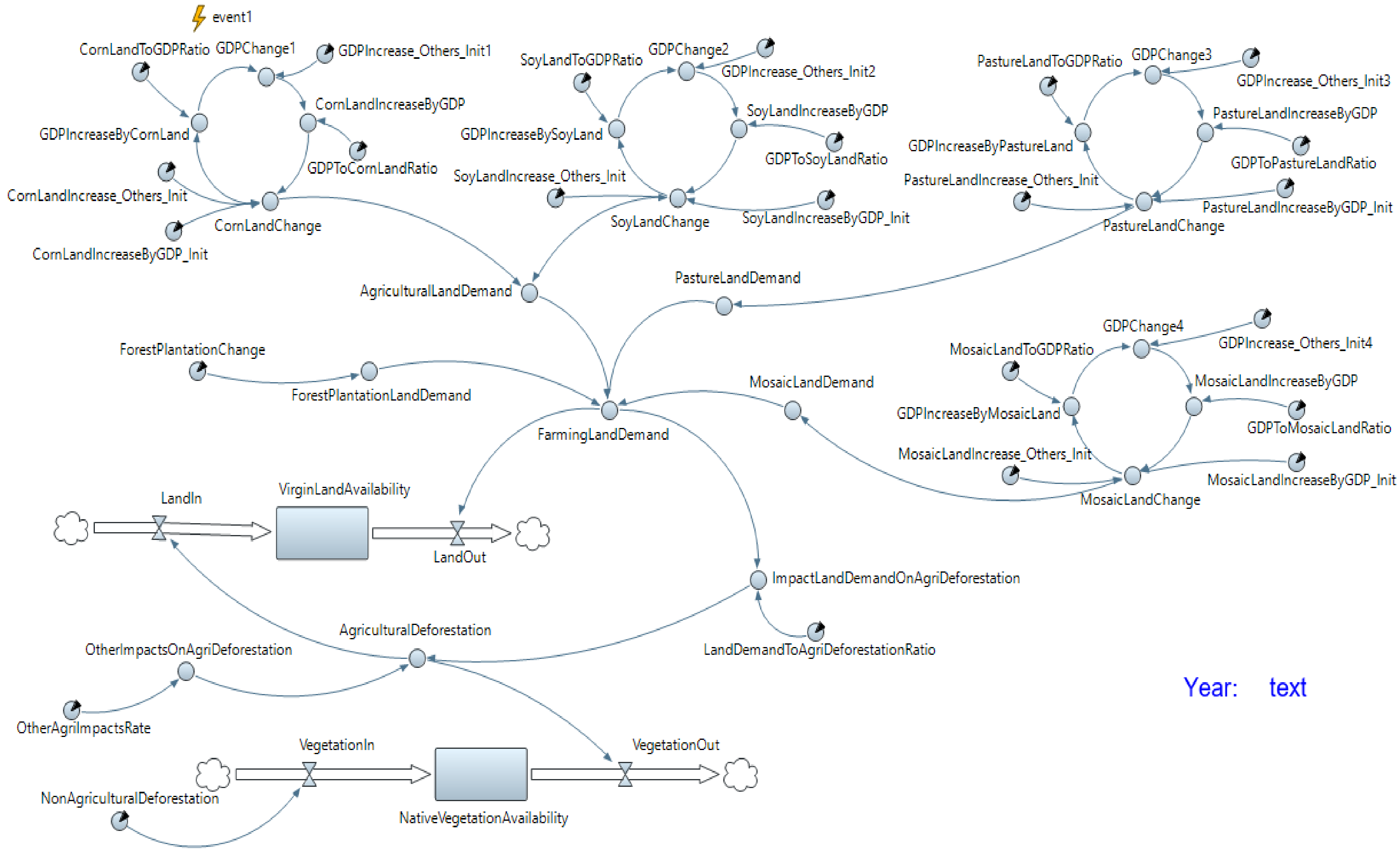
"GDPChange" = "GDPIncreaseBySoyLand" + GDPIncrease_Others_Init

"GDPIncreaseBySoyLand" = delay("SoyLandChange",1) * SoyLandToGDPRatio

Creation of the SDM Simulation Diagrams

Figure 9 shows the structure of the SDM for the Matopiba region. This structure shows the development of sub-models, stock flow, dynamic variables, parameters, and the connections between the SDM components.

Figure 9: Structure of the SDM for Matopiba

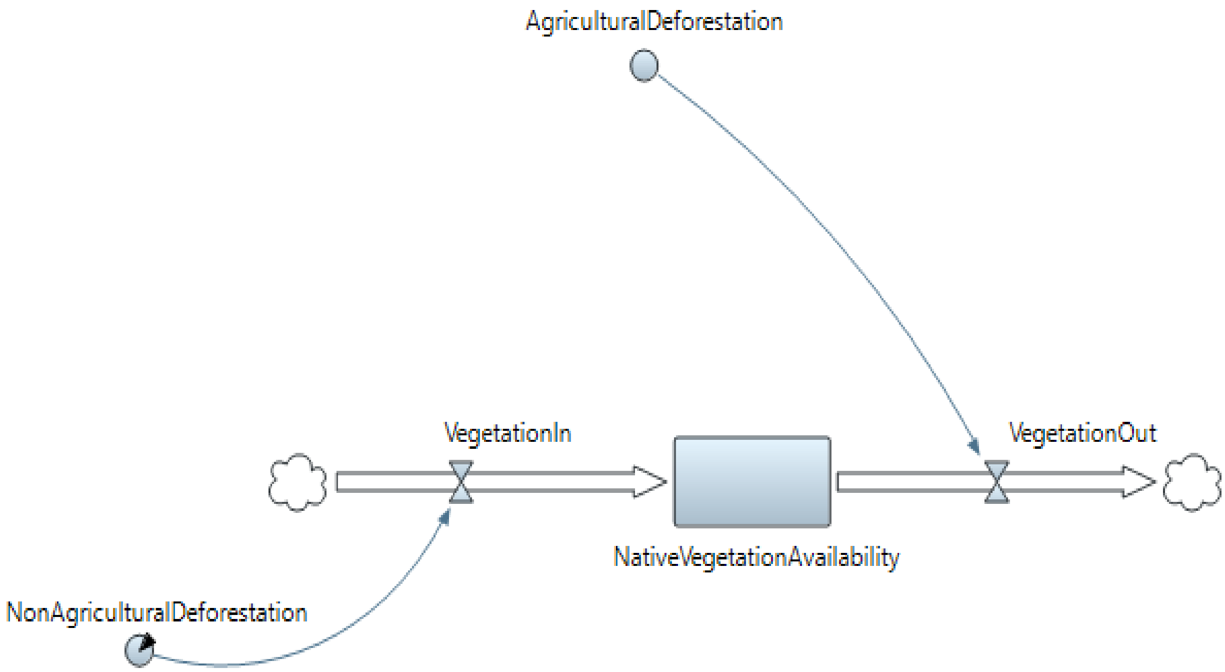


Source: Own Elaboration, based on AnyLogic output.

For a more detailed analysis of the SDM, the discussion of the elements will be divided into three subsystems: Native Vegetation Availability, Virgin Land Availability, and Farming Land Demand, illustrated respectively in Figures 10, 11, and 12.

Stock 1 (Native Vegetation Availability) is made up of two outputs: the impact of Non-Agricultural Deforestation and the impact of Agricultural Deforestation, as illustrated in Figure 10.

Figure 10: Structure of the Native Vegetation Availability Subsystem

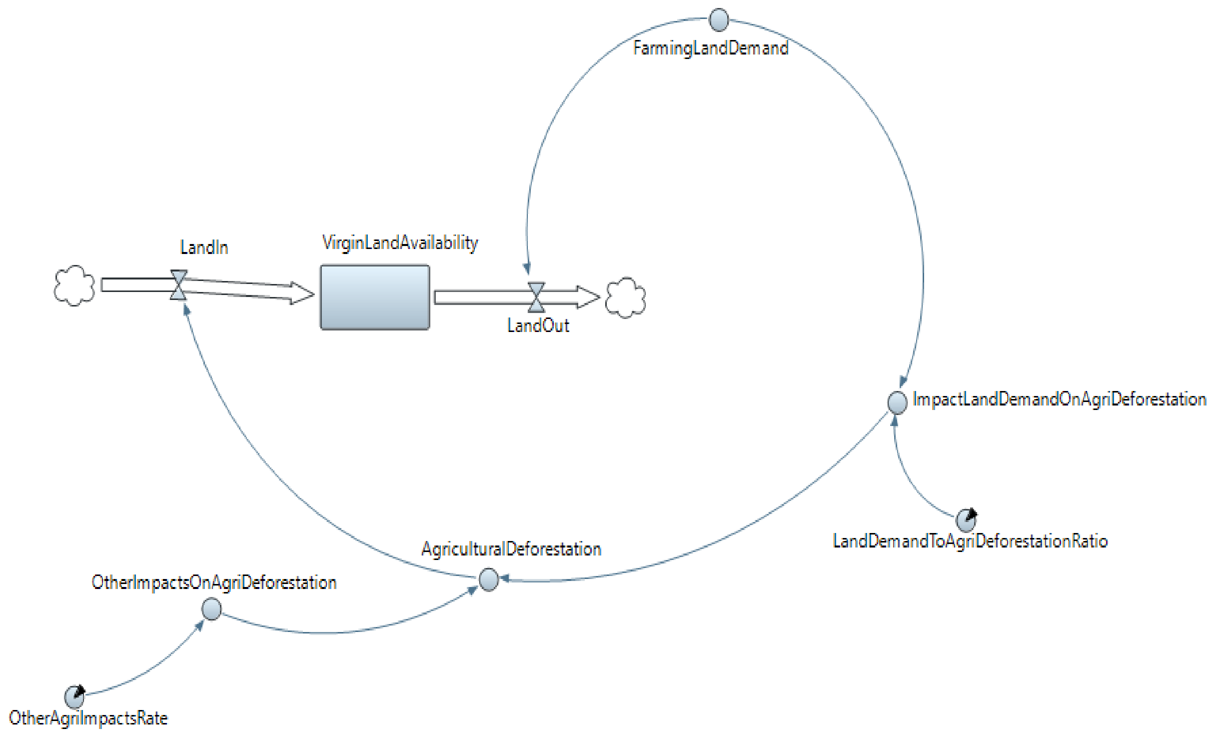


Source: Own Elaboration, based on AnyLogic output.

The Dynamic Variable “AgriculturalDeforestation” is affected by Farming Land Demand and by Other Factors that can affect agricultural deforestation (such as government policies, legislation, etc.), which directly impacts the Native Vegetation Availability (Stock 1) and the Virgin Land Availability (Stock 2).

As illustrated in Figure 11, Stock 2 (Virgin Land Availability) is made up of one input (impact of Agricultural Deforestation) and one output (Farming Land Demand). In other words, Stocks 1 and 2 are directly linked to the impact of Agricultural Deforestation.

Figure 11: Structure of the Virgin Land Availability Subsystem



Source: Own Elaboration, based on AnyLogic output.

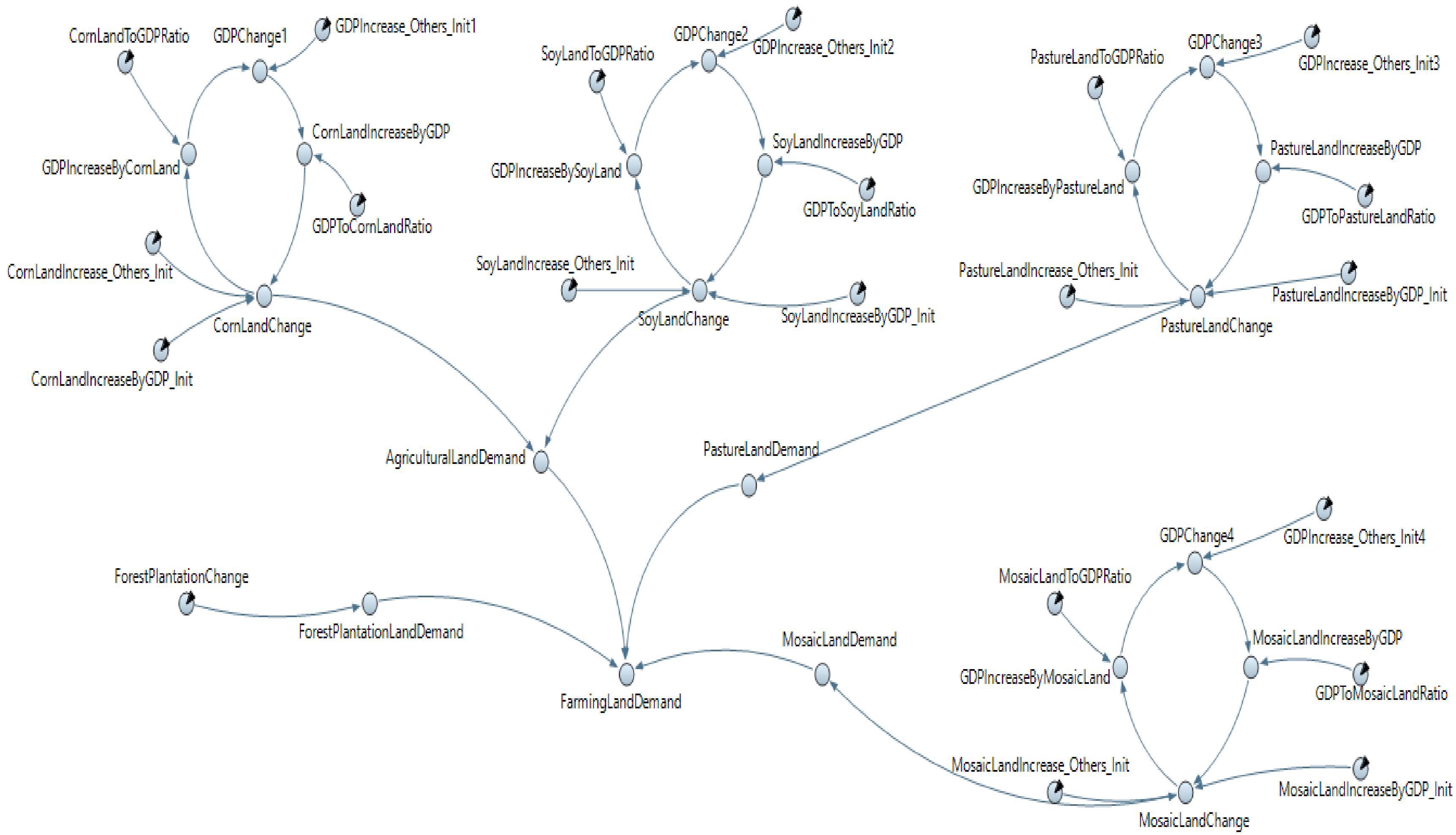
Figure 12 shows that the dynamic variable "FarmingLandDemand" is affected by four other dynamic variables: Forest Plantation Land Demand, Mosaic Land Demand, Pasture Land Demand, and Agricultural Land Demand.

In this analysis, "ForestPlantationLandDemand" has a fixed value, i.e. it is not affected positively or negatively. This is because the land area and demand for forest plantations remained almost constant compared to the other agricultural land covers during the study period (these data are presented in Chapter 3 of this study).

In turn, 'MosaicLandDemand', 'PastureLandDemand', and 'AgriculturalLandDemand' have a cyclical relationship with GDP. This means that an increase in GDP affects these land demand variables and, at a certain point, the increase in land demand will also affect GDP, and so on.

The variable "AgriculturalLandDemand" is further subdivided into two other dynamic variables: 'CornLandChange' and 'SoyLandChange'. These two crops were chosen because, as presented in Chapters 3 and 4, soybean and corn production are the largest and most land-intensive in the region.

Figure 12: Structure of the Farming Land Demand Subsystem



Source: Own Elaboration, based on AnyLogic output.

Analysis of the system's behavior (modeling tests)

The SDM simulation was run from 2020 until the exhaustion of the main source of natural resources available for agricultural production in Matopiba (Native Vegetation Availability). However, before analyzing these values, it is necessary to discuss the model's calibration and validation process, as well as the system's behavior.

Calibration Process:

To verify that the parameters used in the SDM simulation are reliable, the calibration process was initially carried out, which consisted of simulating the SDM until 2020 (the year the SDM simulation for Matopiba began) and verifying that the results correspond to the real data. In the calibration process, the analysis was carried out from 2001 to 2011.

In this process, the average difference between the model's simulated values and the real values of the main elements that make up the SDM (Native Vegetation Availability, Virgin Land Demand Availability, Farming Land Demand, and Agricultural Deforestation) was observed. The difference between the average values of these elements and the actual values is expected to be a maximum of 2%.

Table 8 shows the average difference between the actual and simulated values from the calibration process. As shown in Table 8, the average difference between the real values and the simulated values in the calibration process was between -2% and 0%, thus demonstrating the strong reliability of the parameters that make up the SDM.

Table 8: Average difference between real and simulated values (SDM Calibration)

Year	Native Vegetation Availability		Virgin Land Demand Availability		Farming Land Demand		Agricultural Deforestation	
	Diff	Diff %	Diff	Diff %	Diff	Diff %	Diff	Diff %
2001	631.28	-1%	117.50	-4%	-162.69	34%	-44.50	9%
2002	677.80	-1%	82.31	-3%	-61.05	13%	-95.93	20%
2003	703.65	-1%	-184.06	7%	222.98	-50%	-43.09	9%
2004	510.25	-1%	-149.94	5%	134.04	-31%	168.46	-36%
2005	396.76	-1%	-57.28	2%	3.99	-1%	96.93	-21%
2006	370.66	-1%	50.48	-2%	-89.87	21%	18.19	-4%
2007	415.99	-1%	83.09	-3%	-71.16	17%	-38.27	8%
2008	386.47	-1%	200.33	-7%	-94.21	23%	23.31	-5%
2009	414.29	-1%	221.35	-8%	-54.45	14%	-33.16	8%
2010	429.51	-1%	274.18	-9%	-57.17	15%	-4.08	1%
2011	448.48	-1%	17.87	-1%	229.57	-60%	-26.48	6%
Average	**-1%**		**-2%**		**0%**		**0%**	

Source: Own Elaboration.

Validation Process:

The validation process, like the calibration process, consists of simulating the SDM until 2020 and verifying whether the results correspond to the real data. However, in the validation process, the analysis was carried out from 2001 to 2020.

Table 9 shows the average difference between real and simulated values in the validation process.

Table 9: Average difference between real and simulated values (SDM Validation)

Year	Native Vegetation Availability		Virgin Land Demand Availability		Farming Land Demand		Agricultural Deforestation	
	Diff	Diff %	Diff	Diff %	Diff	Diff %	Diff	Diff %
2001	631.28	-1%	117.50	-4%	-193.40	38%	-87.71	16%
2002	677.80	-1%	82.31	-3%	-107.00	21%	-150.87	28%
2003	703.65	-1%	-184.06	7%	166.85	-33%	-105.84	19%
2004	510.25	-1%	-149.94	5%	70.23	-14%	99.82	-18%
2005	396.76	-1%	-57.28	2%	-66.28	13%	23.36	-4%
2006	370.66	-1%	50.48	-2%	-165.95	34%	-59.84	11%
2007	415.99	-1%	83.09	-3%	-152.72	31%	-120.49	23%
2008	386.47	-1%	200.33	-7%	-181.03	37%	-62.94	12%
2009	414.29	-1%	221.35	-8%	-146.37	30%	-123.33	23%
2010	429.51	-1%	274.18	-9%	-154.06	32%	-98.08	19%
2011	116.40	0%	-252.04	8%	127.82	-26%	-124.22	24%
2012	-31.62	0%	-315.14	9%	205.90	-42%	142.80	-27%
2013	-260.68	1%	-105.06	3%	-22.54	5%	187.54	-36%
2014	-290.82	1%	-75.02	2%	-18.69	4%	11.34	-2%
2015	-300.54	1%	30.48	-1%	-117.07	24%	-11.57	2%
2016	-196.20	0%	62.90	-2%	-141.84	29%	-109.42	21%
2017	-90.09	0%	92.29	-3%	-138.01	29%	-108.62	21%
2018	-29.45	0%	59.82	-2%	-47.80	10%	-80.27	15%
2019	-57.72	0%	-12.41	0%	83.34	-17%	11.11	-2%
2020	-125.32	0%	29.21	-1%	48.06	-10%	89.68	-17%
Average	**0%**		**1%**		**0%**		**0%**	

Source: Own Elaboration.

As its name suggests, the validation process aims to "validate" the parameters and initial values of the elements that make up the SDM. Once validated, these values will be used as the basis for the (future) simulation of the SDM for Matopiba.

As shown in Table 9, the average difference between the model's simulated values and the actual values of the main elements that make up the model (Availability of Native Vegetation, Availability of Virgin Land Demand, Agricultural Land Demand, and Agricultural Deforestation) in the validation process were between 0% and 1%, thus demonstrating the strong reliability of the SDM data.

In both processes (calibration and validation) the same initial values were used for the elements that make up the SDM, based on the average of the time series (2001 to 2020). However, due to a trend observed in the SDM elements from 2011 onwards (more precisely between 2015 and 2020), the values of some parameters had to be adjusted in the validation process.

System's behavior:

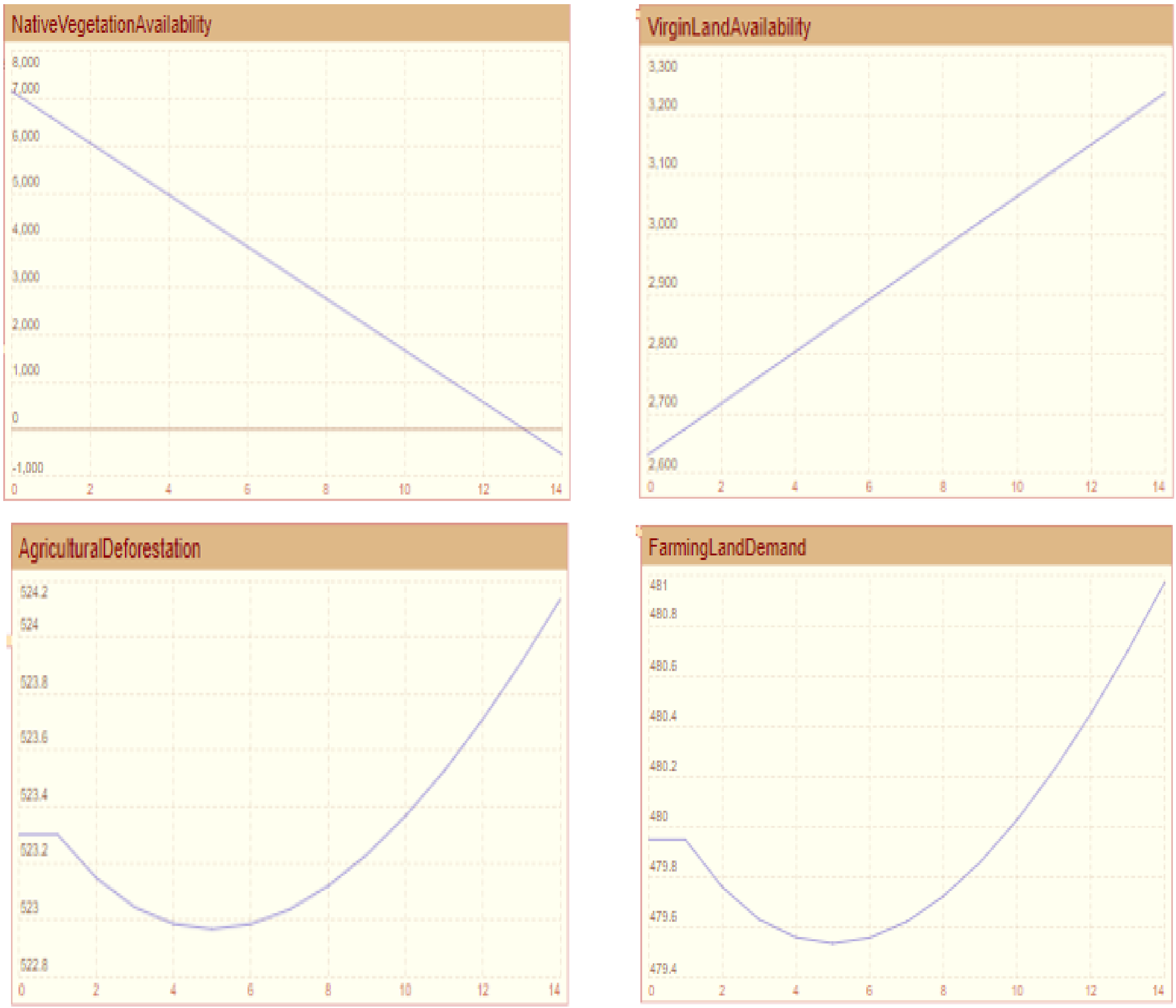
The behavior of the system shows the trend of the elements that make up the SDM for Matopiba from 2020 onwards. This system's behavior then reflects the continuation of the trend observed in the validation process. Figure 13 shows the behavior of the dynamic system for the main elements of the SDM in Matopiba[15].

In the coming years (from 2020 onwards), the area of land suitable for farming is expected to increase as the region's native vegetation is depleted. This is stimulated by a growing demand for farming land and agricultural deforestation.

The analysis of the values that make up the behavior of the system dynamics will be detailed in the next section "*Results of the System Dynamics Modeling*".

[15] Figures illustrating the behavior of the dynamic system for other SDM elements can be found in Appendix B.

Figure 13: Dynamic behavior of the main SDM elements

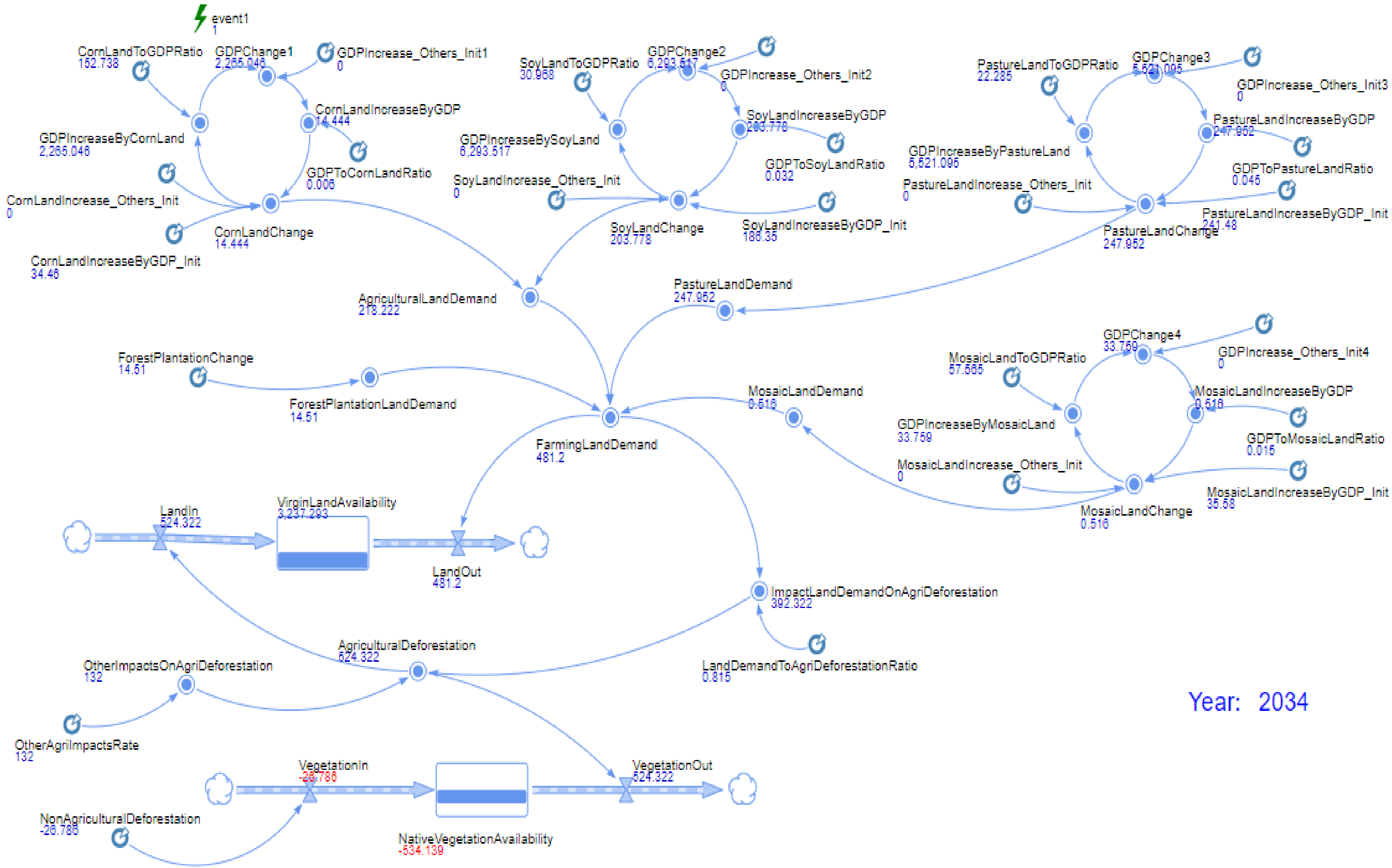


Source: Own Elaboration, based on AnyLogic output.

System Dynamics Modeling Results for Matopiba Region

The final values of the elements that make up the SDM for Matopiba are shown in Figure 13. As illustrated in figures 13 and 14, the SDM for Matopiba showed that Native vegetation in areas with high and medium agricultural suitability in Matopiba is expected to be exhausted within 20 years if no environmental intervention or policy is implemented in the region. As the analysis was carried out from the year 2020, native vegetation is expected to be extinct by around 2034.

Figure 14: SDM Simulation Results for Matopiba



Source: Own Elaboration, based on AnyLogic output.

As the area of native vegetation is the main source of intensive agricultural production, this result confirms the high environmental impact of Matopiba's agricultural frontier, as well as showing that producers and the government will have to stimulate innovative measures to try to meet the demand for land for this intensive production.

Driven mainly by the increase in the area coming from agricultural deforestation (which is expected to be around 525,000 hectares per year), the data shows that the virgin area suitable for agriculture is set to increase within 20 years. In addition, there is also an upward trend in the demand for new agricultural land (virgin land demand), which is expected to reach more than 480,000 hectares per year within 20 years.

The increase in demand for virgin farming land can be explained by to increased demand for pasture and agriculture, as demand for forest plantations and mosaic areas decreases. The demand for virgin land for pasture is expected to be approximately 248,000 hectares per year within 20 years, 218,000 hectares for agriculture, 14,000 for forest plantations, and just over 500 hectares of new agricultural land for mosaic areas.

It was also noted that, in agriculture, the demand for land for soybeans is expected to increase, while the demand for land for corn is expected to decrease. The demand for virgin farming land for soybeans is expected to increase from 196,000 hectares in 2020 to approximately 204,000 hectares within 20 years; the demand for new land for corn production, which was 20,000 hectares in 2020, is expected to be 14,400 hectares.

These results confirm that there is a high conversion cycle between agricultural areas in Matopiba, with pasture and soybean production requiring the largest percentage of new agricultural areas in the region in the coming years. Therefore, the innovative measures that will be proposed must be based on the demand for land for these two crops.

Suggestions for problem-solving

The SDM results showed that the area of native vegetation is the main source of intensive agricultural production in Matopiba, with pasture and soybean production demanding the most new areas. The problem is how to maintain production and the growing demand for agricultural land using the minimum area of native vegetation.

Measures such as tightening environmental tax legislation, environmental regeneration and reforestation policies, and the use of sustainable agricultural technologies, among others, could be useful in solving this problem. However, without ruling out the other measures mentioned, this study presents the incentive for crop-livestock-forest integration (CLFI) as a viable solution for maintaining Matopiba's agricultural frontier and the Cerrado biome at the same time.

Data from EMBRAPA (Skorupa et al., 2019) confirms that 65% of agricultural expansion in Matopiba has been due to the conversion of native forests and 35% to the conversion of pastures and other crops. As a result, the expansion of agricultural production is expected to be exhausted in native areas in the coming years, causing productive development to occur based on changes in the economic uses of the land. In addition, the study by Solidaridad Brasil (Brasil, 2021) states that Matopiba has 6.6 million hectares of pastures with agricultural aptitude, of which 4 million hectares are degraded pastures. Converting degraded pasture areas into crops through the CLFI system is therefore a viable option for expanding sustainable agricultural production in the region.

Furthermore, crop rotation using the CLFI system in non-degraded pasture areas can also be encouraged. The SDM showed that, in addition to the 4 million hectares of degraded pasture, the area of virgin pasture suitable for agriculture is expected to reach an area of approximately 3.2 million hectares within 20 years. This means a pasture area of 7.2 million hectares suitable for agricultural production in the region.

The CLFI system is a way of developing changes in land use through environmental preservation and greater agricultural productivity. In short, the CLFI system integrates crops (agriculture), pastures (livestock) and forest in the same area and can be applied through crop rotation or succession at specific times (Puech & Stark, 2023; Sekaran et al., 2021; Vinholis et al., 2020; Asai et al., 2018; Ryschawy et al., 2017; Martin et al., 2016; Moraine et al., 2016; Cordeiro et al., 2015; Bonaudo et al., 2014; Lemaire et al., 2014; Martha Júnior, Alves & Contini, 2011; Balbinot Junior et al., 2009; Vilela et al., 2008; Gonçalves & Franchini, 2007; Alvarenga & Noce, 2005).

As well as increasing agricultural production, the CLFI system is more sustainable, as there is crop rotation, recovery of degraded areas, and, consequently, a reduction in the deforestation of native forests. The CLFI system can then be configured as one of the preventive actions (political implications) for the environmental restructuring of the Cerrado Biome and the Matopiba region (Leite et al., 2024; Oliveira et al., 2024; Júnior & Figueiredo, 2023; Barbosa et al., 2022; Da Silva et al., 2021; Gontijo Neto et al., 2018; Torres, Assis & Loss, 2018; Gil, Garrett & Berger, 2016;

Rangel et al., 2016; Costa et al., 2015; De Moraes et al., 2014; Garcia et al., 2013; Balbino et al., 2011; Silva et al., 2011; Vilela et al., 2011).

EMBRAPA has been developing the CLFI system in Matopiba since 2005, considering the environmental and economic specificities of each state and sub-region. Table 10 presents a summary of the main crop combinations in CLFI systems developed by EMBRAPA (Skorupa et al., 2019) for Matopiba.

According to Rangel et al. (2016), the form of integration best suited to Matopiba is Agropastoral Integration (API) due to the practice of intensive agriculture. In this system, grain production and livestock are rotated in the same area. However, in addition to API, Agrosilvopastoral Integration (ASPI), Silvopastoral Integration (SPI) and Agroforestry Integration (AFI) are also being developed in the region. In the ASPI system, grains, livestock, and wood products are produced in the same area; in the SPI system, livestock and wood products are rotated; and in the SFI system, grains and wood products are produced in the same area.

In addition to presenting the main crop combinations in CLFI systems, the EMBRAPA report (Skorupa et al., 2019) analyzed the expansion potential of CLFI systems in Matopiba. According to the report, the states of Maranhão and Piauí and the western region of Bahia have the potential to expand CLFI in the current grain and livestock-producing areas due to the millions of hectares of crops and pastures developed in these regions, as well as the large cattle herd of high genetic quality. In Tocantins, on the other hand, the potential for expanding CLFI lies in the degraded areas, which, according to the IBGE (2022), already comprise an area of more than 800,000 hectares.

Through the research carried out by Skorupa et al. (2019) over ten years with partner farms in the Matopiba region, an increase in the economic and productive development of the region was observed due to the increased production of corn and soybeans in CLFI systems and the generation of employment and income due to crop rotation. In addition, the report shows important results in terms of environmental regeneration (mainly of the soil) in Matopiba through the increase in water retention capacity in the soils using the CLFI system, as well as a considerable increase in the content of organic matter present in the soil. It is therefore believed that the implementation and increasing encouragement of the CLFI system represents an alternative for meeting the demand for land suitable for agriculture (mainly through the regeneration of degraded soils), as well as for more sustainable production in Matopiba.

Table 10: Main Crop Combinations in CLFI Systems for Matopiba Region

CLFI	Maranhão (MA), Piauí (PI) and Western of Bahia (BA)	Tocantins (TO)
Agropastoral Integration (API)	In grain-producing areas: soybeans and corn + forage crops in no-till at the beginning of the rainy season, followed by corn + forage crops, cowpeas, and sorghum in the second harvest, as well as millet and forage crops for over-sowing soybeans at the end of the rainy season, followed by finishing and fattening cattle on pastures in the off-season.	In grain-producing areas: soybean + forage plant rotation and single pasture during the harvest to support the cattle during the summer + finishing and fattening of cattle on pastures in the off-season.
	In areas with predominantly pasture: corn or rice + forage grass + finishing and fattening cattle on pasture in the off-season.	In areas with predominantly pasture: corn + forage grass + remaining pasture in the off-season.
Agrosilvopastoral Integration (ASPI)	Eucalyptus or other tree species in clumps of up to four rows, interspersed with strips of up to 28 meters with soybean + millet crops in over-seeding in the first two years and corn + forage in the third year, followed by animals from the third to the seventh year or more, if the forest component is destined for the sawmill.	Small areas of forestry crops of eucalyptus, rubber trees, or other forest species, use the inter-rows to grow soybeans in the first few years until the inter-rows are closed by the treetops.
Silvopastoral Integration (SPI)	Eucalyptus or another tree species in clumps of up to two rows interspersed with pasture in strips of at least 10 meters. Recovery or implementation of the pasture through corn + forage in the first year of planting the tree species, followed by animals until the seventh year or more, if the forest component is destined for the sawmill.	Planting of tree species (mainly eucalyptus) + pasture after the third year of planting tree seedlings.
Agroforestry Integration (AFI)	Eucalyptus or other tree species in rows of up to four lines interspersed with strips of up to 36 meters with soybean and corn crops in direct planting at the beginning of the rainy season, followed by cowpea and grain sorghum in the off-season after the soybean harvest, and also millet and forage crops overseeded on the soybean at the end of the rainy season acting as soil cover for the following harvest.	Eucalyptus or other forest species + management of the areas between the fields for other agricultural activities. Up until the third year, the areas between the plantations are cultivated with soybeans, corn, or rice during the harvest season and corn, sorghum, or cowpeas during the off-season, with the possibility of associating forage plants in a consortium to provide soil cover and straw for direct sowing of the next harvest's crops. When the trees reach a larger size, soybeans or corn are grown during the harvest, with animals brought in during the off-season to graze the forage plants from the consortium, over-seeding, or sowing after the grain harvest. Once the trees have reached their maximum height, the area is only used for pasture.

Source: Own Elaboration, based on Skorupa et al., 2019.

Summary

This chapter developed System Dynamic Modeling (SDM) to predict the environmental impacts caused by agricultural frontiers in the coming years, with a focus on the Matopiba region in Brazil.

The SDM showed that native vegetation in areas with high and medium agricultural suitability in Matopiba is expected to be extinct within 20 years (expected around 2034) if current intensive agricultural production continues and no environmental intervention is implemented in the region. This will occur due to increased agricultural production and, consequently, increased demand for land and agricultural deforestation.

By way of comparison, if the trend observed in the calibration process is used, it is expected that the area of native vegetation will also be reduced within 20 years. However, this process would be slower (expected around 2037), as there would be a downward trend in agricultural deforestation in Matopiba. In addition, the demand for new agricultural land has also shown a downward trend. These trends are the opposite of what was observed in the validation process and the main studies discussed here, which show a more pronounced upward trend in agricultural deforestation and demand for land in Matopiba since 2015.

This chapter suggested crop-livestock-forest integration (CLFI) as a way of trying to contain or slow down this process of environmental depletion in the region, through crop rotation (conservation of degraded pasture areas in crops). The CLFI system, which integrates crops, pastures, and forests in the same area in a sustainable way, has already been developed in Matopiba and has great potential for growth in degraded pasture areas in the state of Tocantins, as well as in current agricultural and pasture areas in the states of Maranhão, Piauí, and western Bahia.

6. Chapter 6: Theses of the Doctoral Dissertation

6.1. Theses

This chapter presents my research theses based on the results of the Systematic Literature Review, Canonical Correlation Analyses, and System Dynamics Modeling, presented in *Chapters 2, 4,* and *5*, respectively. Although each of the chapters has a specific focus, the main objective of this study is to analyze the environmental impacts promoted by agricultural frontiers in emerging countries, with a focus on the Matopiba region in Brazil, and to contribute to guiding more sustainable agricultural public policies.

To present my critical and argumentative statement of the theses (T1, ..., Tx), I first check and reaffirm the answers to the research questions (RQ1, ..., RQx) and then assess whether the hypotheses linked to each research question are accepted or rejected (H1, ..., Hx).

Chapter 2 presented a Systematic Literature Review on agricultural frontiers and the environment in emerging countries. As well as being the main theoretical source of the dissertation, this chapter provided answers to Research Questions 1 and 2:

RQ1. Is the Matopiba region in Brazil a hot topic in the global literature on agricultural frontiers and the environment in emerging countries?

RQ1.1. Are some emerging countries/regions more prominent in studies on agricultural frontiers and the environment?

To find out whether the Matopiba region in Brazil is an important topic in the global literature on agricultural frontiers and the environment in emerging countries, the analyses presented in subchapters 2.2 (Geographical distribution and main terms of studies) and 2.3 (Main studies by country/region) were checked. Subchapter 2.2 showed that most studies on the agricultural frontier and the environment in emerging countries are concentrated in Brazil. However, this focus is especially (almost exclusively) on the Amazon rainforest (Subchapter 2.3). Subchapter 2.3 also showed that research on the Cerrado Biome and the Matopiba Region is still at a regional level, in which there are few studies written in English and with a high impact factor (inclusion and exclusion criteria for this study).

Thus, based on the results presented in Subchapters 2.2 and 2.3, **Hypothesis 1** of this study is accepted, and **Thesis 1** of this dissertation is formed:

THESIS 1

The literature on agricultural frontiers and the environment in emerging countries has focused mainly on Brazil's Amazon rainforest. Despite the growing number of studies on Brazil's Matopiba, this region has not yet been given as much prominence in the world literature on agricultural frontiers and the environment, since most of this research is concentrated among Brazilian researchers and is written in Portuguese.

To answer how we can systematize the literature on agricultural frontiers and the environment in emerging countries (RQ2), I initially checked whether there are similarities between these studies amidst the great diversity that exists between emerging countries (RQ2.1).

RQ2. How can we systematize literature on agricultural frontiers and the environment in emerging countries?
RQ2.1. Are there any similarities between research on agricultural frontiers and the environment in emerging countries?

In subchapters 2.3 and 2.4 (The Connections between Agricultural Frontiers and the Environment) of the Systematic Literature Review, it was observed that research in emerging countries has two main focuses: measuring the effects of intensive agriculture on remaining natural resources and analyzing and/or proposing more sustainable agricultural public policies and technologies. With this finding, **Hypothesis 2** of this study is accepted, and **Thesis 2** of this dissertation is formed:

THESIS 2

Despite the enormous diversity between emerging countries, the literature on agricultural frontiers and the environment in these countries is similar, as it essentially seeks to measure the environmental impacts caused by intensive agriculture, as well as analyze agricultural technologies and public policies. Thus, these two research focuses are currently the best way to systematize the literature on agricultural frontiers and the environment in emerging countries.

Using machine learning techniques, *Chapter 4* analyzed the environmental conditions generated by Matopiba's agricultural frontier. This empirical study provided answers to Research Questions 3 and 4:

RQ3. Is there any relationship between the economic aggregates and the environmental impacts generated on Matopiba's agricultural frontier?

RQ3.1. Which economic aggregate contributes the most to environmental impacts in the Matopiba region?

To answer whether there is any relationship between the economic aggregates and the environmental impacts generated by the Matopiba agricultural frontier, subchapter 4.2.1 was checked. Subchapter 4.2.1 brought the results of the canonical correlation analysis between the economic variables (GDP aggregates) and the environmental variables (deforestation, CO_2 emissions). The analysis showed that there is a strong relationship between economic aggregates and environmental impacts in Matopiba, with agricultural GDP contributing the most to environmental degradation.

Based on these results, **Hypothesis 3** of this study is accepted, and **Thesis 3** of this dissertation is formed:

THESIS 3

There is a relationship between economic aggregates of GDP and environmental impacts in the Matopiba region of Brazil, with the agricultural sector having a positive and the highest correlation with deforestation and one of the highest magnitudes with CO_2 emissions in the region.

Subchapter 4.2.2 provided an analysis of the canonical correlation between the production of Matopiba's main crops (soybeans, corn, sugarcane, rice, etc.) and the variables that represent environmental impacts, thus providing answers to Research Question 4:

RQ4. Is agricultural production in Matopiba related to the environmental impacts generated in the region?

RQ4.1. Which crops contribute most to environmental impacts in Matopiba's agricultural frontier?

The analysis presented in Subchapter 4.2.2 showed that there is a strong relationship between agricultural production and environmental impacts in the Matopiba region, with soybean and corn production contributing the most to these impacts. Thus, Hypothesis 4 of this study is accepted, and Thesis 4 of this dissertation is formed:

THESIS 4

Agricultural production has a relationship with environmental impacts in the Matopiba region of Brazil, with soybean and corn production consecutively being the biggest contributors to deforestation and agricultural CO_2 emissions in the region.

Chapter 5 used System Dynamics Modeling (SDM) to predict the future of the Matopiba Region regarding available natural resources and intensive agricultural production. This empirical study provided the answer to Research Question 5:

RQ5: How soon will the native vegetation be exhausted in the agriculturally suitable areas of Matopiba?

Subchapter 5.2.2 (Development of the SDM Simulation for Matopiba) showed that the area of native vegetation with high and medium agricultural suitability is expected to be extinct within 20 years in Matopiba if no environmental intervention or policy is implemented in the region. This will occur due to intense agricultural production and increased demand for land. Based on these results, Hypothesis 5 of this study is accepted, and Thesis 5 of this dissertation is formed:

THESIS 5

Native vegetation in areas with high and medium agricultural suitability in Matopiba is expected to be extinct within 20 years if current intensive agricultural production continues and no environmental intervention is implemented in the region. As the SDM analysis was carried out from the year 2020, native vegetation is expected to be extinct by around 2034. This extinction of native vegetation is associated with intensive agricultural production and increased demand for agricultural land in the region.

6.2 New and Novel Results

This dissertation has brought new and innovative results to the literature on agricultural frontiers and the environment in emerging countries, as well as in the Matopiba region in Brazil.

Firstly, the Systematic Literature Review showed that there is a certain similarity in the studies on agricultural frontiers and the environment in emerging countries, in which the authors essentially sought to measure the environmental impacts caused by intensive agriculture and evaluate public policies and the use of agricultural technologies. In addition, the SRL showed that there are still few studies on the agricultural frontier of Matopiba written in English, thus opening up an important gap to be filled in the literature on emerging countries.

Secondly, using Canonical Correlation Analyses, it was possible to verify which of the GDP aggregates and which of the main crops produced in Matopiba are directly correlated with CO_2 emission rates and the deforestation of native vegetation in the region. As well as being a pioneer in the use of Machine Learning technologies, the results of the CCA help to develop more sustainable public policies.

Through System Dynamics Modeling, it was observed that native vegetation in areas with high and medium agricultural suitability in Matopiba is expected to be extinct within 20 years, mainly due to intensive soybean production and the increased demand for agricultural land for pasture areas, as well as for soybean production. These results make a relevant contribution to the implementation of environmental actions in Matopiba, as they show the fields that should be prioritized and worked on to promote more sustainable agricultural production.

In addition to all the new results presented, this study is a pioneer in the use of a Systematic Literature Review to analyze the literature on the environment and agricultural frontiers in emerging countries; it is a pioneer in the use of Machine Learning techniques to analyze environmental and economic variables (together) for Matopiba; as well as a pioneer in the formulation of a System Dynamics Modeling on agricultural production and environmental impacts for the Brazilian Cerrado.

6.3. Study Limitations and Future Research

It should be noted that this study has some limitations. Firstly, the Systematic Literature Review used inclusion and exclusion criteria which, even following the guidelines of the literature, are subjective and, once used, can obscure important studies. In addition, the key terms used for the analysis may also have obscured some emerging countries or regions. Therefore, a suggestion for future research is, in addition to updating the period of analysis, to include emerging countries or regions that were not used in the study.

Secondly, for the Canonical Correlation Analysis, only the proxies for deforestation of native vegetation and CO_2 emissions were used as environmental variables. The initial idea was to use a variable that represented the reduction of drinking water in the region, believing that this inclusion would bring an important debate to Matopiba's agricultural frontier. However, no database was found that represented the reduction of drinking water. Therefore, an important suggestion is to include this variable in the analysis.

It was noted by System Dynamics Modeling that there is a tendency for agricultural deforestation to be greater than the demand for land in Matopiba in the coming years. Moved to try and discuss this issue, and I came across a report by the Climate Observatory (2023) which explains that the SAD Cerrado alert detection system has been incorporated operationally, which provides more accurate data on deforestation in the Cerrado (Matopiba). The report also provides the relevant information that deforestation in Matopiba is spreading to Legal Reserves and Permanent Protection Areas, areas that could not even be touched. From these two pieces of information, it can be deduced that the deforestation surplus in Matopiba is due to improved detection systems in the region compared to other data, as well as the fact that the data on demand for agricultural land does not include Legal Reserves and Permanent Protection Areas in the Cerrado. As this is only an assumption, it opens up a gap for future research.

Through the SDM it was also seen the dynamic connections between the environmental and economic components of Matopiba, as well as the “duration” of each of these components. However, the model did not include variables representing solutions to the problem presented. Despite mentioning that the CLFI system is one of the preventive actions (political implications) for the environmental restructuring of Matopiba and the Cerrado Biome, there was no simulation to verify the effect of this action. I, therefore, suggest including the CLFI system, or another relevant preventive action, in System Dynamics Modeling for Matopiba.

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Appendices

Appendix A

List of the municipalities and geographic microregions of Matopiba

Table A1: List of the municipalities and geographic microregions of Matopiba

Table A1: List of the municipalities and geographic microregions of Matopiba

State	Microregion	Number of Microregion	Municipality	Number of Municipality
MA Maranhão	Lençóis Maranhenses	1	Barreirinhas	1
			Humberto de Campos	2
			Paulino Neves	3
			Primeira Cruz	4
			Santo Amaro do Maranhão	5
			Tutóia	6
	Itapecuru Mirim	2	Cantanhede	7
			Itapecuru-Mirim	8
			Matões do Norte	9
			Miranda do Norte	10
			Nina Rodrigues	11
			Pirapemas	12
			Presidente Vargas	13
			Vargem Grande	14
	Imperatriz	3	Açailândia	15
			Amarante do Maranhão	16
			Buritirana	17
			Cidelândia	18
			Davinópolis	19
			Governador Edison Lobão	20
			Imperatriz	21
			Itinga do Maranhão	22
			João Lisboa	23
			Lajeado Novo	24
			Montes Altos	25
			Ribamar Fiquene	26
			São Francisco do Brejão	27
			São Pedro da Água Branca	28
			Senador La Rocque	29
			Vila Nova dos Martírios	30
	Médio Mearim	4	Bacabal	31
			Bernardo do Mearim	32
			Bom Lugar	33
			Esperantinópolis	34
			Igarapé Grande	35
			Lago do Junco	36
			Lago dos Rodrigues	37
			Lago Verde	38
			Lima Campos	39

			Olho d'Água das Cunhãs	40
			Pedreiras	41
			Pio XII	42
			Poção de Pedras	43
			Santo Antônio dos Lopes	44
			São Luís Gonzaga do Maranhão	45
			São Mateus do Maranhão	46
			São Raimundo do Doca Bezerra	47
			São Roberto	48
			Satubinha	49
			Trizidela do Vale	50
	Alto Mearim e Grajaú	5	Arame	51
			Barra do Corda	52
			Fernando Falcão	53
			Formosa da Serra Negra	54
			Grajaú	55
			Itaipava do Grajaú	56
			Jenipapo dos Vieiras	57
			Joselândia	58
			Santa Filomena do Maranhão	59
			Sítio Novo	60
			Tuntum	61
	Presidente Dutra	6	Fortuna	62
			Dom Pedro	63
			Gonçalves Dias	64
			Governador Archer	65
			Governador Eugênio Barros	66
			Governador Luiz Rocha	67
			Graça Aranha	68
			Presidente Dutra	69
			São Domingos do Maranhão	70
			São José dos Basílios	71
			Senador Alexandre Costa	72
	Baixo Parnaíba Maranhense	7	Água Doce do Maranhão	73
			Araioses	74
			Magalhães de Almeida	75
			Santa Quitéria do Maranhão	76
			Santana do Maranhão	77
			São Bernardo	78
	Chapadinha	8	Anapurus	79
			Belágua	80
			Brejo	81
			Buriti	82

			Chapadinha	83
			Mata Roma	84
			Milagres do Maranhão	85
			São Benedito do Rio Preto	86
			Urbano Santos	87
	Codó	9	Alto Alegre do Maranhão	88
			Capinzal do Norte	89
			Codó	90
			Coroatá	91
			Peritoró	92
			Timbiras	93
	Coelho Neto	10	Afonso Cunha	94
			Aldeias Altas	95
			Coelho Neto	96
			Duque Bacelar	97
	Caxias	11	Buriti Bravo	98
			Caxias	99
			Matões	100
			Parnarama	101
			São João do Soter	102
			Timon	103
	Chapadas do Alto Itapecuru	12	Barão de Grajaú	104
			Colinas	105
			Jatobá	106
			Lagoa do Mato	107
			Mirador	108
			Nova Iorque	109
			Paraibano	110
			Passagem Franca	111
			Pastos Bons	112
			São Francisco do Maranhão	113
			São João dos Patos	114
			Sucupira do Norte	115
			Sucupira do Riachão	116
	Porto Franco	13	Campestre do Maranhão	117
			Carolina	118
			Estreito	119
			Porto Franco	120
			São João do Paraíso	121
			São Pedro dos Crentes	122
	Gerais de Balsas	14	Alto Parnaíba	123
			Balsas	124
			Feira Nova do Maranhão	125

			Riachão	126
			Tasso Fragoso	127
	Chapadas das Mangabeiras	15	Benedito Leite	128
			Fortaleza dos Nogueiras	129
			Loreto	130
			Nova Colinas	131
			Sambaíba	132
			São Domingos do Azeitão	133
			São Félix de Balsas	134
			São Raimundo das Mangabeiras	135
TO Tocantins	Bico do Papagaio	16	Aguiarnópolis	136
			Ananás	137
			Angico	138
			Araguatins	139
			Augustinópolis	140
			Axixá do Tocantins	141
			Buriti do Tocantins	142
			Cachoeirinha	143
			Carrasco Bonito	144
			Darcinópolis	145
			Esperantina	146
			Itaguatins	147
			Luzinópolis	148
			Maurilândia do Tocantins	149
			Nazaré	150
			Palmeiras do Tocantins	151
			Praia Norte	152
			Riachinho	153
			Sampaio	154
			Santa Terezinha do Tocantins	155
			São Bento do Tocantins	156
			São Miguel do Tocantins	157
			São Sebastião do Tocantins	158
			Sítio Novo do Tocantins	159
			Tocantinópolis	160
	Araguaína	17	Aragominas	161
			Araguaína	162
			Araguanã	163
			Arapoema	164
			Babaçulândia	165
			Bandeirantes do Tocantins	166
			Carmolândia	167
			Colinas do Tocantins	168

			Filadélfia	169
			Muricilândia	170
			Nova Olinda	171
			Palmeirante	172
			Pau-d'Arco	173
			Piraquê	174
			Santa Fé do Araguaia	175
			Wanderlândia	176
			Xambioá	177
	Miracema do Tocantins	18	Abreulândia	178
			Araguacema	179
			Barrolândia	180
			Bernardo Sayão	181
			Brasilândia do Tocantins	182
			Caseara	183
			Colméia	184
			Couto de Magalhães	185
			Divinópolis do Tocantins	186
			Dois Irmãos do Tocantins	187
			Fortaleza do Tabocão	188
			Goianorte	189
			Guaraí	190
			Itaporã do Tocantins	191
			Juarina	192
			Marianópolis do Tocantins	193
			Miracema do Tocantins	194
			Miranorte	195
			Monte Santo do Tocantins	196
			Pequizeiro	197
			Presidente Kennedy	198
			Rio dos Bois	199
			Tupirama	200
			Tupiratins	201
	Rio Formoso	19	Araguaçu	202
			Chapada de Areia	203
			Cristalândia	204
			Dueré	205
			Fátima	206
			Formoso do Araguaia	207
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			Oliveira de Fátima	210
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	Gurupi	20	Aliança do Tocantins	215
			Alvorada	216
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			Peixe	224
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			Monte do Carmo	233
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			Pedro Afonso	235
			Porto Nacional	236
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	Jalapão	22	Barra do Ouro	240
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			Santa Tereza do Tocantins	253
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PI Piauí	Alto Parnaíba Piauiense	24	Baixa Grande do Ribeiro	275
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			Santa Filomena	277
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	Bertolínia	25	Antônio Almeida	279
			Bertolínia	280
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			Gilbués	293
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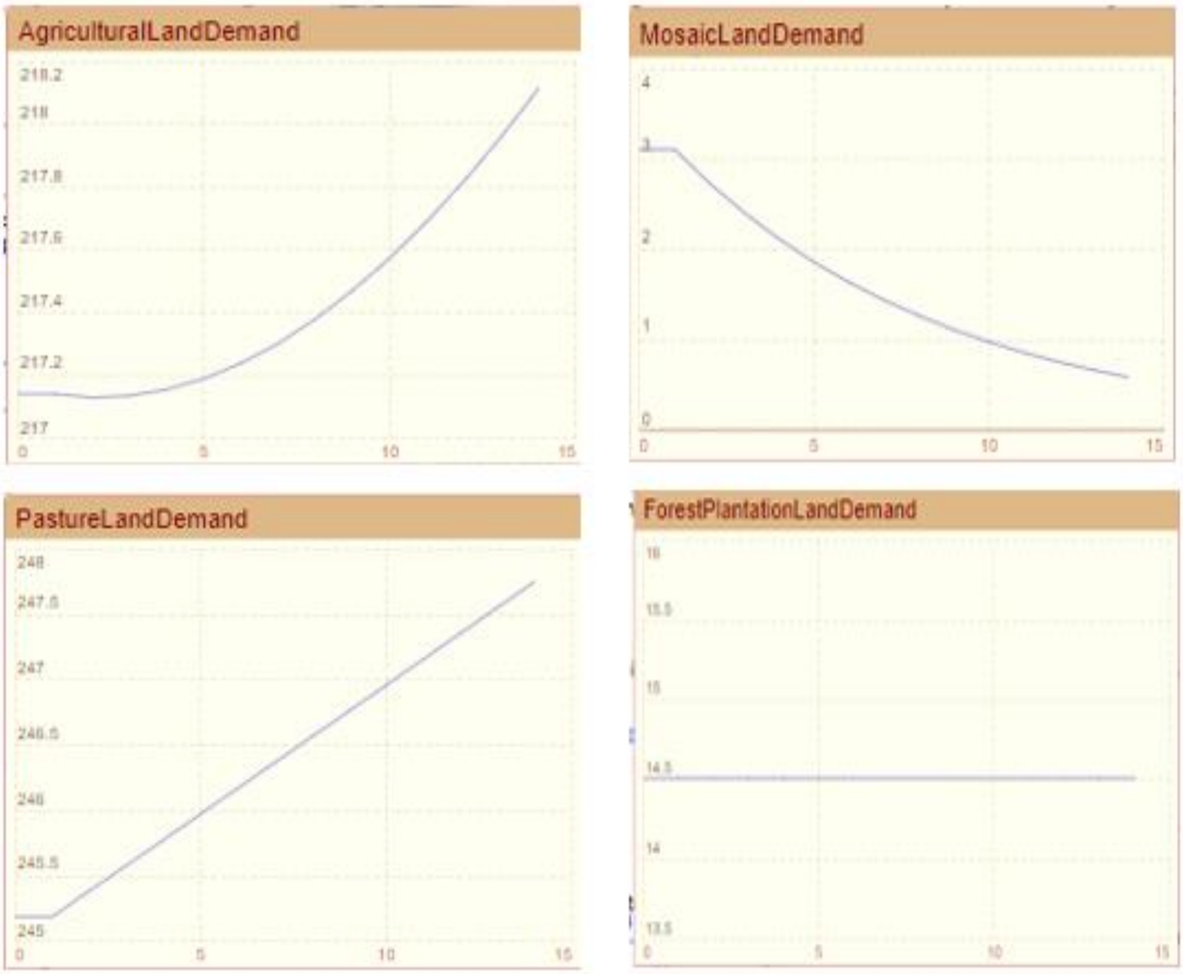
Source: Own Elaboration, based on IBGE.

Appendix B

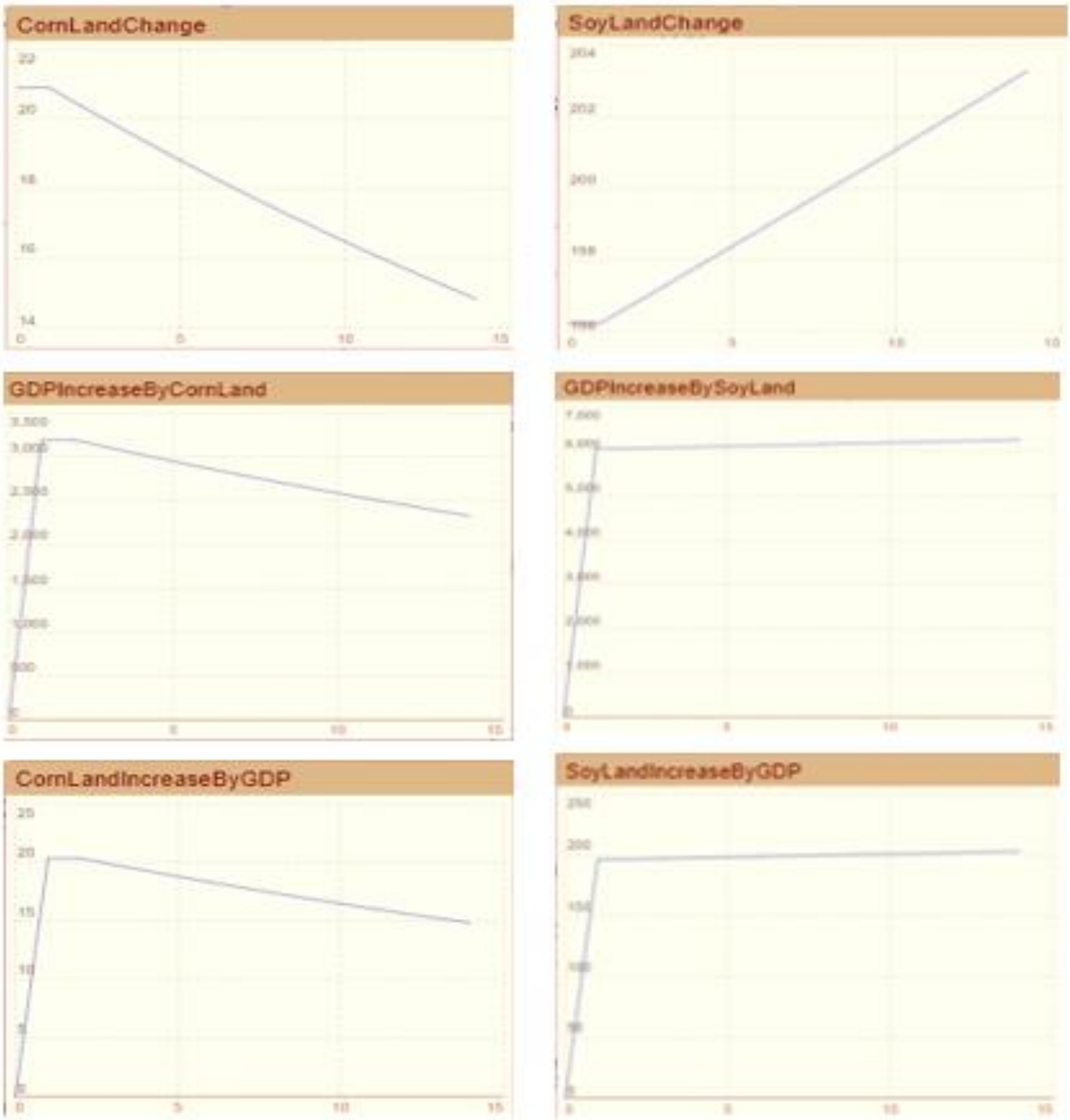
Figures of the Dynamic Behavior of SDM Elements

Figure B1: Dynamic behavior of the Farming Land Demand elements (SDM)



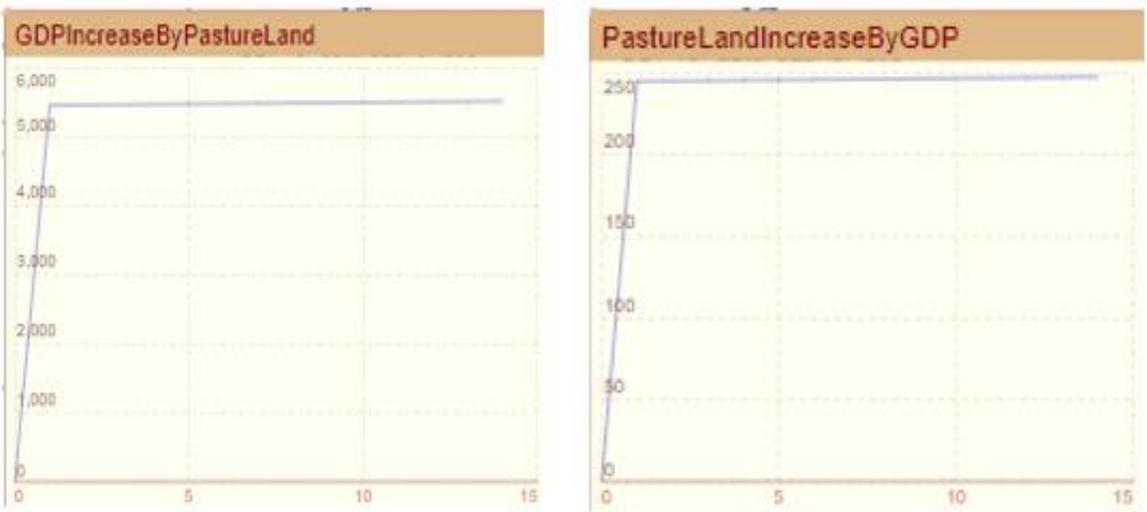
Source: Own Elaboration, based on AnyLogic output.

Figure B2: Dynamic behavior of the main elements of Agriculture Land Demand (SDM)



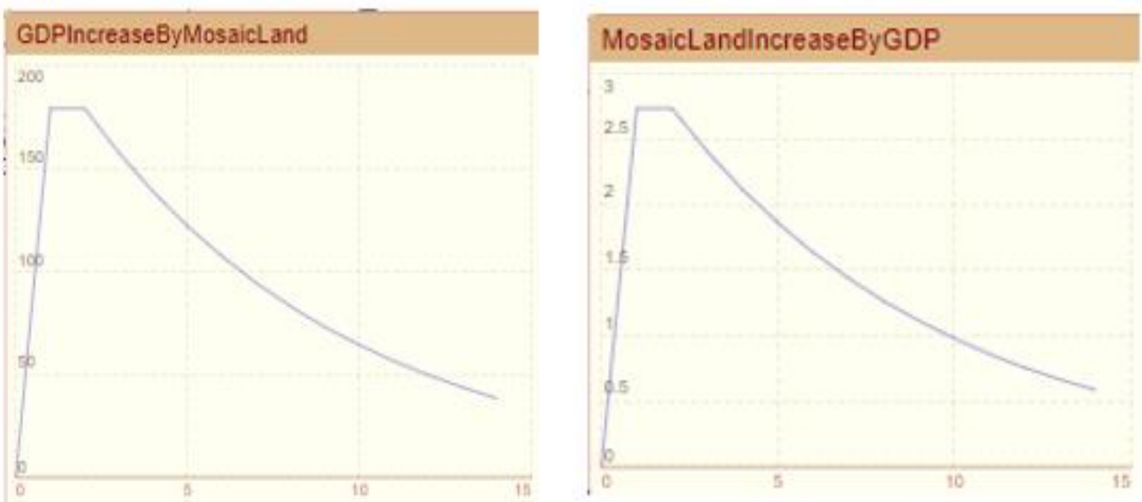
Source: Own Elaboration, based on AnyLogic output.

Figure B3: Dynamic behavior of the main elements of Pasture Land Demand (SDM)



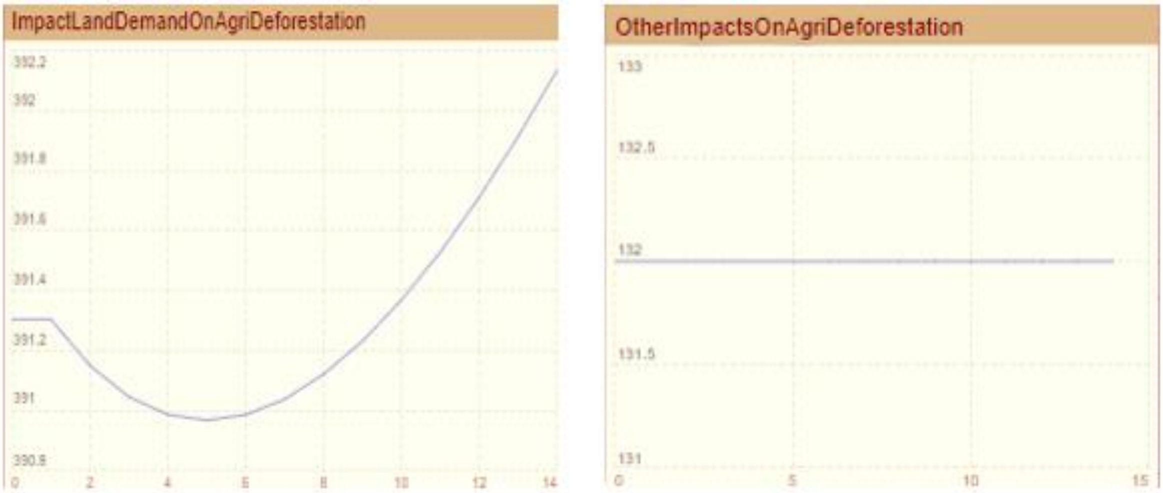
Source: Own Elaboration, based on AnyLogic output.

Figure B4: Dynamic behavior of the main elements of Mosaic Land Demand (SDM)



Source: Own Elaboration, based on AnyLogic output.

Figure B5: Dynamic behavior of the main elements of Deforestation (SDM)



Source: Own Elaboration, based on AnyLogic output.

Appendix C

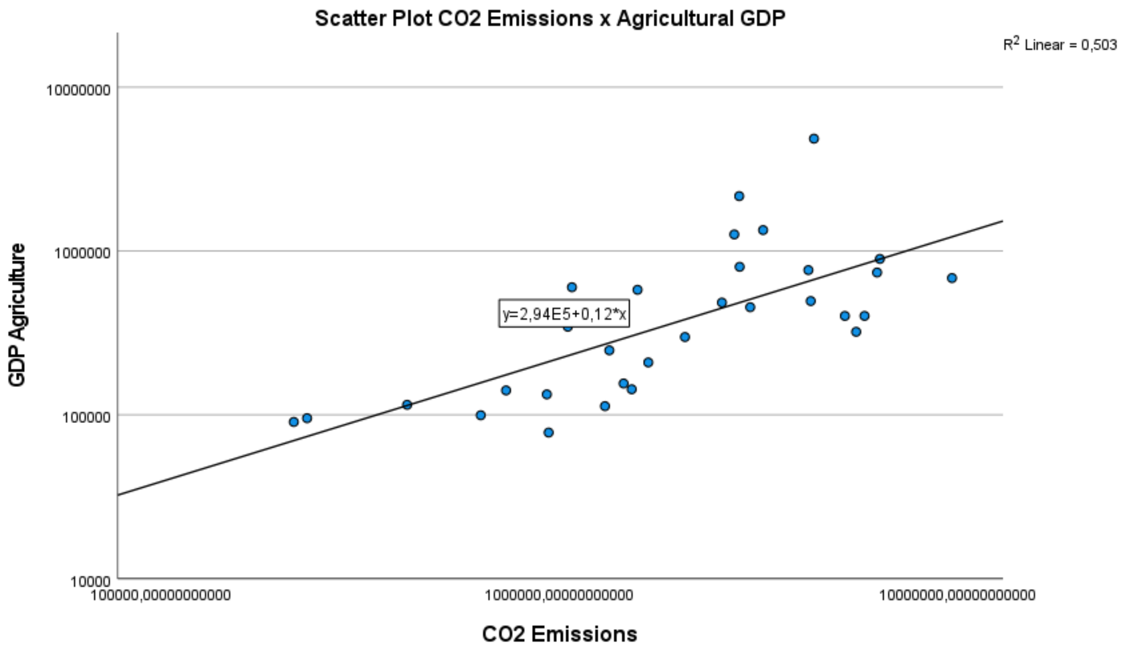
Verification of Assumptions of Canonical Correlation Analysis (CCA)

Linearity
Normality
Multicollinearity

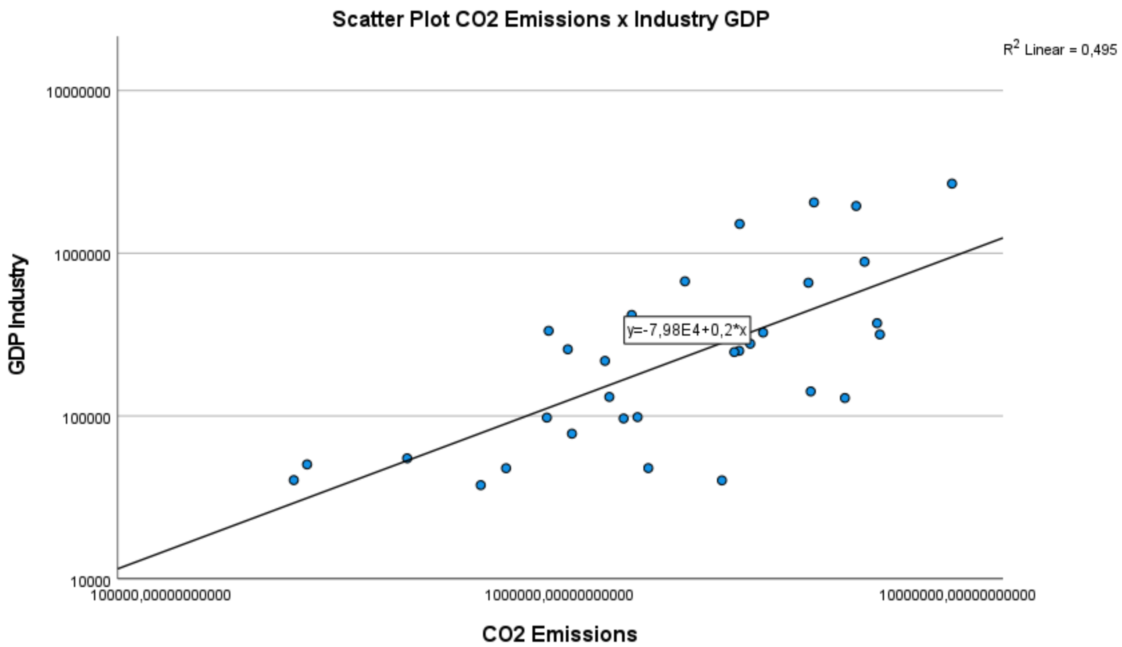
1. Linearity:

The scatter plot was used to check the linearity between the variables. When observing the dispersion of the data points, it is expected that they are close to the trend line, as this means that the values of the two variables are similar and consistent.

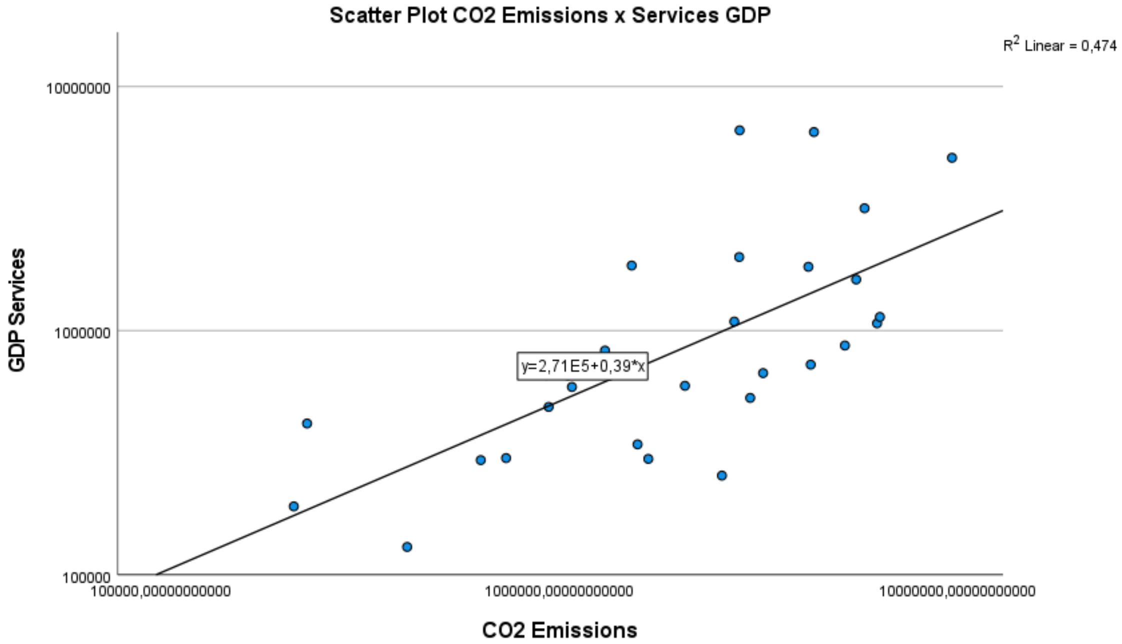
Model 1:



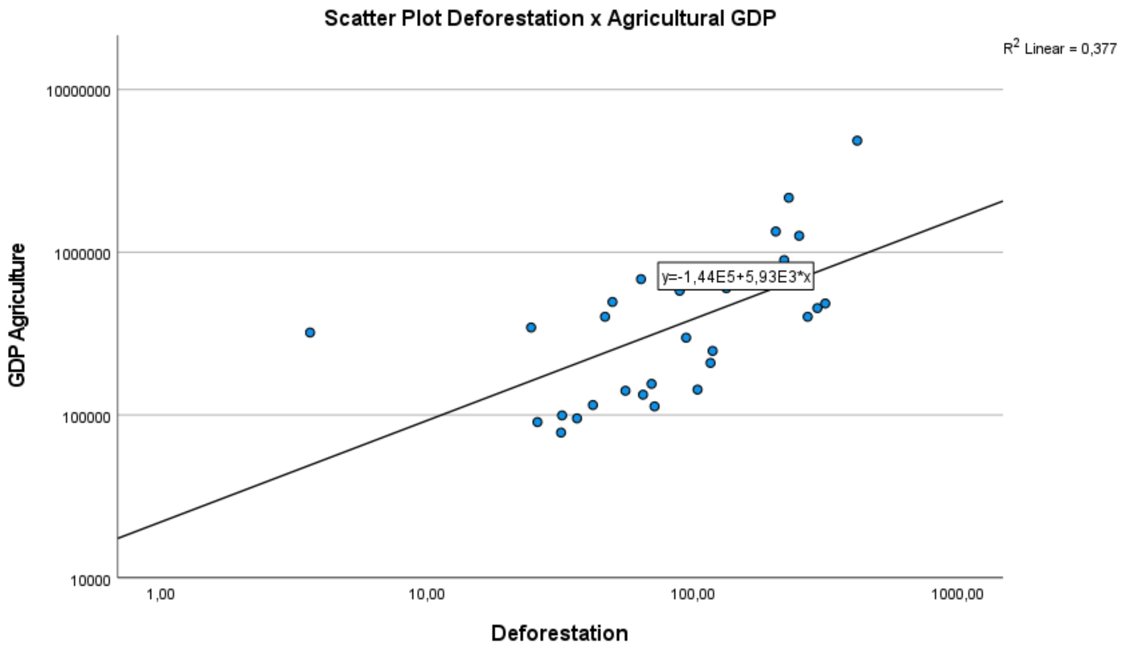
Source: SPSS output.



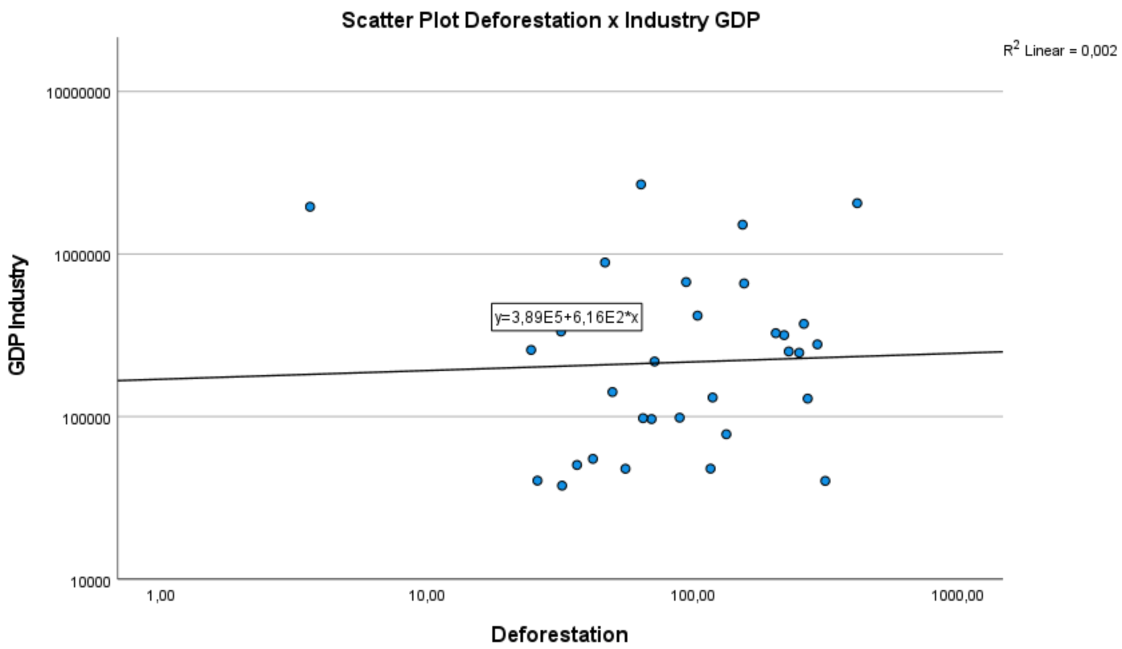
Source: SPSS output.



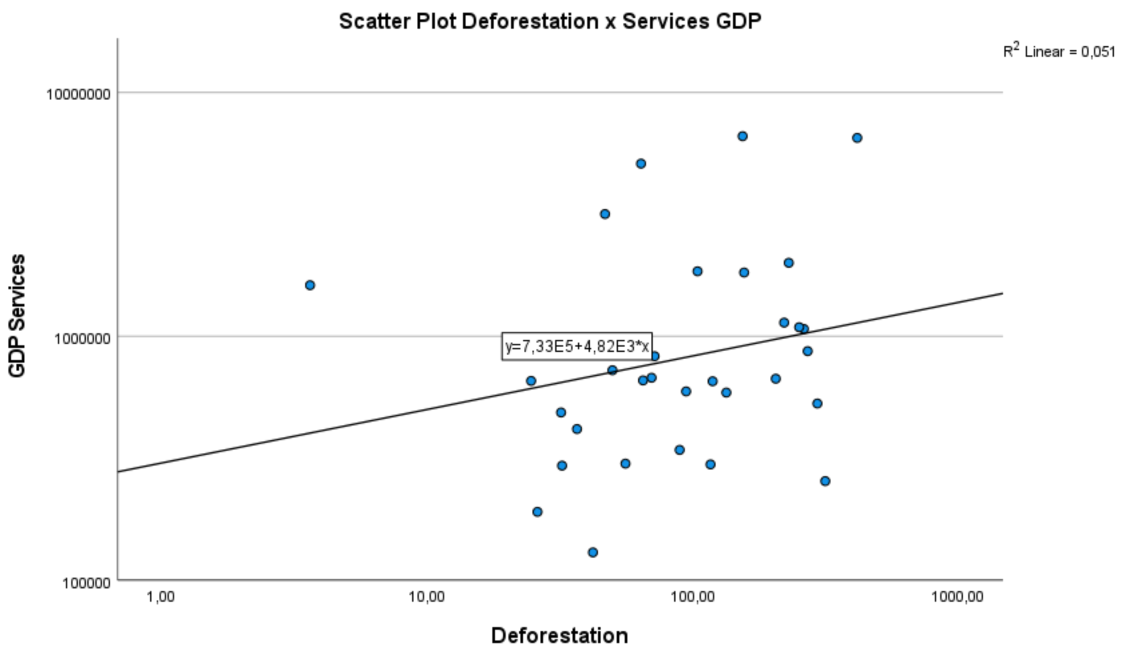
Source: SPSS output.



Source: SPSS output.

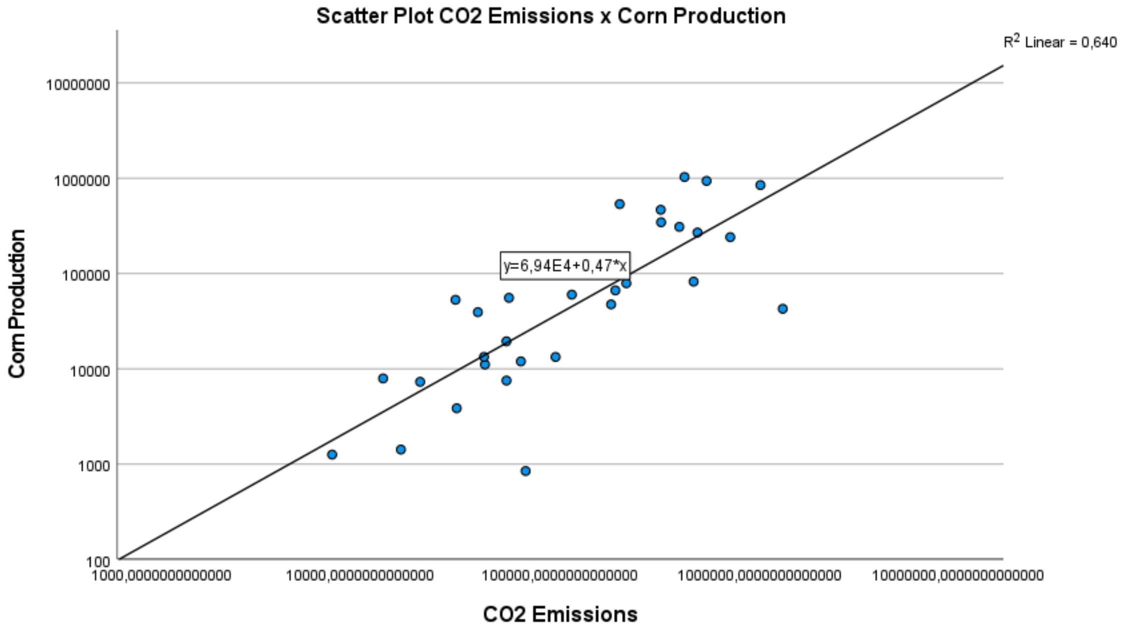


Source: SPSS output.

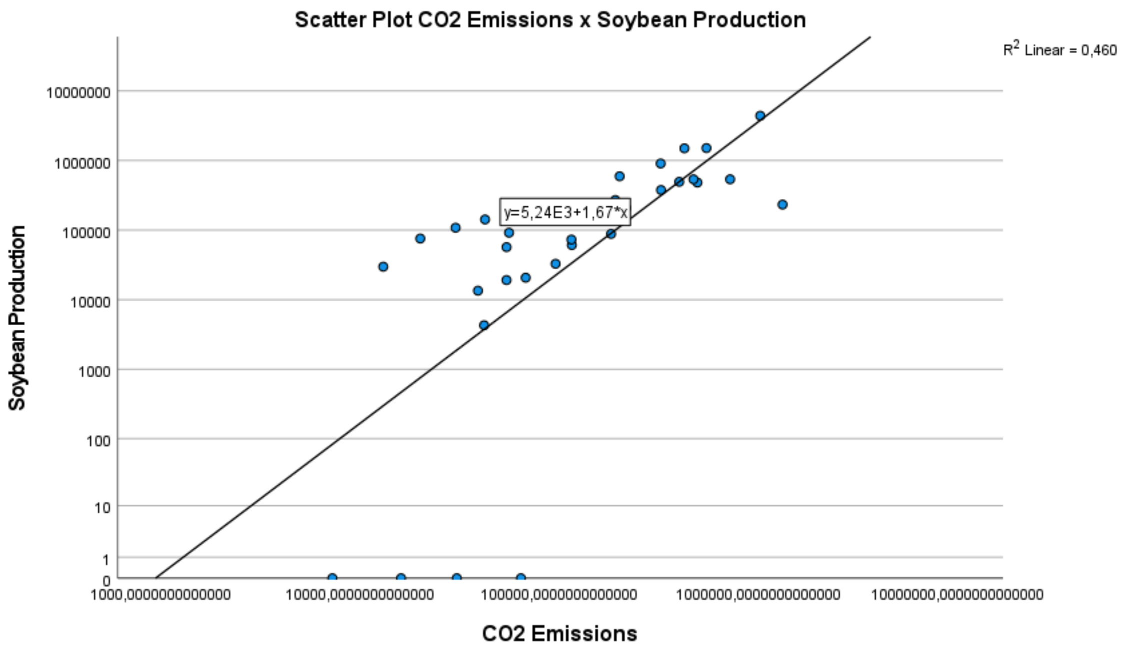


Source: SPSS output.

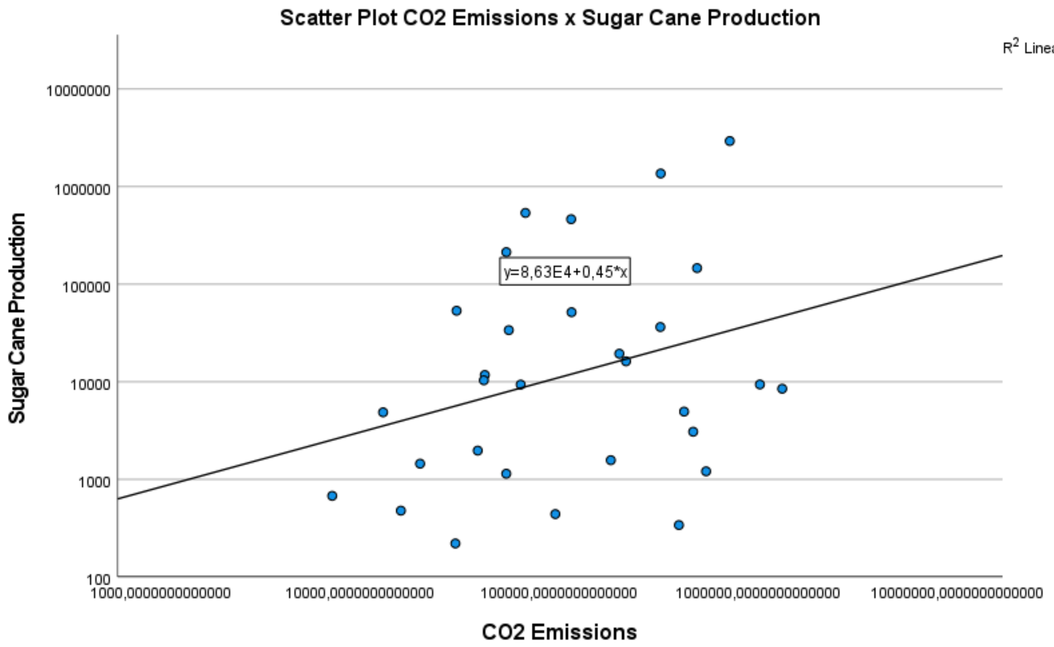
Model 2:



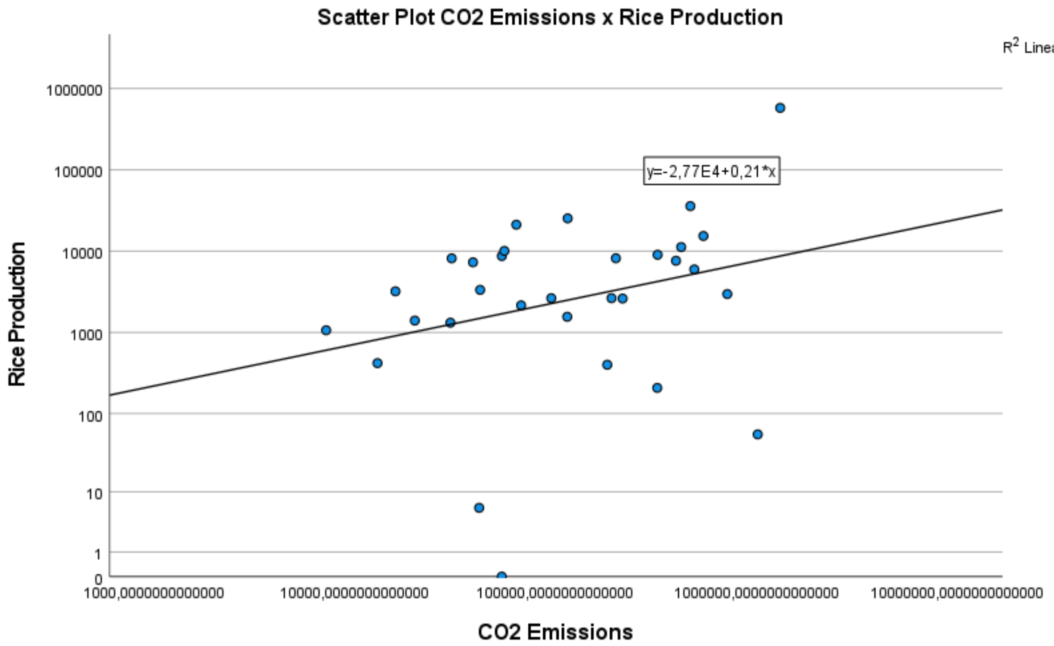
Source: SPSS output.



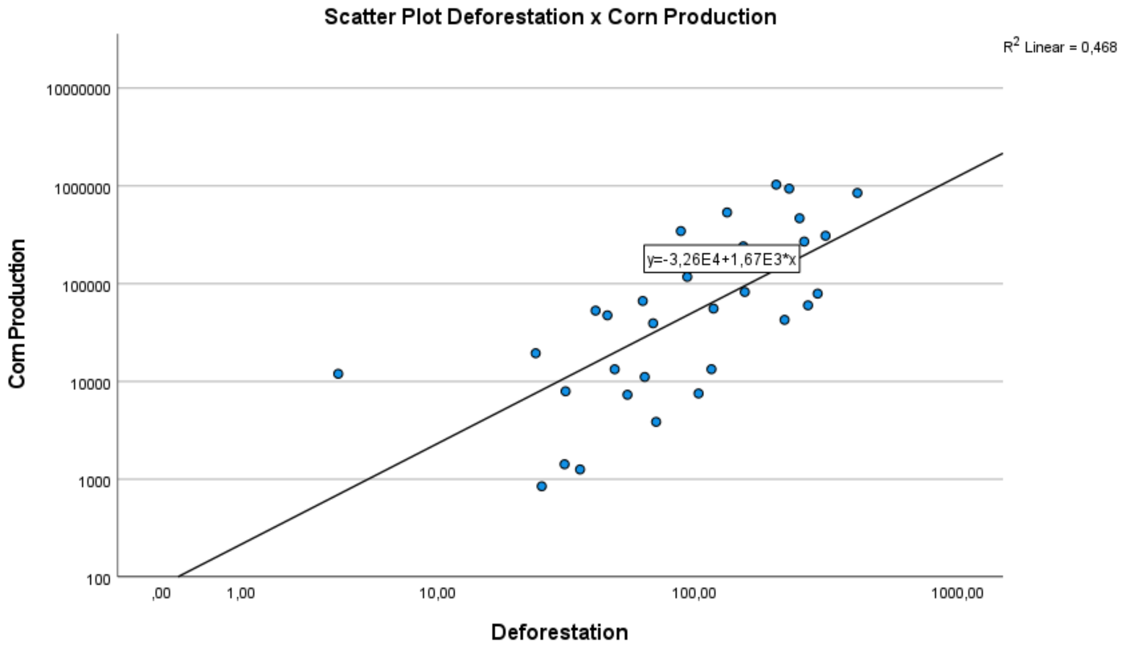
Source: SPSS output.



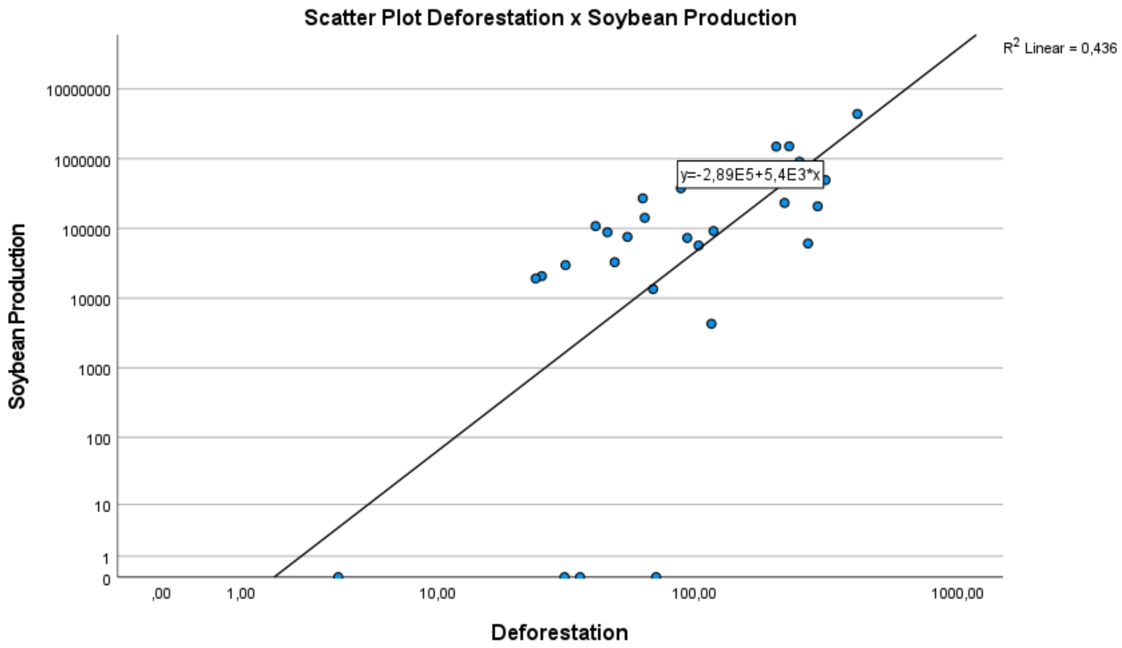
Source: SPSS output.



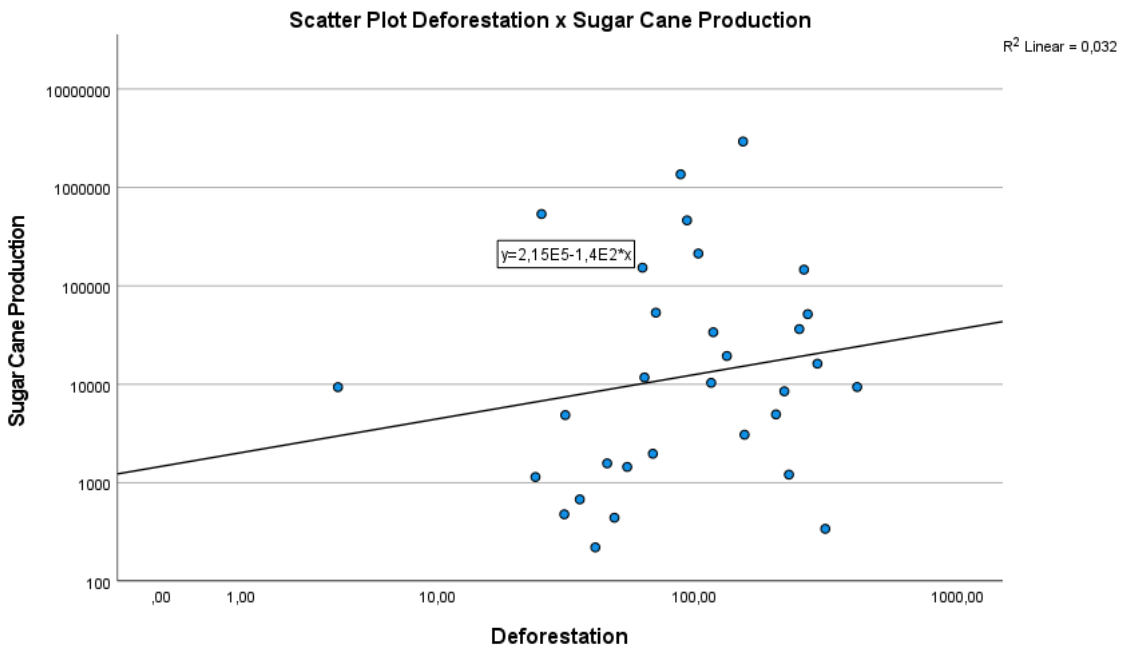
Source: SPSS output.



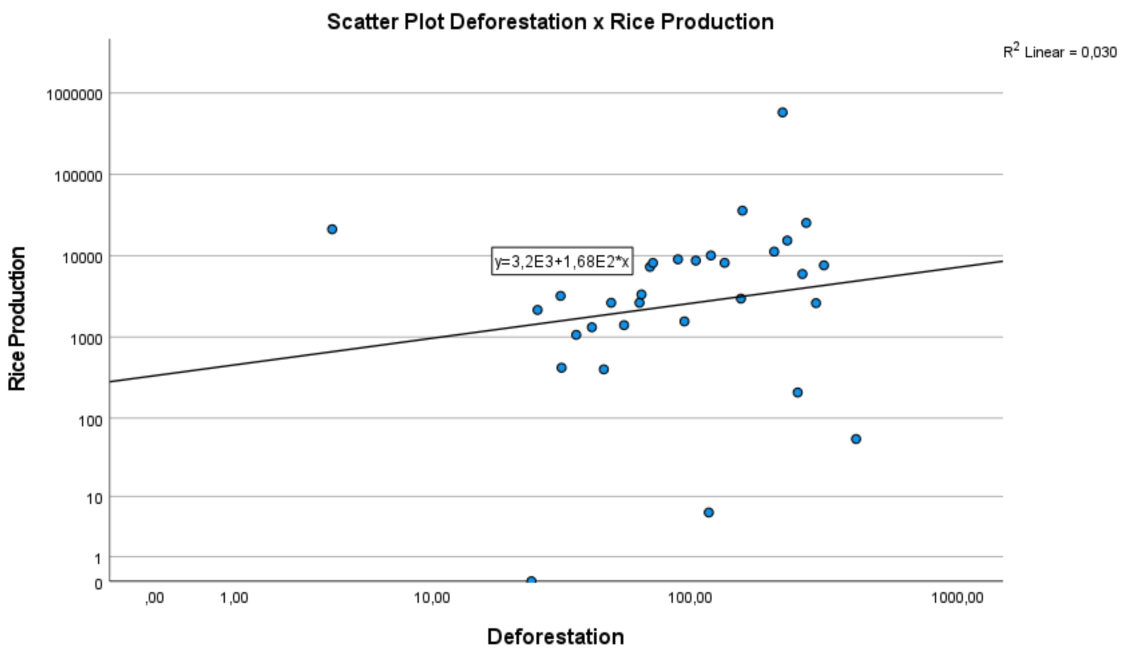
Source: SPSS output.



Source: SPSS output.



Source: SPSS output.



Source: SPSS output.

2. **Normality:**

The normality assumption for models 1 and 2 was met by the Central Limit Theory (Ellenberg, 2015; Salsburg, 2009). According to this theory, the distribution of sample means can be satisfactorily approximated by a normal distribution when the sample size is greater than 30. In this study, there was a sample of 31 microregions.

3. **Multicollinearity:**

The absence of multicollinearity will be analyzed using the value of the Variance Inflation Factor (VIF). A VIF between 5 and 10 indicates a high correlation, which can be problematic. Furthermore, if the VIF is above 10, it is assumed that the regression coefficients are poorly estimated due to multicollinearity. The VIF value is therefore expected to be less than 5.

Table C2: Variance Inflation Factor (VIF) results – CCA analysis

Model	Independent Variables	Tolerance	VIF
Model 1	Agricultural GDP	0.613	**1.631**
	Industry GDP	0.297	**3.366**
	Services GDP	0.232	**4.308**
Model 2	Corn Production	0.377	**2.654**
	Soybean Production	0.377	**2.637**
	Sugarcane Production	0.989	**1.011**
	Rice Production	0.988	**1.012**

Source: Own Elaboration, based on SPSS output.

Appendix D

Bivariate Regression Analysis (SDM)

- **Results**
- **Verification of Assumptions**

Results

To estimate the internal parameters "LandDemandToAgriDeforestationRatio", "CornLandToGDPRatio", "SoyLandToGDPRatio", "PastureLandToGDPRatio", "MosaicLandToGDPRatio", "GDPToCornLandRatio", 'GDPToSoyLandRatio', 'GDPToPastureLandRatio', and 'GDPToMosaicLandRatio' of the SDM for Matopiba, bivariate regression analyses were carried out.

The analysis used annual data from 2000 to 2020 (n = 21) for most of the parameters, except for the parameters that used data from the mosaic and pasture areas. For these, an analysis was carried out from 2011 to 2020 (n = 10) due to the availability and consistency of the database.

The results of the parameter coefficients are shown in Table D1. The coefficient values are raw, i.e. they are the values found from the analysis of the bivariate regression analyses before the SDM calibration and validation process.

Table D1: Bivariate Regression Analysis Results

Parameter	Coefficient	Std. Err.	P > |T|	R^2
LandDemandToAgriDeforestationRatio	**0.7504548**	0.0504411	0.00	0.9209
CornLandToGDPRatio	**152.4438**	8.893755	0.00	0.9393
SoyLandToGDPRatio	**30.86192**	1.361294	0.00	0.9644
PastureLandToGDPRatio	**38.23967**	8.661106	0.00	0.7885
MosaicLandToGDPRatio	**49.9381**	27.8559	0.00	0.4664
GDPToCornLandRatio	**0.006161**	0.000359	0.00	0.9393
GDPToSoyLandRatio	**0.031247**	0.001378	0.00	0.9644
GDPToPastureLandRatio	**0.027822**	0.003489	0.00	0.7885
GDPToMosaicLandRatio	**0.009825**	0.003220	0.00	0.4664

Source: Own Elaboration, based on STATA output.

Assumptions

As these are bivariate regression analyses, the models must meet the assumptions that the variables have a normal distribution (normality), that the variance of the errors is constant (homoscedasticity), and that the errors of one period are not correlated with the errors of previous periods (no serial autocorrelation).

1. **Normality:**

The normality assumption for the variables of the models was checked and met by Test Shapiro-Francia W'. The variables are expected to have a P-value > 0.05.

Table D2: Shapiro-Francia Test Results – Bivariate Regression Analyses

Variables	W'	V'	Sig
Farming land demand	0.90226	2.206	**0.05826**
Deforestation	0.89249	2.472	**0.05273**
Corn land demand	0.90124	2.315	**0.05572**
Soybeans land demand	0.92649	2.002	**0.10646**
Mosaic Area	0.96318	1.002	**0.49823**
Pasture Area	0.94417	1.520	**0.22605**
GDP	0.93694	1.717	**0.16592**

Source: Own Elaboration, based on STATA output.

2. **Homoscedasticity:**

Breusch-Pagan / Cook-Weisberg test was used to check the homogeneity of the variance errors. The models are expected to have a P-value > 0.05. As seen in Table D3, the homoscedasticity assumption was met.

Table D3: Breusch-Pagan Test Results – Bivariate Regression Analyses

Parameter	Breusch-Pagan Statistics	Sig
LandDemandToAgriDeforestationRatio	0.41	**0.5227**
CornLandToGDPRatio	3.49	**0.0542**
SoyLandToGDPRatio	3.88	**0.0491**
PastureLandToGDPRatio	0.85	**0.3570**
MosaicLandToGDPRatio	0.97	**0.3249**
GDPToCornLandRatio	2.84	**0.0918**
GDPToSoyLandRatio	3.51	**0.0497**
GDPToPastureLandRatio	0.45	**0.5026**
GDPToMosaicLandRatio	0.17	**0.6807**

Source: Own Elaboration, based on STATA output.

3. No Serial Correlation:

Durbin's alternative test was used to check the serial autocorrelation. The models are expected to have no serial autocorrelation (P-value > 0.05). As seen in Table D4, this assumption was met in all models.

Table D4: Durbin's Test Results – Bivariate Regression Analyses

Parameter	Durbin's Statistics	Sig
LandDemandToAgriDeforestationRatio	3.541	**0.0599**
CornLandToGDPRatio	0.032	**0.8585**
SoyLandToGDPRatio	3.595	**0.0526**
PastureLandToGDPRatio	1.902	**0.1678**
MosaicLandToGDPRatio	4.109	**0.0495**
GDPToCornLandRatio	0.009	**0.9253**
GDPToSoyLandRatio	4.101	**0.0499**
GDPToPastureLandRatio	1.157	**0.2820**
GDPToMosaicLandRatio	3.567	**0.0589**

Source: Own Elaboration, based on STATA output.