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Technologies

SPATIO-TEMPORAL ANALYSIS OF FOREST COVER CHANGE CONSIDERING EUDR-RELEVANT COMMODITIES TRADE IN THE BRAZILIAN AMAZON

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Dissertation submitted in partial fulfilment of the requirements
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by

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Master Dissertation presented as partial requirement for obtaining the Master's Degree in Geospatial Technologies

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"All models are wrong. We make tentative assumptions about the real world which we know are false but which we believe may be useful" - George Box

STATEMENT OF INTEGRITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

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USE OF GENERATIVE ARTIFICIAL INTELLIGENCE

Tasks	NO	YES	Generative Artificial Intelligence
Better understand issues related to the research		X	ChatGPT, LLMnotebook, DeepSeek
Summarizing text from bibliography / resources		X	ChatGPT, LLMnotebook, DeepSeek
Summarizing the method(s) used		X	ChatGPT, LLMnotebook, DeepSeek
Translating text		X	ChatGPT, DeepSeek
Grammar check		X	ChatGPT, DeepSeek
Paraphrase or rewriting text from other people / resources		X	ChatGPT, LLMnotebook, DeepSeek
Coding in R, Python, etc.		X	ChatGPT, DeepSeek
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Creating and editing images, maps, videos, etc.	X		
Data analysis		X	ChatGPT, DeepSeek
Specify below other tasks not mentioned above:			
Systematic Research		X	Scopus AI, Litmaps

DEDICATION

I would like to dedicate this work, first and foremost, to my father, Guilherme Trovão, who, though sadly passed away in 2016, continues to inspire me every day. To my mother, Tereza Araújo, whose unwavering support and guidance shaped the best aspects of my personal and academic growth. I am deeply grateful to my beloved aunts, Fátima and Almerinda, who have always been there for me, offering love, care, and encouragement throughout my journey.

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Finally, I dedicate this work to my six-year-old daughter, Nina Trovão, whose boundless energy, love, and curiosity have been my greatest source of inspiration and motivation to overcome every challenge.

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ANÁLISE ESPAÇO-TEMPORAL DA MUDANÇA NA COBERTURA FLORESTAL CONSIDERANDO O COMÉRCIO DE COMMODITIES RELEVANTES PARA O EUDR NA AMAZÔNIA BRASILEIRA

RESUMO

A expansão agrícola é amplamente reconhecida como o principal motor do desmatamento, especialmente em regiões tropicais. Gado, cacau, café, óleo de palma, soja e madeira são identificados como as principais commodities de risco florestal. A demanda internacional é apontada como responsável por 26% do desmatamento incorporado à produção. O consumo da União Europeia é considerado um fator significativo na perda florestal. Em maio de 2023, o Parlamento Europeu ratificou o Regulamento sobre Cadeias de Suprimentos Livres de Desmatamento (EUDR), com o objetivo de mitigar o desmatamento global, restringindo o comércio dessas commodities. Ainda há poucos estudos que estimam o desmatamento causado pela agricultura em toda a região tropical. Este estudo analisa a relação espaço-temporal entre a mudança na cobertura florestal e o comércio total de commodities relevantes para o EUDR na Amazônia Legal brasileira, em nível municipal. Utilizando a metodologia de Regressão Ponderada Geográfica e Temporal (GTWR), avaliamos o impacto do volume total de comércio e dos valores Free on Board (FOB) para gado, soja, madeira e outras commodities sobre a cobertura florestal ao longo de 12 anos (2011–2023). Os resultados indicam que o comércio de gado e soja apresenta a correlação negativa mais forte com a cobertura florestal, reforçando seu papel como principais vetores do desmatamento. O comércio de madeira apresenta resultados mistos, com alguns municípios demonstrando até correlações positivas. Em algumas localidades, os valores FOB do comércio servem como um indicador mais forte da perda florestal do que o volume total comercializado. Em 33 municípios, foi identificada uma correlação estatisticamente significativa e negativa entre a cobertura florestal e o valor FOB. Os achados ressaltam a natureza heterogênea do desmatamento impulsionado pelo comércio de commodities, destacando municípios onde os mecanismos de conformidade do EUDR devem ser priorizados. O estudo considera o comércio total, e não apenas aquele destinado à União Europeia, para oferecer uma perspectiva mais ampla sobre como tais políticas podem afetar a cobertura florestal. Dessa forma, esperamos

contribuir para o desenvolvimento de políticas direcionadas para práticas comerciais sustentáveis e apoiar a avaliação da eficácia do EUDR na mitigação do desmatamento em áreas de alto risco.

PALAVRAS-CHAVE

EUDR; mudança na cobertura florestal; Amazônia Legal; desmatamento impulsionado pelo comércio; GTWR; políticas de comércio sustentável.

Objetivos do Desenvolvimento Sustentável (ODS):

SPATIO-TEMPORAL ANALYSIS OF FOREST COVER CHANGE CONSIDERING EUDR-RELEVANT COMMODITIES TRADE IN THE BRAZILIAN AMAZON

ABSTRACT

The agriculture expansion is well recognized as the main deforestation driver, especially in tropical regions. Cattle, cocoa, coffee, palm oil, soy, and wood are identified as the main forest risk commodities. International demand is highlighted as responsible for 26% of the deforestation embodied in production. The European Union consumption is considered a significant driver of forest loss. On May 2023, the European Parliament ratified the Regulation on deforestation-free supply chains (EUDR) to mitigate global deforestation by restricting the trade of those commodities. There are not many studies that estimate deforestation caused by agriculture across the tropical region. This study analyzes the spatio-temporal relationship between forest cover change and EUDR-relevant commodities total trade within Brazil's Legal Amazon at the municipal level. Using Geographically and Temporally Weighted Regression (GTWR), we assess the impact of total trade volume and trade Free on Board (FOB) values for cattle, soy, wood, and other commodities on forest cover over a 12-year period (2011–2023). Results indicate that cattle and soy trade exhibit the strongest negative correlation with forest cover, reinforcing their role as primary deforestation drivers. Wood trade presents mixed results, with some municipalities showing even positive correlations. For some municipalities Trade FOB values serve as a stronger predictor of forest loss than total trade volume. In 33 municipalities there were identified a significative statistical negative correlation of forest cover with FOB value. The findings underscore the heterogeneous nature of commodities trade driven deforestation, highlighting municipalities where the EUDR's compliance mechanisms should be prioritized. The study considers the total trade, not only what had the EU as final destination, to provide a broader perspective of how such policies can affect the forest cover. This way we hope to contribute to the design of targeted policies for sustainable trade practices and supports the evaluation of the EUDR's potential effectiveness in curbing deforestation in high-risk areas.

KEYWORDS

EUDR; forest cover change; Legal Amazon; trade-driven deforestation; GTWR; sustainable trade policies

Sustainable Development Goals (SGD):

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ACRONYMS

AICc - Corrected Akaike Information Criterion

COM - Component Object Model

GTWR - Geographically and Temporally Weighted Regression

EUDR - European Union Regulation on deforestation-free supply chains

EUTR – European Union Timber Regulation

EU - European Union

FAO - Food and Agriculture Organization

FRA - Global Forest Resources Assessment

FOB - Free On Board

HS - Harmonized System (used for trade classification)

IBGE - Instituto Brasileiro de Geografia e Estatística (Brazilian Institute of Geography and Statistics)

INPE - Instituto Nacional de Pesquisas Espaciais (National Institute for Space Research)

LDCs - Least Developed Countries

LULC - Land Use and Land Cover

PRODES - Projeto de Monitoramento do Desmatamento na Amazônia Legal por Satélite (*Measurement of Deforestation by Remote Sensing*)

R^2 - Coefficient of Determination (R-Squared)

RSS - Residual Sum of Squares

SAR - Spatial Autoregressive Model

SDG - Sustainable Development Goals

UNFCCC - United Nations Framework Convention on Climate Change

VIF - Variance Inflation Factor

1. INTRODUCTION

1.1 CONTEXT

On 31 May 2023, the European Parliament ratified the Regulation 2023/1115[1], which prohibits the placement or availability of commodities and products associated with forest degradation and deforestation on the European Union (EU) market. This regulation comes replacing the EU Timber Regulation (EUTR), which was restricted to illegal timber products (Köthke et al., 2023). The new regulation identifies EU consumption as a significant driver of global forest loss. Without intervention, consumption of the considered relevant commodities (cattle, cocoa, coffee, palm oil, soy, and wood) would result in the annual loss of 240,000 hectares of forest by 2030 (Pendrill, Persson, Godar, & Kastner, 2019).

The European Parliament underscored that the decline in natural land cover is primarily attributed to agricultural expansion, which accounts for approximately 90% of global deforestation, with crops and pasture being the primary activities (*Global Forest Resources Assessment - FAO*, 2020). Consequently, the Commission was tasked with proposing an 'EU legal framework to halt and reverse EU-driven global deforestation,' leading to the approval of the *EU Regulation on deforestation-free supply chains* (EUDR). European Commission's trade department highlights Brazil as a key player in global agricultural trade, the largest exporter of agricultural commodities to the EU[2].

Although the Regulation came into force on 29 June 2023, operators and traders were, initially, granted an 18-month adaptation period, while micro and small enterprises have until 30 June 2025 to comply under different conditions and support mechanisms. In October 2024,

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1 European Parliament. (2023). Regulation (EU) 2023/1115 of the European Parliament and of the Council of 31 May 2023. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32023R1115&qid=1687867231461

2 European Commission. (n.d.). EU-Brazil trade relations. [Online]. Available: https://policy.trade.ec.europa.eu/eu-trade-relationships-country-and-region/countries-and-regions/brazil_en#:~:text=EU%20imports%20from%20Brazil%20are,products%20to%20the%20EU%20worldwide

the EU Council decided to postpone the EUDR application by one year, shifting the effective date to December 30, 2025, for the majority of operators and traders [3]. For micro and small businesses, the revised effective date will be June 30, 2026. They argued that the delay was necessary to give more time for operators, traders and Member Stated to be fully prepared.

The EUDR aligns with several Sustainable Development Goals (SDGs), notably those related to life on land (SDG 15), climate action (SDG 13), responsible consumption and production (SDG 12), zero hunger (SDG 2), and good health and well-being (SDG 3) (European Commission, 2023a). Therefore, this work expects to some extent contribute to such goals as well.

Recent study from Berman et al. (2023) indicates that one-third of the tropical forest loss was due to the increase in the crop prices from 2001-2018. There are several studies suggesting that the global demand expansion for commodities drives the crops prices, which contributes for the reduction of forest cover (Angelsen, 1999; Angelsen and Kaimowitz, 1999; Angelsen, 2010; Rudel et al., 2009; Busch and Ferretti-Gallon, 2017 as cited by Berman et al., 2023).

The EUDR mentions that between 1990 and 2008, the EU accounted for one-third of the global trade in agricultural products linked to deforestation. During this time, EU consumption contributed to 10% of global deforestation associated with goods and services production. Although its relative share has been declining, the EU is still a significant driver of deforestation. This underscores the need for action to reduce global deforestation and forest degradation tied to its consumption of specific commodities and products. Such measures would also help lower greenhouse gas emissions, mitigate biodiversity loss, and foster sustainable production and consumption practices both within the EU and globally. To achieve maximum effectiveness, EU policies should target the global market rather than exclusively focusing on supply chains within the Union.

The main study addressed by the EUDR from Pendrill et al. (2019), analyzed the deforestation embodied in agricultural and forestry production, consumption and trade. They identified the international demand as responsible for 26% of the embodied deforestation. They made it by

3 https://www.consilium.europa.eu/en/press/press-releases/2024/10/16/eu-deforestation-law-council-agrees-to-extend-application-timeline/

using a land-balance model based on two major assumptions: "(1) where cropland expands, it first expands into pastures (if there was a gross loss of pasture area) and then into forests (if there was gross forest loss), and (2) where pastures and forest plantation areas expand, they primarily replace forest land". They recognize that it comes with a drawback, since it cannot distinguish between direct and indirect agent, the land uses that are expanding and replacing the forest cover from those that are being pushed into forests because of the expansion of other land-use.

Further review publication from Pendrill et al. (2022), disentangles the numbers associated with tropical deforestation driven by agriculture. The article addresses different key points, including a literature review of the pantropical agriculture-driven deforestation. They identified only a few studies providing estimates of deforestation caused by agriculture across the tropical region and, while agriculture being the primary land use following forest clearing, their estimates of agriculture-driven deforestation rates between 2011 and 2015 vary significantly, ranging from 4.3 to 9.6 million hectares (Mha) annually. In that sense, they consider that a synthesized estimate places this range between 6.4 and 8.8 Mha per year. While the vast majority (90–99%) of tropical deforestation occurs in areas where agriculture is the dominant driver of tree cover loss, only a portion (45–65%) of this deforestation directly results from agricultural expansion into forested areas.

Other contributing factors include speculative land clearing, land tenure disputes, temporary or abandoned agricultural practices, and agriculture-related fires spreading into nearby forests. Deforestation is often driven by interactions among various land uses and commodities, with pasture expansion being the single largest contributor, responsible for approximately half of the deforestation tied to agricultural production in the tropics. Oil palm and soy cultivation together account for roughly one-fifth, while other crops such as rubber, cocoa, coffee, rice, maize, and cassava make up most of the remainder, with significant regional differences and high levels of uncertainty (Pendrill et al., 2022).

The European Commission will undertake reviews and assessments of the EUDR over the coming years to evaluate its effectiveness, the adopted concepts and consider expanding its scope. This assessment will examine the cut-off date specified in Article 2 and evaluate the impact of commodities on deforestation and forest degradation to reduce the EU's contribution to ecosystem conversion (European Commission, 2023a).

A general review of the Regulation will take place by 30 June 2028, with subsequent reviews occurring every five years. This review will evaluate the need for trade facilitation tools, particularly for Least Developed Countries (LDCs) and high-risk areas, assess the impact of the Regulation on smallholders, Indigenous peoples, and local communities, and examine support measures for sustainable supply chains. Additionally, it will explore extending the definition of forest degradation, the use of polygons for monitoring deforestation, changes in trade patterns indicating the effectiveness of compliance checks. These periodic reviews aim to adapt the Regulation to evolving challenges and ensure its goals are met effectively (European Commission, 2023a).

The present analysis focuses on the impact of EUDR-Relevant products trade over forest cover in the Legal Amazon region, not restricting to what was traded only with the EU. The Legal Amazon was established to foster inclusive and sustainable development within its area of operation, while also enhancing the competitive integration of the regional productive base into both national and international economies. The Legal Amazon encompasses a total area of about 5.0 million square kilometers, covering approximately 59% of Brazil's territory, spanning across eight states: Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins, as well as a portion of Maranhão (west of the 44ºW meridian) (de Almeida et al., 2022; Silveira et al., 2025). This region holds about 60% of the total Amazon rainforest, 20% of the Cerrado (Brazilian Savannah) and roughly on third of the Pantanal (wetlands).

The relationship between economic complexity and deforestation in that region revealed a nuanced relationship. While economic complexity initially appears to drive deforestation, it can have a mitigating effect over time. Specifically, a 0.1 unit rise in regional economic complexity correlates with a 27.8% increase in deforestation in the current period, followed by an 8.4% reduction in the subsequent years. It suggest that while economic diversification may not provide immediate environmental benefits, it can foster long-term reductions in deforestation (Silveira et al., 2025).

1.2 Research Gap

The primary motivation for this study is to assess the correlation of the EUDR-Relevant Commodities trade with the forest cover change within the municipalities of Legal Amazon, which is a major exporter to the EU. Most studies focus on global deforestation driven by commodities, but there is a lack of specific quantification of forest cover changes linked to EUDR-Relevant products trade (Pendrill, Persson, Godar, & Kastner, 2019).

There are not many studies that estimates deforestation caused by agriculture across the tropical region (Pendrill et al., 2022). In that sense, the present study aims to fill some of the research gaps related to the impact of trade in EUDR-relevant commodities on forest cover in the Legal Amazon. While it is known that cattle ranching, soy cultivation, and palm oil production are associated with deforestation in the Legal Amazon, more detailed research is needed to understand how these commodities drive land-use changes in each municipality (Santos et al., 2021; Silveira et al., 2025).

A key question is whether the policies, such EUDR, will be effective in curbing commodity-driven deforestation. The evaluation of the EUDR-Commodities trade dynamics in the Legal Amazon municipalities and the forest cover increase or decrease, can contribute to evaluate whether EUDR could genuinely lead to a more sustainable supply chain (Corona et al., 2023; Köthke et al., 2023; Vasconcelos et al., 2024).

By combining temporal remote sensing data with trade data, using a spatial-temporal explicit approach, it is expected to deliver a deeper and new perspective of the relationship between forest cover changes and EUDR-Commodities trade. It means that not only deforestation is evaluated, but the forest cover itself, which enables us to identify municipalities where eventually the trade increase occurs with net forest cover expansion.

1.3 Objectives and Research Questions

1.3.1 Research Questions

RQ1: In which municipalities the EUDR-Relevant Commodities trade significantly affect forest cover?

RQ2: Which commodities export trade are negatively affecting forest over the Legal Amazon and in which municipalities?

Ultimately, the study aims to provide a framework to assess the trade impact of EUDR-Relevant Commodities over forest cover change and, with that, contribute to further analysis focused on the extent to which the Regulation achieves its primary goals. It is relevant to highlight that there is no differentiation between the amount traded with the EU and the rest of the world. In that sense, the present analysis explores how the overall EUDR relevant products trade can affect the forest cover.

1.3.2 Main Objectives

The main objective is the evaluation of the EUDR-Relevant Commodities trade impact over the forest cover in the Legal Amazon, Brazil. To understand if and how the EUDR-Relevant Commodities trade affect forest cover, correlating trades and forest cover change data under municipalities context using a spatial explicit approach, considering the spatial unit the municipalities and the temporal unit years.

1.4 Thesis Organization

The present thesis divides into 5 Chapters. Chapter 1 provides a general context of the research, the related research gaps, the objectives and research questions. The following Chapter 2 presents a comprehensive literature review, with the methods and tools used for the review, main research related concepts and an overview of the methods that can perform spatio-temporal explicit analysis. Chapter 3 is dedicated to delivering the necessary information regarding the methodology, study area, the data characteristics and manipulation steps, software applied, exploratory analysis performed, and the parameters used for the models processing. The results and the discussion are presented in Chapter 4. Finally, Chapter 5 focuses on the conclusion, presenting research questions answers, the limitations of the present work and some recommendations for future research.

2. LITERATURE REVIEW

2.1 LITERATURE REVIEW METHODS

The literature review began by utilizing the keywords identified in the primary study referenced within the EUDR from Pendrill et al 2019. These keywords were applied in searches across Scopus[4] and Litmaps[5] throughout the development of this research. Given the recent implementation of the regulation, relevant studies are continuously being published, as illustrated in the Litmaps visualization provided below. The survey conducted yielded 128 articles, of which twenty-two were deemed most relevant to the present topic and objectives. These selected studies contributed to the research by providing key concepts, contextual understanding, and methodological approaches.

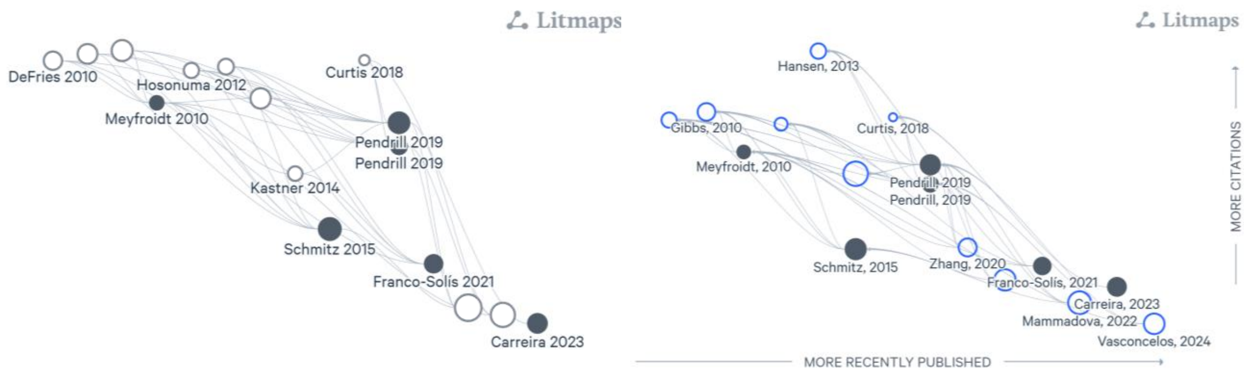

Figure 1 - Limap from December 2023 (left) and December 2024 (right)

Moreover, a few queries were performed with Scopus AI, to get more insights about how to measure the effects of commodities trade over forest cover, by employing land cover and trade data, using spatial temporal approach with explicit spatial relation model. Scopus AI is an artificial intelligence-powered tool designed to aid users in comprehending and navigating academic material by using the Scopus database. It produces concise summaries derived from Scopus abstracts, complete with references, to simplify complex topics[6].

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[4] https://www.scopus.com/

[5] https://www.litmaps.com/

[6] https://elsevier.libguides.com/Scopus/ScopusAI

In addition to that, the supervisors pointed out important references focused on the statistics methods such as Chatterjee's correlation coefficient (Chatterjee, 2021) and Geographic Regression models (Fotheringham et al., 2015; Santos et al., 2021; C. Wu et al., 2019). It is relevant to mention that the references provided contributed with methods not presented in the performed search, despite the new tools and platforms explored. This indicates the importance of not depending solely on platforms and similar tools. Moreover, some references cited in the papers were also included in the literature review.

Finally, the NotebookLM7 was used to improve the analysis of the references, which is a Google AI-driven research assistant designed to streamline access to key insights, using the supplied documents as its foundation. It comes with a feature that generates an audio stream in podcast format with the summarized content of the provided references.

2.2 Key Concepts and Definitions

Understanding forest cover change, its drivers, and the effects of international trade requires a clarification of the basic concepts related. This section outlines these foundational concepts to provide the necessary theoretical framework for analyzing the impact of EUDR-relevant commodity trade on forest cover in the Legal Amazon. Cosimo et al. (2024) highlighted the importance of defining concepts considering four Voluntary sustainability standards (VSS) schemas regarding EUDR compliance. They recommended that almost all of them, except Fairtrade[8], should adjust the definitions of forest, deforestation, and forest degradation to encompass those outlined in the EUDR.

The work from Pendrill et al. (2022) presents a comprehensive review of the studies and concepts related to agriculture-driven tropical deforestation, which greatly contributed to the present section structuring.

[7] https://notebooklm.google

[8] https://www.fairtrade.net/

2.2.1 FOREST

For the present analysis, the Forest definition is a key concept, since it can lead to different results, making the comparison between studies difficult or even impossible. Forests can be defined, in a broad perspective, as ecosystems characterized by a high density of trees and a diverse range of flora and fauna. They play a critical role in maintaining global ecological balance by providing ecosystem services such as carbon sequestration, biodiversity conservation, water regulation, and soil protection (FAO, 2020). Forests in the tropics, such as the Amazon, are particularly important for their high biodiversity and ability to regulate regional and global climate systems. They are also vital for local communities, providing livelihoods, food, and cultural significance. Forests can also have different practical definitions, from which the ones more relevant for the present analysis are:

> *"Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use".(FAO, 2020)*

> *"Land spanning more than 0,5 hectares with trees higher than 5 meters and a canopy cover of more than 10 %, or trees able to reach those thresholds in situ, excluding land that is predominantly under agricultural or urban land use". (European Commission, 2023a)*

> *"Forest formations are considered as arboreal structures exceeding 5 meters in height, encompassing the physiognomies of Dense Forest (…), Open Forest (…), Seasonal Forest (…), and Mixed Ombrophilous Forest (…), as well as mangrove areas. This category includes remnants of primary forest and advanced stages of forest regeneration (…) across various phytogeographic regions classified as forested.".(Instituto Brasileiro de Geografia e Estatística - IBGE 2013)*

In the FAO Global Forest Resources Assessment (FRA), the United Nations Framework Convention on Climate Change (UNFCCC), and various other international frameworks, the term "forest" is primarily defined based on land use rather than land cover. This means that a piece of land can still be classified as a forest even in the absence of trees, while areas used for agriculture or urban development, despite having tree cover, may not be considered forests. This distinction poses challenges for automated satellite remote sensing analyses, as these technologies are limited to observing land cover rather than land use.

The land cover data for the present work comes from MapBiomas initiative, developed using hierarchical system classification framework, that integrates land use and land cover categories aligned with the classification standards of both the FAO and IBGE (Souza et al., 2020). It is possible to notice that the Forest definition from FAO and EUDR are essentially the same, on the other hand, the definition from Brazil's official Land Use Technical Guide (Brazilian Institute of Geography and Statistics, 2013) does not establishes a threshold for the spanning area. As consequence, an important share of the forest defined by IBGE is not covered by the FAO/EUDR definition, such as Savannas which will remain unprotected (Azevedo et al., 2022; Cesar De Oliveira et al., 2024).

Moreover, the definition of forests adopted from FAO (2020) excludes the conversion of agroforestry systems to agricultural monocultures as a form of deforestation, as agroforestry is classified as an agricultural land use rather than forest land. This creates additional challenges in contexts where national forest definitions differ from the EUDR's criteria, particularly regarding minimum tree cover and the minimum area required to qualify as forest (Köthke et al., 2023). The EUDR also define and differentiate 'primary forest', 'naturally regenerating forest', 'planted forest', 'plantation forest' and 'other wooded land'. The purpose and consequences of that differentiation holds connection with deforestation and degradation concepts, further explored.

According to the EUDR, primary forests are natural, untouched forests with native species and intact ecological processes, while naturally regenerating forests recover through natural processes after disturbance, with minimal human intervention. Planted forests are human established, using native or non-native species for environmental or economic purposes, and plantation forests are intensively managed monocultures focused on goods like timber or biomass, typically with lower biodiversity. Other wooded land refers to areas with sparse tree cover (5–10% canopy) or short trees, such as shrublands and savannas.

By 30 June 2024, the Commission will present an impact assessment, possibly accompanied by a legislative proposal, to determine whether the Regulation should include other wooded land. By 30 June 2025, another impact assessment will explore the inclusion of additional natural ecosystems, such as grasslands, peatlands, and wetlands, into the Regulation's scope. In that sense, for the present work, the classes from MapBiomas considered as forest are: Forest, Flooded Forest, Mangroves and Natural Woodlands (Azevedo et al., 2022). Moreover, their methodology also accounts for regeneration, making it possible to calculate the net forest change.

Lastly, for deforestation mapping purposes, the methodology from PRODES (Measurement of Deforestation by Remote Sensing), the official Brazilian system for deforestation monitoring, consider as forest only the primary forest cover (does not account for regeneration deforestations). These are areas classified as having forest physiognomy, which includes Dense Ombrophiles Forest, Open Ombrophiles Forest, Seasonal Deciduous Forest, Alluvial Vegetation, Oligotrophic Woody Vegetation in Swamps and Sandy Accumulations, Ecological Tension Areas (Forest/Savannah Transition), where forest physiognomy predominates (de Almeida et al., 2022).

2.2.2 Agriculture

The definition for agriculture use appears to be less controversial and for the present analysis it "means the use of land for the purpose of agriculture, including for agricultural plantations and set aside agricultural areas, and for rearing livestock" (European Commission, 2023a). Nevertheless, it is also important to mention the definition of agricultural plantation, which refers to land with tree stands used in agricultural production systems such as fruit tree plantations and agroforestry systems where crops are cultivated beneath tree cover is included. This encompasses all plantations of relevant non-wood commodities. However, agricultural plantations are explicitly excluded from the definition of "forest" (European Commission, 2023a).

2.2.3 Forest change, Deforestation, Degradation

It is important to set the concepts and relationships between forest change, deforestation, degradation, considering the present context. FRA (FAO, 2020) defines forest area net change as the summing, over a period, of all gains from afforestation and natural forest expansion, and the subtraction of all losses due to deforestation from the gains. According to FRA FAO (2020), forest expansion implies a transformation of land use from non-forest to forest. If forest expansion exceeds deforestation, the net change is positive, indicating an overall increase in forest area. If deforestation outweighs forest expansion, the net change is negative, reflecting an overall loss of forest area (FAO, 2020).

For the EUDR deforestation "means the conversion of forest to agricultural use, whether human-induced or not", whereas forest degradation "means structural changes to forest cover, taking the form of the conversion of: (a) primary forests or naturally regenerating forests into plantation forests or into other wooded land; or (b) primary forests into planted forests" (European Commission, 2023a).

There are important practical implications from those definitions. Deforestation followed by non-agricultural use is not considered as deforestation for the regulation, such as roads or urban expansion. Primary forests, existing until 31 December 2020, turned into planted forests, plantation forests or other wooded land will be considered as degradation. Naturally, regenerating forests, existing until 31 December 2020, converted into Plantation forests or other wooded land will be considered degradation. Nevertheless, forest degradation might not be applied when there is a sustainable wood harvesting framework, as it comes with proof that it will not lead to forest degradation. Another exception comes from forest areas degraded due to climate change, diseases or fires not caused by the wood harvesting. In all cases there will be the need for robust evidences to support (European Commission, 2023a).

Finally, it worths to emphasize that the PRODES methodology does not account for deforestation in regenerated areas, in other words the deforestation is only mapped once and will be like that even if the area gets reforested (de Almeida et al., 2022).

2.2.4 DEFORESTATION-FREE

The importance of the deforestation-free definition lies in the application or not of the EUDR restrictions. In that sense, that concept decouples from the deforestation definition due to the cut-off date. In other words, deforestation-free cannot be applied for relevant products made with commodities from areas that were subject of deforestation or degradation after 31 December 2020.

2.2.5 EUDR - COMMODITIES

The EUDR establishes the relevant commodities (cattle, cocoa, coffee, oil palm, rubber, soya and wood) and the products listed in Annex 1 (which are essentially the ones produced using the relevant commodities) that the regulation must be applied (European Commission, 2023a). The Annex 1 presents a table with the commodity and its respective products associated with the Combined Nomenclature (CN) name and code from the Regulation (EEC) Nº 2658/87. The CN code is an eight-digit commodity classification system that refines the global Harmonized System (HS) Nomenclature, providing greater specificity to meet the unique requirements of the European Community.

These codes are the basis for goods declaration during import and export processes, as well as for compiling trade statistics. In the EUDR Annex 1 there is an “ex” before the some of the product’s codes, meaning is an “extract” from all items that can be classified under a particular CN code, narrowing the scope to meet the Regulation’s specific requirements. For example, while CN code 9401 includes seats made from various raw materials, only wooden seats fall under the Regulation's scope (European Commission, 2024).

	… made of a commodity listed in Annex I	**… not made of a commodity in Annex I**
Relevant product listed in Annex I…	Subject to the Regulation (EUDR)	Not subject to the Regulation
Other product not listed in Annex I…	Not subject to the Regulation	Not subject to the Regulation

Figure 2 – Matrix to EUDR relevant product identification (FAQ European Commission, 2024)

The first two digits from CN refers to a generic description of the good, or Chapter, for instance “16” is related to “Preparations of meat, of fish or of crustaceans, mollusks or other aquatic invertebrates”. Thereof, all the codes starting with that number concerns to derived product and the increase of digits makes the description even more specific, such as “160250” that is “Of bovine animals”, which is the product subjected to the EUDR *de facto*. In that sense, it is not easy to properly interpretate nor implement the selection of the traded goods affected by EUDR.

By 30 June 2025, the Commission will evaluate the feasibility of extending coverage to commodities like maize and consider updates to Annex I to include additional products, such as biofuels (HS code 382600). Furthermore, this review will assess the role of financial institutions in preventing financial flows contributing to deforestation, potentially recommending new obligations for these entities.

2.2.3 AGRICULTURE-DRIVEN DEFORESTATION

Agriculture-driven deforestation refers to the clearing of forests where agriculture is a contributing factor, either directly or indirectly. This encompasses deforestation for agricultural production as well as deforestation influenced by agricultural needs without necessarily expanding agricultural production (Pendrill et al., 2022). Agriculture is not always the unique or primary cause and, for instance, deforestation can also be driven by the demand for timber in addition to agricultural expansion (S. D. Tarigan et al. 2015; D. Kleinschmit et al. 2016; D. L. A. Gaveau et al. 2013 as cited by (Pendrill et al., 2022). Moreover, indirect or underlying factors often play a interfere in this process (Meyfroidt, 2016). The establishment of agricultural activities over deforested areas also occurs with different time lags. For instance, Pendril et al. 2019, considered 3 years from the deforestation to soya crops implementation in Brazil.

An important indirect factor influencing deforestation is land speculation, which is often associated with unclear or disputed land ownership (Pendrill et al., 2022). In some countries, such as Brazil, deforestation is used to assert land tenure rights, particularly in regions where laws link land ownership to the act of clearing land. Land tenure disputes further exacerbate deforestation in contested regions, frequently exceeding what is required for agricultural productivity (Azevedo-Ramos and Moutinho 2018; Miranda et al. 2019).

Social dynamics also play a significant role. In Brazil, the anticipation of future agricultural profits fueled by planned infrastructure projects, rising commodity prices (Berman et al., 2023), and uncertainties surrounding forest conservation policies encourages speculative land clearing (Miranda et al., 2019; Azevedo-Ramos et al., 2018). This speculation can result in cycles of agricultural expansion and abandonment, where land is cleared up but left unused due to unfavorable market conditions or failed ventures. For instance, in the Brazilian Amazon, land cleared for speculation often becomes low-yield pasture, which may quickly degrade and eventually be abandoned (Garrett et al., 2017; Strassburg et al., 2014). In the Amazon, fire can be another important indirect deforestation driver, even when they were not meant to do so. When used for clearing areas during agricultural land management, they can spread into nearby forests, causing degradation or complete deforestation (Barlow et al., 2020).

2.3 Spatio-Temporal Explicit Methods

The spatially explicit methods are approaches that consider the geographic location of data in analyses. These methods are crucial for understanding patterns and processes that vary across space, such as deforestation and its driving factors. The Geographically Weighted Regression (GWR) method allows for modelling relationships that vary across space (Fotheringham et al. 2002). Instead of assuming a global and uniform relationship, GWR estimates local regression coefficients, meaning that the relationship between dependent and independent variables can change from one location to another. This is achieved by assigning weights to neighboring observations based on their geographic proximity. GWR is particularly useful for handling spatial non-stationarity, which occurs when statistical relationships are not constant across space (Fotheringham et al., 2015; C. Wu et al., 2019).

The Geographically and Temporally Weighted Regression (GTWR) extends GWR by incorporating a temporal dimension into the analysis (Fotheringham et al., 2015). This allows relationships between variables to vary not only spatially but also over time. Similar to GWR, GTWR assigns weights to neighboring observations based on both spatial and temporal proximity, using a spatiotemporal kernel function. The GTWR model has been widely applied in housing price studies, proving its ability to capture significant spatio-temporal variations. Huang et al. (2010) introduced the GTWR model to address spatial and temporal heteroscedasticity, constructing a weight matrix based on spatio-temporal distances. Later, Fotheringham et al. (2015) extended GWR into a new GTWR framework for panel data, allowing the separation of spatial and temporal bandwidth selection. GTWR is valuable for analyzing phenomena that change over time and space, such as the impact of exports on forest cover.

Spatial Autoregressive Models (SAR) & Conditionally Autoregressive Models (CAR) models account for spatial autocorrelation in the data. Spatial autocorrelation occurs when the value of a variable at a given location is influenced by the values of the same variable in neighboring locations(B. Wu et al., 2014). SAR and CAR models help capture this spatial dependency in the residuals of a regression, ensuring that analyses properly account for spatial effects (Kawsar, 2013). Many studies apply spatial regression models to examine factors influencing land use and deforestation on the Amazon. These models assess the relationships between deforestation and variables such as proximity to roads, indigenous reserves, urban centers, development policies, and various environmental, socioeconomic, and demographic factors (De Espindola et al., 2012).

Point process models are used to analyze the spatial distribution of events, such as deforestation hotspots or conflict zones. These models help examine the spatial intensity of events, the dependence between events, and the influence of covariates on their distribution. They are especially useful in understanding the relationship between climate and conflict and include spatiotemporal K-function analysis (Kawsar, 2013). Lattice Models involve analyzing data that is aggregated into spatial units, such as municipalities or regions. The data is structured in a grid (or lattice), allowing for statistical analyses to explore the spatial distribution of events and relationships between variables (Kawsar, 2013).

There are additional spatial methods such as Spatial Spillover Analysis, which examines how a phenomenon in one location influences nearby locations or areas connected through trade networks, communication systems, or other flows (Yin et al., 2020). The Economic Complexity Index (ECI) assesses the diversity and sophistication of economic activities within a region. While not inherently a spatial method, ECI can be mapped and analyzed geographically to understand how economic complexity influences deforestation patterns across municipalities (Silveira et al., 2025).

3. METHODOLOGY

The present Chapter is divided into parts responsible for explaining the study area, the datasets and software employed, pre-processing steps, the conducted exploratory analysis and the parameters for GTWR computation. The diagram in Figure 3 presents the methodology general workflow.

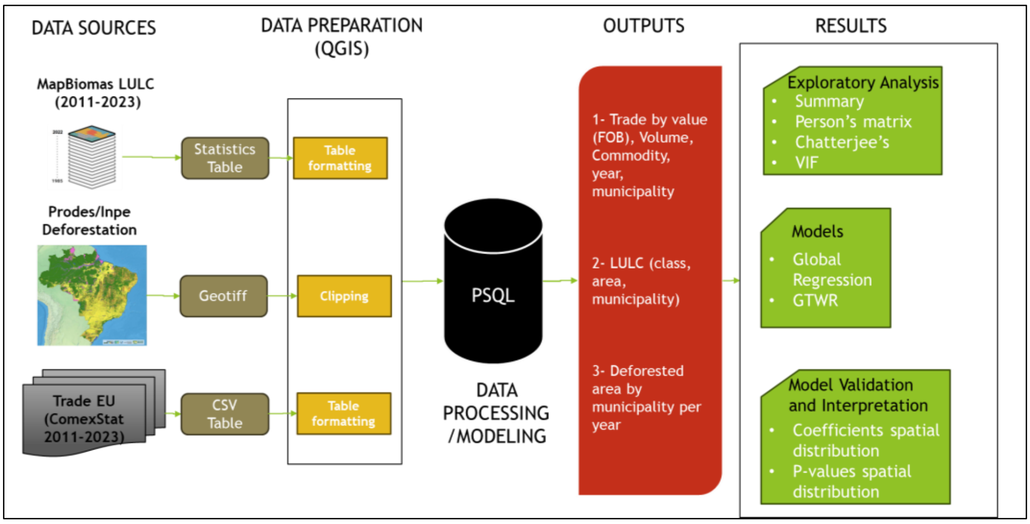

Figure 3 – Diagram with the workflow for present analysis.

3.1 Study Area

The Brazilian Legal Amazon was established as a political and planning concept for regional development through Law 1,806 on January 6, 1953, later modified by other Laws in 1966 and 1977, altering limits and other points. It covers, approximately, 59% of Brazil's territory, encompassing totaling around 5 million km² (de Almeida et al., 2022; Silveira et al., 2025). Currently, there are 772 municipalities considered officially within the Legal Amazon[9], which spreads over eight entire states (Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, and Tocantins) and part of Maranhão (west of the 44°W meridian), as presented in Figure 4.

[9] https://www.ibge.gov.br/geociencias/informacoes-ambientais/geologia/15819-amazonia-legal.html

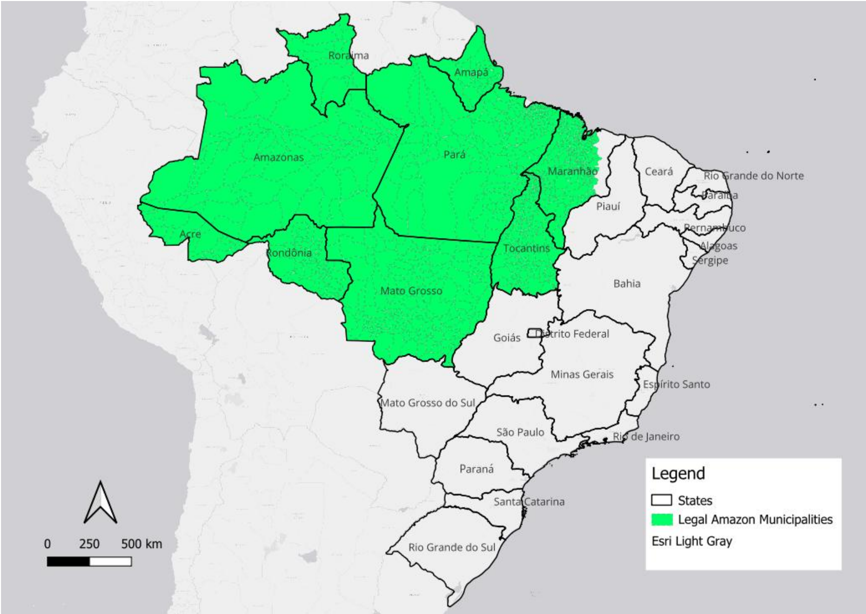

Figure 4 - Legal Amazon municipalities in green

According to the data sources employed in the present research, the Legal Amazon overall relevant numbers are presented in the Table 1.

Table 1 – Relevant numbers for the Legal Amazon from data sources, where FOB = *Free on Board* (USD).

Description	Total (Million)
Deforestation 2011-2022	27
Forest Cover 2023	340
Forest Cover 2011	354
Forest Cover Change 2011/23	-14
Value Traded (FOB)	11.870.000
Volume Traded (kg)	17.000.000
EU Volume Traded (kg)	3.784.000
EU Value Traded (FOB)	2.565.000
Wood Volume Traded (kg)	8.754.000
Wood Value Traded (FOB)	5.207.000
Soya Volume Traded (kg)	6.840.000
Soya Value Traded (FOB)	3.128.000
Others Volume Traded (kg)	6.554
Others Value Traded (FOB)	8.917

Cattle Volume Traded (kg)	1.336.000
Cattle Value Traded (FOB)	3.441.000

Between 2011 and 2023, 27.23 million hectares of deforestation were identified by PRODES, whereas the net forest cover indicates a reduction of 13.72 million hectares. According to MapBiomas data, the total forested area decreased from 353.9 million hectares in 2011 to 340.1 million hectares in 2023. The total trade volume reached 17 trillion kg, with a corresponding trade value of 11.87 trillion USD (FOB). The EU accounted for approximately 22% of total trade, importing 3.78 trillion kg of goods valued at 2.57 trillion USD, reinforcing its role as a major market for forest-risk commodities.

Among the most traded commodities, wood products dominated exports, representing 51% of total trade volume (8.75 trillion kg) and 44% of trade value (5.21 trillion USD). Soy exports were the second largest contributor, accounting for 40% of the trade volume (6.84 trillion kg) and 26% of total trade value (3.13 trillion USD). Cattle trade, while representing only 8% of total volume (1.34 trillion kg), had a high trade value of 3.44 trillion USD, making up 29% of total trade earnings. Other commodities, including palm oil and cocoa, represented a relatively small share of global trade, with a combined volume of 65.5 billion kg and a total trade value of 89.2 billion USD.

The spatial distribution of the percentual of EUDR-Relevant commodities that were exported to EU between 2011 and 2023, in quantile intervals, is presented in the Figure 5. For the municipalities in yellow, the importance of the EU union market is particularly high, with more than 43% of the external trade being sent to EU, representing 20% of the 226 municipalities that exported EUDR-Relevant commodities.

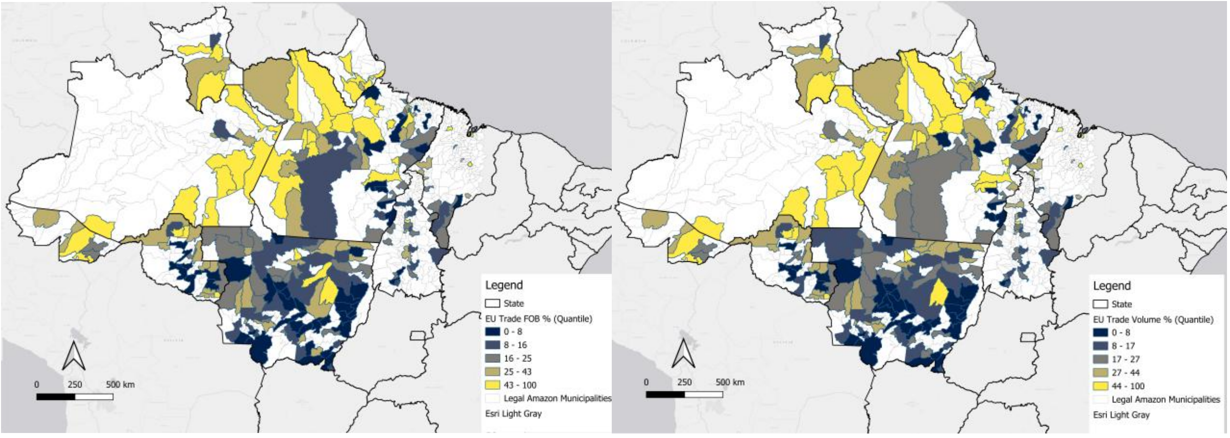

Figure 5 - Percentual of EUDR-Relevant commodities trade with EU regarding the total exportation. On the left in Trade FOB value (USD) and on the right in volume (kg).

3.2 DATA

3.2.1 LAND USE LAND COVER (LULC)

The MapBiomas LULC data was built using the random forest algorithm applied to Landsat imagery within the Google Earth Engine platform. Their classification framework includes five primary categories: forest, non-forest natural formations, farming, non-vegetated areas, and water. These categories are further subdivided into two hierarchical levels, resulting in a detailed and extensive mapping of Brazil at a 30-meter spatial resolution. According to (Souza et al., 2020), the validation for the classification from 1988 to 2017, using a stratified random sample of 75,000 pixels, indicates an average overall accuracy of 89%, with biome-specific accuracy ranging from 73% to 95%.

Within their platform[10] there are available various products, including the tiff files with the classification for every year and statistics sheets summarizing the data by distinct spatial units, such as municipalities. For the present analysis, the latter was selected, because by using the geocode field it is possible to join with the corresponding spatial database published by the

[10] https://brasil.mapbiomas.org/

Brazilian Institute of Geography and Statistics (IBGE)[11] and perform the spatial-temporal analysis.

For the present analysis only Forest, Flooded Forest, Mangroves and Natural Woodlands were selected from the MapBiomas data, since they would better represent the forest cover according to the EUDR definition, as mentioned in section 2.2.1 Forest.

3.2.2 TRADE

The data from external trade comes from "ComexStat" [12], a Brazilian Government platform with foreign trade data, which enables tracking of commodity exports destinations and their origins within specific municipalities. There are diverse ways to access the data, the complete database being selected, provided in csv format. It comes detailed by municipalities with columns representing: HS product codes with 4 digits; Year; Month; Country codes for product origin/destination; State (UF) and municipal codes of the fiscal domicile for exporting/importing companies; Net weight (kilograms); and Free On Board (FOB) value in US dollars.

The FOB value refers to the products price at the point of shipment, excluding transportation costs, insurance, and customs duties. Consequently, we end up with two different units to represent the amount of trade within a period. Additionally, the platform provides auxiliary tables to correlate with destination countries and other nomenclatures. It is necessary to mention that some of the goods referred in the EUDR have a 6 digits HS code, whereas the ComexStat data comes only with the 4 digits code. In that sense, were included products/commodities that do not concern to the Regulation, such as Porch and chicken, by the impossibility to identify and exclude them. Finally, the HS codes referred in the EUDR Annex were typed directly in a database table, for further use in the selection of the relevant traded products.

[11]https://www.ibge.gov.br/geociencias/downloads-geociencias.html?caminho=cartas_e_mapas/bases_cartograficas_continuas/bc250/versao2023/

[12] Comex Stat. (n.d.). Comex Stat. [Online]. Available: http://comexstat.mdic.gov.br/en/home

3.2.3 DEFORESTATION

The data comes from PRODES, developed by the National Institute for Space Research (INPE). The system has yearly deforestation data series from 2008 to 2022 through Landsat image classification, despite more recently it is being also used SENTINEL-2 and CBERS4/4A satellite images (de Almeida et al., 2022). The data is available in GeoTiff format in the TerraBrasilis[13] platform for the whole country. The PRODES methodology follows specific assumptions for mapping deforestation in the Amazon. As explained in section 2.2.1, they only map primary forest deforestation. In that sense, the natural cover that do not belong to the forest domain, INPE has classified and mapped as “non-forest” areas, as presented in the Figure 6.

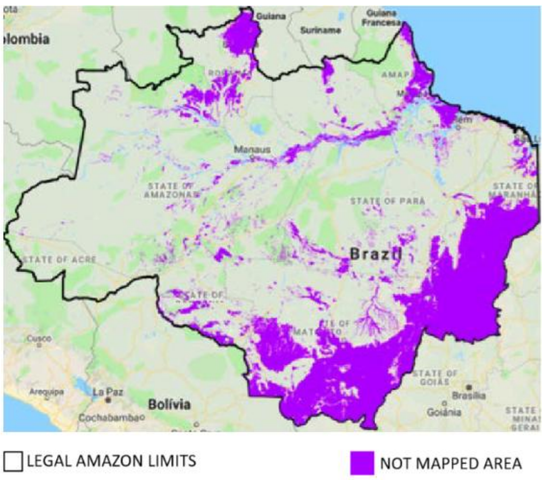

Figure 6 - Legal Amazon Limits and PRODES “non-forest” not mapped area (de Almeida et al., 2022)

Deforestation increments are mapped using expert photointerpretation of satellite imagery. It is assumed that most deforestation occurs during the dry season when vegetation spectral characteristics are ideal for detection, and cloud cover is minimal. Satellite images are therefore preferentially acquired during this period, which varies by latitude across the Amazon. The images employed by PRODES have a spatial resolution of approximately 20-30 meters, a revisit cycle of 5 to 26 days, and at least three spectral bands. In cases of high cloud cover, multiple images from different sensors or acquisition dates may be combined to form a complete dataset. Deforested areas are mapped if they exceed 1 hectare, but only polygons larger than 6.25 hectares are included in official deforestation rate calculations. The

[13] https://terrabrasilis.dpi.inpe.br/en/home-page/

deforestation rate for a given PRODES year estimates forest loss between August 1 of the previous year and July 31 of the current year. For example, the 2020 deforestation rate accounts for deforestation between August 1, 2019, and July 31, 2020 (de Almeida et al., 2022).

3.3 SOFTWARE AND PACKAGES

The analysis was implemented using QGIS, PostgreSQL/Postgis, Visual Studio, Rstudio, R (RPostgres, dplyr, sf, GWmodel, ggplot2, tidyr, car, XICOR).

3.4 PRÉ-PROCESSING

The pre-processing step started using QGIS to open the csv and *GeoTiff* files, because it can handle well with columns datatypes identification and the exportation to the *PostgresSQL* database. The QGIS *"PostGIS Raster Import"* plugin was very helpful to load the deforestation data to the database, which had the *PgRaster* extension installed. Once in the database, the deforestation data was polygonised using the ST_*DumpAsPolygons* function, which allowed the calculation of the deforested area by municipality per year using the st_*intersection* and st_*area* functions.

In the database, the trade and land cover data were transformed from wide to long format, in which the years are stored in one column and each row represents a certain value within the respective year. To filter the relevant products, the list of EUDR products codes was joined with the auxiliary table from ComexStat with the complete description using SQL queries. It began by selecting HS2, HS4, and HS6 columns and then joining the values according to the codes referred in the EUDR, while excluding records containing certain keywords related to recycling and bamboo. The number of relevant possible products HS6 codes grouped by HS2 codes are presented in the Table 2.

Table 2 – Number of products by HS2 codes

HS2	Description	Count
44	Wood and articles of wood; wood charcoal	171
48	Paper and paperboard; articles of paper pulp, of paper or of paperboard	137
40	Rubber and articles thereof	71

41	Raw hides and skins (other than furskins) and leather	29
94	Furniture; bedding, mattresses, cushions and similar stuffed furnishings; others	27
49	Books, newspapers, pictures and other products of the printing industry; others	21
47	Pulp of wood or of other fibrous cellulosic material, others,	15
18	Cocoa and cocoa preparations	11
2	Meat and edible meat offal	9
15	Animal or vegetable fats and oils; Others	6
12	Oil seeds and oleaginous fruits; Grains, Seeds, others	5
9	Coffee, tea, maté and spices	5
38	Miscellaneous chemical products	4
29	Organic chemicals	3
1	Live animals	2
23	Residues and waste from the food industries; others	2
16	Preparations of meat, of fish or of crustaceans, others	1

With the table holding the full description of the EUDR relevant products, the trade dataset was joined using the HS4 code to generate the final trade dataset, which was divided into five different tables. The first table summarizes all trade of the relevant products in the study area and the others contain the data from cattle, soya, wood and others related products.

3.5 Exploratory analysis

The exploratory analysis was performed using R and included the general summary of the variables, Pearson's correlation matrix, Chatterjee's correlation coefficients with P-values, temporal trends and Variance Inflation Factor (VIF), to address multicollinearity issues. It was performed for forest cover, total trade (FOB value and volume kg) and the relevant products from cattle, soya, wood and others.

Chatterjee, 2021 mentions that Pearson's correlation coefficient is effective in identifying linear or monotonic relationships but suffers with a limitation in detecting non-monotonic associations, even in scenarios where there is no noise in the data. In that sense, the Chatterjee's correlation coefficient is relevant to the current analysis due to its ability to detect nonlinear and non-monotonic dependencies between variables (Chatterjee, 2021). This is important because the relationship between EUDR-regulated trade and deforestation may be complex and nonlinear, influenced by various socioeconomic and environmental factors. The coefficient quantifies the strength of the relationship between variables, ranging from 0 (independence) to 1 (perfect functional dependence) (Chatterjee, 2021). This allows an assessment of how strongly EUDR trade is associated with forest cover, even if the relationship is not linear.

Since the Chatterjee coefficient is rank based, it is robust to outliers and invariant under monotonic transformations of the data (Chatterjee, 2021). This is particularly useful when dealing with deforestation and trade data, which may contain outliers or measurement errors. The Chatterjee coefficient converges to a limit that provides an intuitive measure of dependence. The coefficient also has a straightforward asymptotic theory under the assumption of independence, which remains approximately valid even for sample sizes as small as 20 observations. This enables theoretical independence tests, avoiding computationally expensive permutation tests required for other methods (Chatterjee, 2021).

The Chatterjee coefficient appears to be equitable, assigning similar scores to relationships of equal noise levels but of different types. For the present analysis, the Chatterjee's coefficient was computed considering times lags from 0 to 5 years, since the effects of the trade in the deforestation might appear later. The P-values were calculated by permutations tests using the R package named XICOR (Association Measurement Through Cross Rank Increments), available on CRAN.

3.6 Geographically and Temporally Weighted Regression Method

For the present research, according to the literature, GTWR seemed to be one of the most suitable methods to be explored. The phenomenon under study occurs differently over the municipalities and over the time, in that case the forest cover change and trade dynamics choice (Köthke et al., 2023; Pendrill, Persson, Godar, Kastner, et al., 2019). The GTWR ability to handle spatial and temporal nonstationarity, capture spillover effects, and incorporate local context makes it a promising (Fotheringham et al., 2015; B. Wu et al., 2014; C. Wu et al., 2019; Yin et al., 2020). The GTWR generic function can be written as

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i \tag{1}$$

where (u_i, v_i) refers to the coordinates in time (t_i), $\beta_0(u_i, v_i, t_i)$ represents the intercept and $\beta_k(u_i, v_i, t_i)$ the parameters for a point i. It is relevant to mention some of the key parameters and characteristics regarding GTWR. It employs a kernel function that accounts for both spatial and temporal distances between observations. This function assigns weights to neighboring data points based on their proximity in space and time, ensuring that the local analysis is influenced by the most relevant observations. Typically, the kernel is a Gaussian or Bi-square function (Fotheringham et al., 2015; Huang et al., 2010; B. Wu et al., 2014).

The equation 2 presents an example of a spatiotemporal weighting function, which applies to data points at a given time t. This function follows a general structure of a spatiotemporal kernel function, where the weights are determined by a spatial kernel function (k_s) and (d_{sij}) represents the Euclidean distance between the regression point ii and the data point j .

$$w_{\{ijS,T\}}^{\{t\}} = k_S\left(d_{\{sij\}}, b_S\right) \times k_T\left(d_{\{tij\}}, b_T\right) \tag{2}$$

The bandwidth determines the spatial and temporal range of neighboring observations used for estimating local coefficients. A smaller bandwidth gives greater weight to nearby observations, capturing more localized variations. A larger bandwidth smooths local variations by incorporating a broader set of observations. Adaptive bandwidths adjust dynamically based on data density. GTWR allows the relationships between dependent and independent variables to change across space and time. Each location has a unique regression model, capturing non-stationarity in the data (Fotheringham et al., 2015; Huang et al., 2010; B. Wu et al., 2014).

The Figure 7 illustrates a potential time-decay spatiotemporal bandwidth, where the regression period is denoted as T, and a temporal bandwidth of three years is taken into account (T − 1, T − 2, and T − 3) (Fotheringham et al., 2015; Huang et al., 2010; B. Wu et al., 2014)). The figure demonstrates that as observations move further away from the reference time point, the spatial bandwidth progressively decreases.

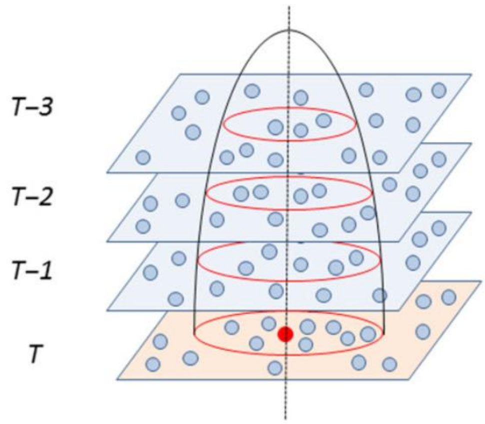

Figure 7 - Example of time-decay spatiotemporal bandwidth (Fotheringham et al., 2015)

Compared to GWR, which only accounts for spatial non-stationarity, GTWR improves modelling accuracy by incorporating both spatial and temporal variations. Additionally, ANOVA tests indicate that GTWR provides significant improvements over global OLS models and other GWR-based approaches (B. Wu et al., 2014).

3.6 GTWR IMPLEMENTATION

The GTWR implementation occurred progressively, starting with the forest cover as dependent variable (y), total trade in volume (kg) and FOB value, later added soya trade FOB, cattle FOB, wood FOB and others FOB as predictors. The complete list of the variables and their abbreviations is presented in Table 3.

Table 3 - List of variables and abbreviation

Abbreviation	Variable Name
Forest	Forest Cover - ha
Trade_FOB	Trade Free on Board (FOB) Value - USD
Trade_Volume	Trade Volume - kg
Deforestation	Deforestation - ha
vl_fob_cattle	Cattle Trade FOB Value - USD
vl_fob_others	Other Commodities Trade FOB Value - USD
vl_fob_soya	Soy Trade FOB Value - USD
vl_fob_wood	Wood Trade FOB Value - USD
Trade_FOB_norm	Normalized Trade FOB (Min-Max Scaling)
Trade_Volume_norm	Normalized Trade Volume (Min-Max Scaling)
Deforestation_norm	Normalized Deforestation (Min-Max Scaling)

The GTWR computation was performed throughout 7 different model configurations, as shown in the Table 4. The Model 1 to 5 considered only the 226 municipalities, the ones that had some trade within the period, and the Model 6 and 7 considered all the 772 municipalities withing the Legal Amazon, in which the processing time was about 3 days. This is why more tests were conducted without considering the whole area, to evaluate the data frame, normalization, parameters and the independent variables behavior.

Table 4 - Overview of the tested models

Model	Formula	Description
Model 1	Forest ~ Trade_FOB + Trade_Volume	Examines the impact of total trade value (FOB) and trade volume on forest cover.
Model 2	Forest ~ Trade_FOB + Deforestation	Adds deforestation as a predictor alongside trade value (FOB) to assess its combined impact on forest cover.
Model 3	Forest ~ Trade_FOB_norm + Trade_Volume_norm + Deforestation_norm	Uses min-max normalization for trade value (FOB), trade volume, and deforestation to standardize their scales.
Model 4	Forest_norm ~ Trade_FOB_norm + Trade_Volume_norm + Deforestation_norm	Applies normalization to both independent and dependent variables for better comparability.
Model 5	Forest ~ vl_fob_cattle + vl_fob_others + vl_fob_soya + vl_fob_wood + Deforestation	Disaggregates trade value into specific commodity groups (cattle, others, soy, wood) along with deforestation.
Model 6	Forest ~ Trade_FOB + Trade_Volume	Similar to Model 1 but computed for all municipalities.
Model 7	Forest ~ vl_fob_cattle + vl_fob_others + vl_fob_soya + vl_fob_wood + Deforestation	A variant of Model 5 but computed for all municipalities.

The kernel selection considered the need to deal with the heterogeneity of the data in space and time, which reflects the phenomenon studied itself. The forest cover varies along the municipalities in many orders of magnitude as the deforestation and trade, whereas the latter suffers from a large amount of zero values. Indeed, there are many municipalities that present forest cover and deforestation, but never exported any of the EUDR-relevant products or did it sparsely between 2011 and 2023.

In that sense, the combination of GTWR with the adaptive bi-square kernel provides a flexible and precise spatio-temporal analysis of the relationship between commodity trade and forest cover in the Legal Amazon. This approach can handle with nonstationarity in data, allowing the scale of analysis to dynamically adjust to variations in data density. This happens because the adaptive kernel function adjusts dynamically by selecting a specific number of nearest neighbors, ensuring a consistent local sample size (B. Wu et al., 2014).

This approach allowed the weighting functions to scale according to variations in data distribution. In regions where data points are sparse, the kernel expands, increasing its bandwidth, whereas in areas with dense data, the bandwidth contracts. The bi-square function assigns fractionally decreasing weights to data points based on their proximity to a given location until a fixed distance or a threshold defined by the N-th nearest neighbors (Lu et al., 2014).

The optimal bandwidth was determined using a corrected version of the Akaike Information Criterion (AICc). To compare the results from the models the R-squared and P-values were considered. Using an R function, the P-values computation was performed with permutations using the cumulative distribution function (CDF) of the t-distribution, the degrees of freedom from the GTWR model. This calculates two-tailed p-value by multiplying by 2 the upper tail probability for the absolute value of the t-values.

4. RESULTS AND DISCUSSION

In this Chapter aims to deliver the results of the exploratory analysis and the GTWR computation as discuss the outcomes. Initially, the variables summary is presented, together with the Person's and Chatterjee's correlation analysis, followed by Variance Inflation Factor (VIF) computing, for variables redundancy verification. The last part is dedicated to the GTWR results, with temporal trends plot and the spatial distribution of the coefficients and of the statistical significance indicators.

4.1 EXPLORATORY ANALYSIS

The statistics summary for the total trade of EUDR related products (Table 5), considering all the 772 municipalities from the study area, revealed that forest shows large disparities, ranging from 277 hectares to 15 million hectares in different municipalities. The trade data (FOB value and trade volume) has a highly skewed distribution, with a significant number of municipalities reporting zero trade in a given year. The mean trade value (FOB) is approximately 1.114 billion USD, while the maximum recorded value is 114.2 billion USD. The mean trade volume is 1.572 billion kg, with a maximum recorded volume of 171.8 billion kg.

Table 5 – Variables summary

Variable	Description	Min	1st	Median	Mean	3rd	Max
forest	Forest cover area (hectares)	277	20,615	55,281	451,687	294,914	15,021,364
vl_fob_total	Total trade value (FOB)	0	0	0	1,11E+12	0	1,14E+14
kg_liquido_total	Total trade volume (kg)	0	0	0	1,57E+12	0	1,72E+14
deforestation	Deforested area (hectares)	0.00	17.03	256.74	1,484.60	1,431.05	79,810.28
vl_fob_cattle	Trade value of cattle (FOB)	0.00	0.00	0.00	3,27E+11	0.00	9,26E+13
vl_fob_others	Trade value of other commodities (FOB)	0.00	0.00	0.00	7,31E+09	0.00	7,72E+12
vl_fob_soya	Trade value of soya (FOB)	0.00	0.00	0.00	2,81E+11	0.00	3,03E+13
vl_fob_wood	Trade value of wood (FOB)	0.00	0.00	0.00	5,00E+11	0.00	7,60E+13

Considering the deforestation and trade FOB value by products commodity type, deforestation data exhibits significant variation, with an average of 1,484.60 hectares deforested per year per municipality, but with some areas reaching up to 79,810 hectares. This highly skewed distribution and with substantial number of zero values poses a challenge and demonstrates the heterogeneity of the variables in space and time. The FOB value was selected for analyzing the trade by commodity type, because changes in prices impact deforestation rates (Berman et al., 2023b; Pendrill et al., 2022; Richards et al., 2012; Silveira et al., 2025).

4.1.1 Pearson's Correlation

The total trade value is composed of cattle, soya, wood and other related EUDR relevant products. This makes the analysis of interrelations among trade variables necessary, since it allows us to evaluate how much related products FOB values contribute more to the total trade volume and value. In that sense, the Pearson's correlation matrix in Figure 8, shows that the Total Trade Value (vl_fob_total) is highly correlated with Cattle Trade (0.73), Soy Trade (0.74), and Wood Trade (0.72), indicating that municipalities engaged in one type of commodity trade tend to have higher overall trade values. Trade volume (kg_liquido_total) shows strong positive correlations with total trade value (0.74), cattle trade (0.73), soy trade (0.74), and wood trade (0.72), suggesting that as the quantity of traded goods increases, their financial value also rises.

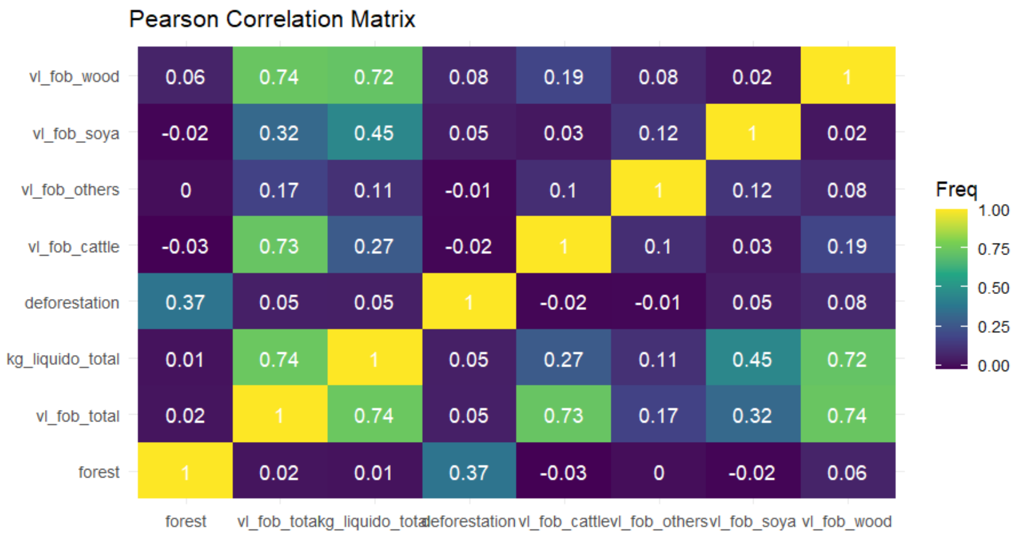

Figure 8 - Person correlation for the analyzed variables.

It is also possible to verify that the Forest cover presents an inverse low correlation with trade values of cattle (−0.03), soy (−0.02), indicating that the decrease in forest cover is not strongly associated with trade volume or value increase for these commodities. Deforestation and Cattle Trade (−0.02) presented a weak correlation, but with an unexpected negative sign, which suggests that the increase in cattle trade would lead to a small decrease in deforestation. On the other hand, Deforestation and Soy Trade (0.05), and, Deforestation and Wood Trade (0.08) presents a weak positive correlation, suggesting that increase in soy and wood-based products may produce a small increase in deforestation. Soy Trade and Cattle Trade (0.45) presented a moderate correlation, possibly indicating that regions engaged in cattle production also participate in soy cultivation.

A moderate positive correlation (0.37) between forest cover and deforestation, suggests that areas with more forest cover also tend to experience higher deforestation. This is expected, as municipalities with extensive forests have more land available for conversion. This highlights the need to analyze whether forest cover acts as a constraint on trade expansion or if deforestation trends are influenced by external policies. The fact that deforestation is not mapped for several municipalities, as mentioned in section 3.2.3 Deforestation, may have led to a moderate correlation, instead of a stronger one.

4.1.2 CHATTERJEE'S CORRELATION

The weak correlations between forest cover and trade values suggest that hidden dependencies might exist, in which further investigation was performed using Chatterjee's correlation. The correlation with forest cover was computed individually for all variables (Table 3), except normalized form, with time lags from 0 to 5 years. Because, the intended land use may occur years later, not being for instance the one happening in the first years, which can be called as lag time or allocation period (Pendrill et al., 2022).

The Figure 9 presents the Chatterjee's coefficients and the respective P-values, with the red dashed line at 0.05 representing the threshold for statistical significance. For Total Trade Volume (Cyan), its correlations remain relatively high with fluctuations and the p-values mostly low, implying consistent and statistically significant relationships over different lags.

The Total FOB Value (blue) correlation gets weaker after lag 2, with statistically significant relationships for 0, 1 and 3 years lag.

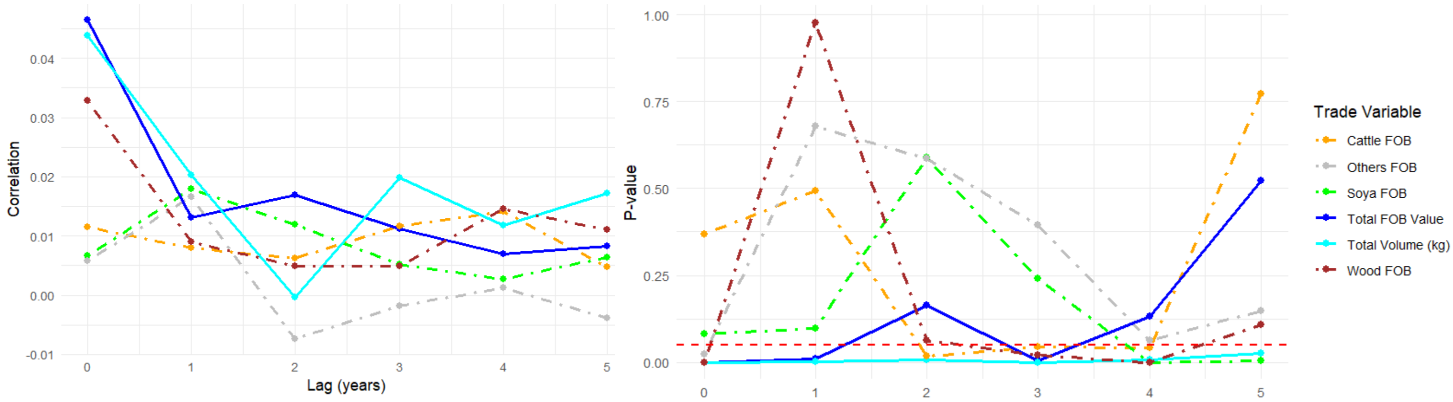

Figure 9 - Chatterjee's correlation coefficient (left) and P-values (right) over different time lags, with forest cover as dependent variable.

For Cattle FOB the highest correlation with the most statistically significant relationship occurs for 4 years lag. The Soya FOB presents statistically significant p-values for 4 and 5 years lag, which the latter hold higher correlation between them. Wood FOB presented a peak for the P-value with 1 year lag, having the higher correlation with the most statistically significant for 0-year lag, followed by 4-year time lag. In general, the correlation is weak but stable for most of the variables. The results support the idea that different commodities affect forest cover differently over time, emphasizing the need for spatiotemporal models like GTWR to capture these patterns more effectively. In that sense, trade dynamics may change over time, and different trade sectors respond differently to lag effects.

Concerning the multicollinearity evaluation for Model 5, 6 and 7 independent variables, all of them presented a VIF < 7.5, which indicates that multicollinearity is not an issue, as can be observed in Table 6 and Table 7.

Table 6 - VIF values for the independent variables of Model 6

vl_fob_total	kg_liquido_total
2.2447	2.2447

Table 7- VIF values for the independent variables of Model 5 and 7

Deforestation	vl_fob_cattle	vl_fob_others	vl_fob_soya	vl_fob_wood
1.0094	1.0445	1.0294	1.0182	1.0466

4.2 GTWR RESULTS

The results from Model 6 (Table 8) and Model 7 (Table 9) are considered the most relevant, because they were performed for all municipalities in the Legal Amazon. Unfortunately, it was not possible to run many tests like this because each computation took about 3 days to be performed. The outputs for the other models are presented in the Appendix.

Table 8 - Results from Model 6

Metric	Global	GTWR
T-value (Trade FOB)	-1.197	-
T-value (Trade Volume)	0.045	-
P-value (Trade FOB)	0.231	-
P-value (Trade Volume)	0.964	-
Global P-value	0.1825	-
AIC	310583	303099
R^2	0.000339	0.531503
RSS	1,62E+22	7,58E+21
Degrees of Freedom	9870	-

Table 9 - Results from Model 7

Metric	Global	GTWR
T-value (Deforestation)	39.529	-
T-value (vl_fob_cattle)	-2.855	-
T-value (vl_fob_others)	-1.083	-
T-value (vl_fob_soya)	-3.759	-
T-value (vl_fob_wood)	4.125	-
P-value (Deforestation)	< 0.0000	-
P-value (vl_fob_cattle)	0.0043	-
P-value (vl_fob_others)	0.2788	-
P-value (vl_fob_soya)	0.0002	-
P-value (vl_fob_wood)	< 0.0000	-
AIC	309082	306344
R^2	0.14	0.34
RSS	1,39E+22	1,06E+21
Degrees of Freedom	10013	-

From Model 6 global regression results, it was possible to notice that the total Trade FOB value presented a lower p-value compared with Trade Volume, even though both did not reach the 5% statistical significance. On the other hand, when considering the P-values from Model 7 global regression, all the commodities presented significant correlations, except for the others type. This reinforces the option of analyzing the FOB values by commodity type, instead of volume.

When testing fixed bandwidth against adaptative bandwidth (Model 6), for the sake of curiosity, the results confirmed that the latter performs better for the present context. The fixed bandwidth produced a R-squared equal to 0.317 and AIC of 306774, whereas the adaptative option returned a R-squared of 0.531 and an AIC of 303099. Therefore, the adaptative option was adopted for further research development. The GTWR improved the R2 in several magnitude degrees compared to the Global Regression, from 0.00039 to 0.53 for the Model 6 (accounting for deforestation and total trade for all municipalities) and from 0.14 to 0.34 for Model 7 (consider trade by commodities type for all municipalities). This indicates that the influence of the EUDR products trade over the forest cover varies with heterogeneity over space.

From the models it was possible to generate the coefficients, y values, predicted values (yhat), residuals, studentized residuals, standard errors, t-values and p-values. For all models, the coefficients did not present temporal trends, considering the overall averages by year, as demonstrated in Figure 10 for Model 7. On the other hand, it was possible to compute temporal trends for y, yhat and residual as Figure 11 shows. We can notice that the Model lowered its underestimation of the forest cover until 2019, when it converged to the real values and then started to overestimate the forest cover. There is a steep decline from 2022 to 2023 in the predictions, possibly because the deforestation data only covered 2011-2022 period.

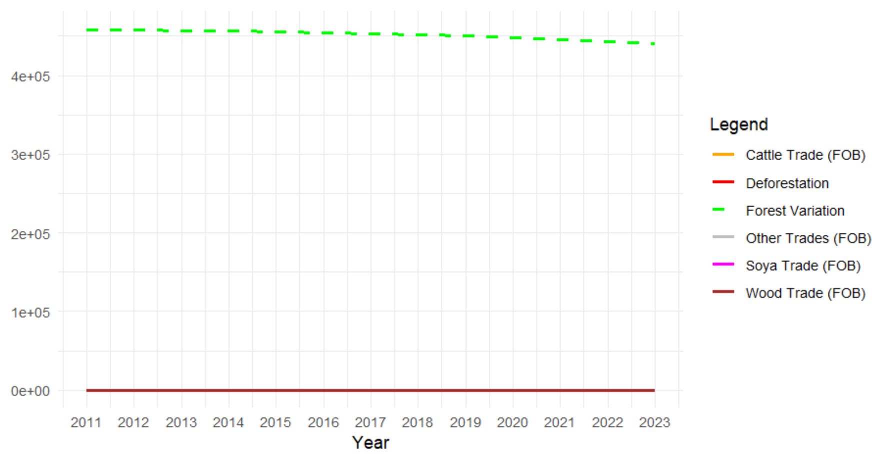

Figure 10 - Temporal trends of GTWR coefficients from Model 7

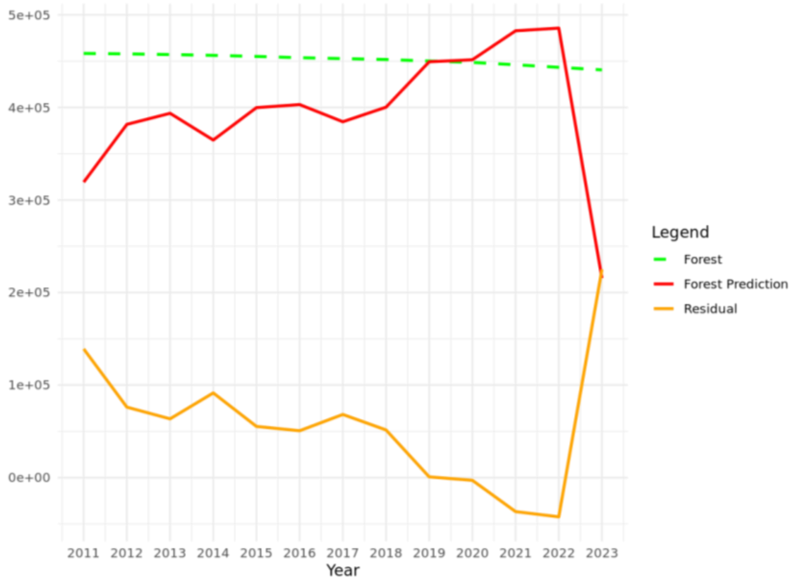

Figure 11 - Temporal trends of y, yhat and residuals from Model 7

The Figure 12 presents the GTWR the coefficients and P-values results for total trade volume (kg) and FOB value. There is clear spatial heterogeneity in how different regions relate to total trade volume and FOB value, in which 444 municipalities showed positive relationships with forest cover, considering volume, and 361 considering FOB value. Negative correlation of trade volume with forest cover was identified for 328 municipalities and for 411 considering FOB value. It is interesting to highlight that some municipalities change its coefficient direction when considering FOB value or volume, the northern states of Amapá and Roraima, for instance, fully changes from negative to positive correlation with forest cover.

Municipalities showing statistically significant results (at the 5% level) are primarily located in central and certain northern regions. However, some municipalities demonstrated significance in volume metrics but not in FOB value, while others showed the opposite pattern. The lack of significance in the east might be related with the deforestation data, which does not cover much of that south-east region, as presented in section 3.2.3 Deforestation.

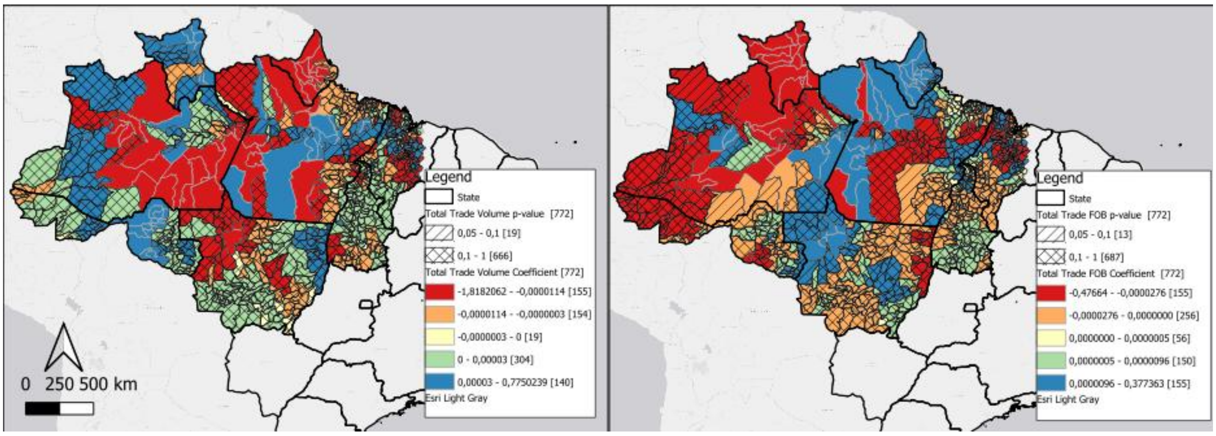

Figure 12 – Model 6 total trade FOB and volume coefficients with respective P-values > 5%.

The standard errors and T-values for total trade volume and FOB value are presented in Figure 13. The northern and some peripheral regions show higher standard errors, suggesting less confidence in the estimates, for both variables. Considering a *rule of thumb*, in which a low t-value typically below 2 or above -2, there were 43 municipalities with significative negative relationship with forest cover regarding volume and 31 for Trade FOB values. Whereas, in yellow there are presented municipalities with significative positive correlation, being 41 regarding trade volume and 39 for FOB values.

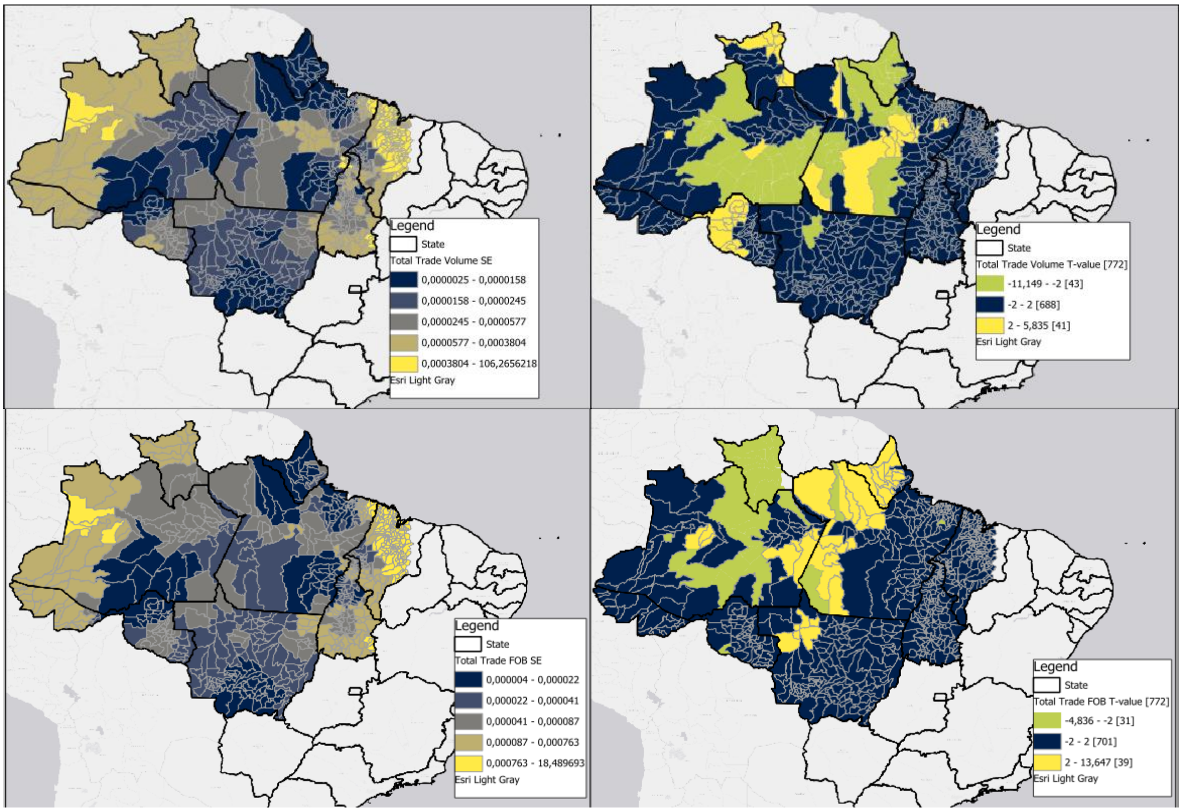

Figure 13 – Model 6 standard errors (SE) and T-value.

There were 33 municipalities where the correlation between Total FOB trade value was negative and within the 5% of statistical significance, presented in Figure 14 with interval in natural breaks.

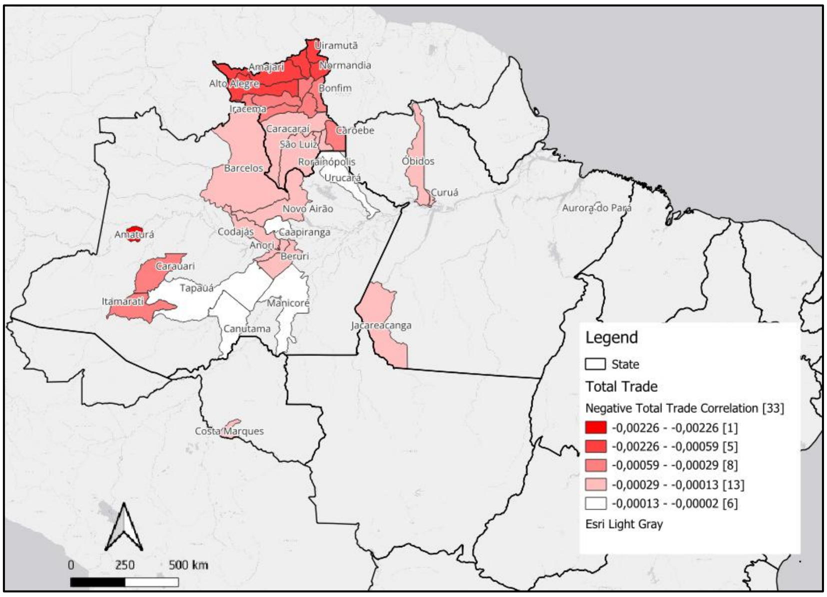

Figure 14 - Municipalities from Model 6 with statistical significance negative correlation between Trade FOB value and forest cover.

The Figure 15 presents the spatial distribution of the independent variables coefficients and the p-value for Model 7. The definition of the bins started by quantile, followed by setting the 0 break in the upper limit of the negative to positive interval, helping in the evaluation of how many municipalities had negative correlations. From the maps we can identify that 72% to 78% of the municipalities presented a negative correlation of cattle and soya trade (FOB) with forest cover, while only 13% had a negative correlation with wood Trade FOB values. In the P-values representation the classes were defined considering the 0.05 and 0.10 statistical significance intervals.

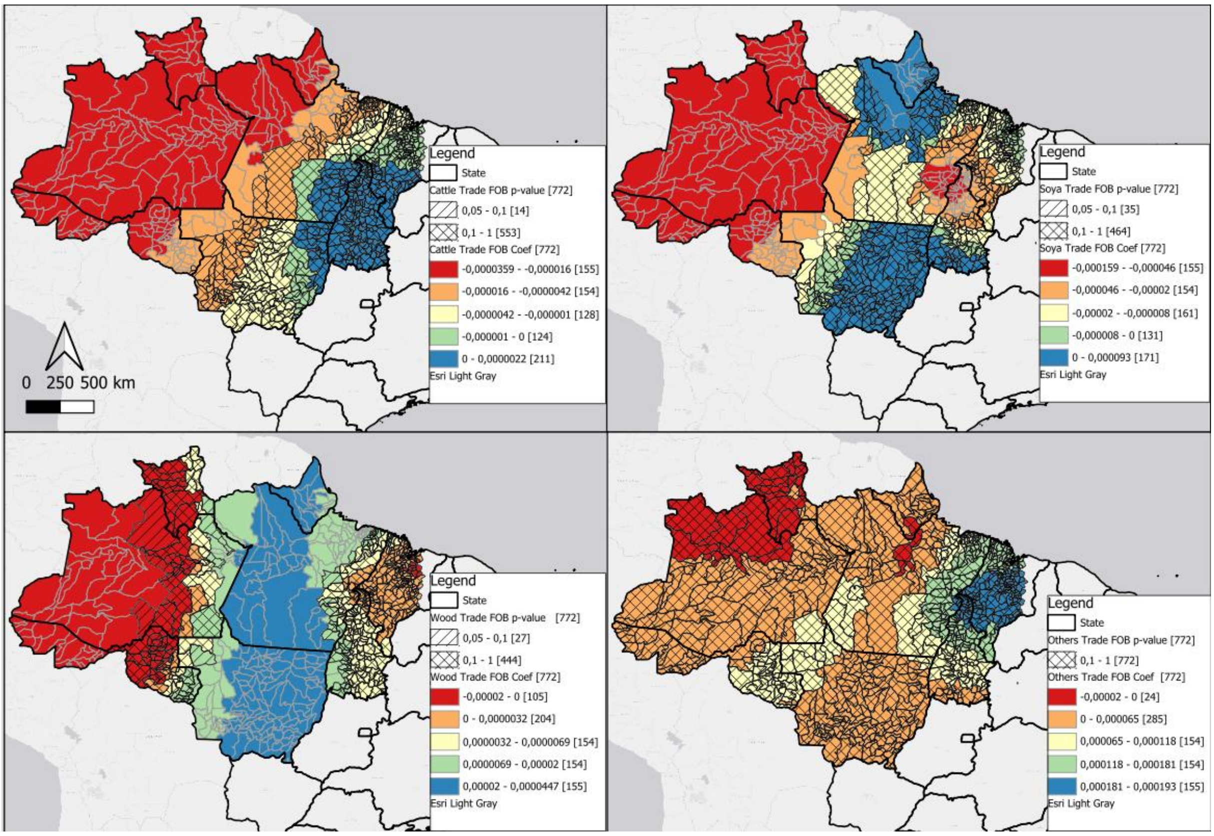

Figure 15 – Model 7 independent variables coefficients and P-values distribution.

The combination of the results indicates different patterns of how this relationship occurs over the municipalities. In the upper left map of Figure 15, the results for cattle trade (FOB) did not reach 5% statistical significance for 73% (567) municipalities. The upper right map shows that the statistical significance was not found for soya trade (FOB) in 64% of the municipalities (499), mostly concentrated in south and almost all east part, with an "island" of negative correlation, which could be a new frontier for soya expansion and deserves to be investigated in further research.

Despite the final R-squared = 0.34, the GTWR proved to be well-suited for studying the spatiotemporal effects of exports on forest cover, as accounts for variations in deforestation rates, trade dynamics across different regions over time. In overall, none of the trade variables presented a strong correlation with the forest cover change with values ranging from -0.000159 for soya (FOB) to 0.000193 for other products (FOB). Temporal trends were not observed for the independent variable's coefficients, which might indicate that spatial patterns overcome the temporal influence.

5. CONCLUSIONS AND FUTURE RESEARCH

Going back to the main objective, the evaluation of the trade impact of EUDR-Relevant Commodities over forest cover, quantifying and identifying which commodities are driving the forest cover reduction and in what municipalities it is happening, throughout a spatially explicit method. In that sense, the results allowed assessment of forest cover can be impacted by the EUDR-relevant products trade, in FOB value, volume and the commodity type.

The impact of EUDR-Relevant Commodities trade on the forest cover in the Legal Amazon occurs with high heterogeneity over space. The results indicate that spatial patterns overcome the temporal influence. Not all municipalities showed a statistically significant relationship between trade and deforestation. Some municipalities may experience trade expansion without significant deforestation, possibly due to differences in land management policies, conservation areas, or economic diversification. While cattle and soy remain the biggest threats to forest cover, the governance of wood trade and the promotion of sustainable agricultural practices could help reduce deforestation risks. Unlike cattle and soy, wood trade FOB values do not show a consistently negative correlation with forest cover. This highlights the importance of localized policies rather than a generalized approach.

RQ1: In which municipalities the EUDR-Relevant Commodities trade significantly affect forest cover?

It was possible to compute the coefficients for the EUDR-Relevant Commodities trade with Forest Cover, with statistical significance of 5%, for 72 municipalities, considering FOB value, and for 85 considering trade volume. For 33 municipalities was identified a significative statistical negative correlation of forest cover with FOB value, in which Amaturá (Amazonas State) and Uiramutã, Amajari, Normandia and Pacaraima (Roraima State) had the strongest relation.

RQ2: Which commodities export trade are negatively affecting forest over the Legal Amazon and in which municipalities?

Around 72%-78% of the municipalities presented a negative correlation of cattle and soya trade (FOB) with forest cover, while 13% had a negative correlation with wood trade (FOB).

The stronger negative correlation between cattle trade FOB values and forest cover (especially in the north and central Amazon) reinforces the link between cattle ranching and deforestation.

From the spatial distribution of the coefficients, it is possible to notice that the strongest negative effects are more presented in center towards to the west, nevertheless soya trade also presented strong negative coefficients in the east region of the study region. The P-value distribution indicates that the results for cattle trade in the east region need to be interpreted with caution. The impact of other traded commodities (e.g., rubber, cocoa, coffee) on deforestation is less consistent across municipalities, not reaching the 5% statistical significance.

Policies such as EUDR could be particularly effective in municipalities with a stronger statistically significant negative correlation between trade and forest cover. Those regions might be experiencing a commodity-driven deforestation, making them priority areas for mitigation policies. I believe that the model can help the assessment of deforestation policies, moratoriums, and certification programs, revealing their effectiveness across different regions and time periods. The calculation of coefficients for municipalities without trade was possible due to the GTWR's spatial and temporal dependency structure. The model does not treat municipalities in isolation but rather derives estimations from neighboring regions, past trends, and associated variables. This is useful for understanding potential trade-driven deforestation risks, even in areas that may currently show no trade activity but are influenced by broader economic and environmental dynamics.

About the limitations and recommendations, there are different kernels, normalizations and other independent variables to be explored, including the trade volume-related commodities type. Unfortunately, the processing time of 3 or 4 days, for the complete region, limited the increase in the number of variables and amount of tests. In that sense, it might be interesting the comparison with other methods that do not account for time, like GWR or MGWR, to evaluate the relevance and cost-benefit of temporal dimension incorporation, since the results suggest that spatial pattern overcomes the influence over temporal. This can accelerate the output generation and make more feasible the incorporation of more variables.

It is also relevant to mention that the selection of the products, according to the EUDR, included more items that it should have, because only the sh4 code was available on the ComexStat platform, whereas would be needed the sh6 to do it properly. Nevertheless, considering the documented economic reality in the study region, it would not greatly affect the results.

Finally, the present approach can contribute with decision-makers to better identify high-risk areas, design targeted conservation strategies, and assess the effectiveness of environmental policies aimed at reducing deforestation while balancing economic activities such as trade and agricultural expansion. By detecting regions where forest cover is most sensitive to trade, GTWR supports targeted conservation efforts and policy interventions.

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APPENDIX A

This section presents the summary of the outputs from the GTWR for all Models.

MODEL 7

Model Information

Package: GWmodel

Formula: forest_variation ~ deforestation + vl_fob_cattle + vl_fob_others + vl_fob_soya + vl_fob_wood

Number of Observations (Data Points): 10,036

Bandwidth (Adaptive): 6077 nearest neighbors

Kernel Function: Bisquare

Distance Metric: Spatio-temporal matrix

Global Regression Results

Residual Summary:

Min: -5,286,528

1st Quartile (Q1): -305,991

Median: -259,465

3rd Quartile (Q3): -121,206

Max: 14,116,336

Coefficients:

Variable	Estimate	Std. Error	t-value	p-value	Significance
Intercept	280,200	12,830	21.833	< 2e-16	***
Deforestation	117.9	2.982	39.529	< 2e-16	***
vl_fob_cattle	-1.076e-05	3.770e-06	-2.855	0.004316	**
vl_fob_others	8.593e-05	7.936e-05	1.083	0.278882	
vl_fob_soya	-2.938e-05	7.815e-06	-3.759	0.000172	***
vl_fob_wood	1.534e-05	3.720e-06	4.125	3.74e-05	***

Residual Standard Error: 1,178,000 (degrees of freedom = 10,030)

R-squared: 0.1396

Adjusted R-squared: 0.1392

F-statistic: 325.6 (on 5 and 10,030 DF)

p-value: < 2.2e-16

AIC: 309082.9

AICc: 309082.9

Residual Sum of Squares: 1.391963e+16

Geographically and Temporally Weighted Regression (GTWR) Results

Coefficient Ranges:

Variable	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Intercept	-84,930	1,698	50,033	225,760	1,373,200
Deforestation	39.255	81.074	108.79	128.76	175.75
vl_fob_cattle	-3.5867e-05	-1.1091e-05	-1.9928e-06	1.5939e-07	0.0000e+00
vl_fob_others	-1.9463e-05	3.5203e-05	7.7018e-05	1.7390e-04	2.0000e-04

Variable	Minimum	1st Quartile	Median	3rd Quartile	Maximum
vl_fob_soya	-1.5899e-04	-4.0460e-05	-1.2119e-05	-2.0370e-06	1.0000e-04
vl_fob_wood	-1.9993e-05	7.2033e-07	5.1624e-06	1.5529e-05	0.0000e+00

Diagnostic Information:
Number of Data Points: 10,036
Effective Parameters: 22.52
Effective Degrees of Freedom: 10,013.48
AICc (GTWR): 306,364.6
AIC (GTWR): 306,344.4
Residual Sum of Squares (GTWR): 1.05913e+16
R-squared (GTWR): 0.3454
Adjusted R-squared (GTWR): 0.3439

MODEL 6 Fixed Bandwidth

```
***********************************************************************
  *                  Package   GWmodel                    *
  ***********************************************************************
  Program starts at: 2025-01-13 00:46:09.504606
  Call:
  gtwr(formula = forest ~ vl_fob_total + kg_liquido_total, data = combined_data_sf,
   obs.tv = combined_data_sf$year, st.bw = bw_gtwr, kernel = "bisquare",
   adaptive = FALSE, t.units = "year", st.dMat = expanded_spatial_distance)

  Dependent (y) variable:  forest
  Independent variables:  vl_fob_total kg_liquido_total
  Number of data points: 10036
  ***********************************************************************
  *               Results of Global Regression                *
  ***********************************************************************

  Call:
   lm(formula = formula, data = data)

  Residuals:
    Min      1Q   Median      3Q     Max
-918742  -427008  -393933  -156450 14574683

  Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
  (Intercept)      4.467e+05  1.300e+04  34.366   <2e-16 ***
  vl_fob_total     4.338e-06  3.623e-06   1.197    0.231
  kg_liquido_total 1.151e-07  2.563e-06   0.045    0.964
```

```
---Significance stars
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1270000 on 10033 degrees of freedom
Multiple R-squared: 0.000339
Adjusted R-squared: 0.0001397
F-statistic: 1.701 on 2 and 10033 DF,  p-value: 0.1825
***Extra Diagnostic information
Residual sum of squares: 1.617353e+16
Sigma(hat): 1269596
AIC:  310583
AICc:  310583
***********************************************************************
*    Results of Geographically and Temporally Weighted Regression     *
***********************************************************************

********************Model calibration information*********************
Kernel function for geographically and temporally weighting: bisquare
Fixed bandwidth for geographically and temporally weighting:  786157.4
Regression points: the same locations as observations are used.
Distance metric for geographically and temporally  weighting: A distance matrix is specified for this model calibration.

***************Summary of GTWR coefficient estimates:*****************
                    Min.    1st Qu.     Median    3rd Qu.     Max.
Intercept        3.4708e+04  7.7357e+04  1.3045e+05  4.1301e+05 3.761e+06
vl_fob_total     -1.5799e-03 -2.6130e-06 -4.3553e-07  3.6134e-07 1.010e-02
kg_liquido_total -1.5026e-01  7.3037e-07  1.9640e-06  5.6702e-06 7.000e-04
***********************Diagnostic information*************************
Number of data points: 10036
Effective number of parameters (2trace(S) - trace(S'S)): 29.03565
Effective degrees of freedom (n-2trace(S) + trace(S'S)): 10006.96
AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 306799.2
AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 306774.4
Residual sum of squares: 1.10497e+16
R-square value:  0.3170349
Adjusted R-square value:  0.3150531
```

MODEL 6

```
***********************************************************************
*                    Package   GWmodel                               *
***********************************************************************
Program starts at: 2025-01-14 15:36:01.936968
Call:
gtwr(formula = forest ~ vl_fob_total + kg_liquido_total, data = combined_data_sf,
 obs.tv = combined_data_sf$year, st.bw = bw_gtwr, kernel = "bisquare",
```

```
 adaptive = TRUE, t.units = "year", st.dMat = expanded_spatial_distance)

Dependent (y) variable:  forest
Independent variables:  vl_fob_total kg_liquido_total
Number of data points: 10036
***********************************************************************
*                 Results of Global Regression                 *
***********************************************************************

Call:
 lm(formula = formula, data = data)

Residuals:
  Min      1Q   Median      3Q     Max
-918742  -427008  -393933  -156450 14574683

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)     4.467e+05  1.300e+04  34.366   <2e-16 ***
vl_fob_total    4.338e-06  3.623e-06   1.197    0.231
kg_liquido_total 1.151e-07  2.563e-06   0.045    0.964

---Significance stars
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1270000 on 10033 degrees of freedom
Multiple R-squared: 0.000339
Adjusted R-squared: 0.0001397
F-statistic: 1.701 on 2 and 10033 DF,  p-value: 0.1825
***Extra Diagnostic information
Residual sum of squares: 1.617353e+16
Sigma(hat): 1269596
AIC:  310583
AICc:  310583
***********************************************************************
*   Results of Geographically and Temporally Weighted Regression    *
***********************************************************************

*********************Model calibration information*********************
Kernel function for geographically and temporally weighting: bisquare
Adaptive bandwidth for geographically and temporally  weighting: 445 (number of nearest neighbors)
Regression points: the same locations as observations are used.
Distance metric for geographically and temporally  weighting: A distance matrix is specified for this model calibration.

****************Summary of GTWR coefficient estimates:*****************
                  Min.    1st Qu.     Median    3rd Qu.      Max.
```

Intercept 1.5590e+04 3.2834e+04 6.3874e+04 3.3513e+05 4.2232e+06
vl_fob_total -4.7664e-01 -1.4527e-05 -6.0604e-07 3.9953e-06 3.7740e-01
kg_liquido_total -1.8182e+00 -5.5020e-06 4.5768e-07 1.4014e-05 7.7500e-01
***********************Diagnostic information************************
Number of data points: 10036
Effective number of parameters (2trace(S) - trace(S'S)): 165.57
Effective degrees of freedom (n-2trace(S) + trace(S'S)): 9870.43
AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 303236.3
AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 303099.3
Residual sum of squares: 7.579056e+15
R-square value: 0.5315503
Adjusted R-square value: 0.5236916

****
Program stops at: 2025-01-14 19:25:00.451221

MODEL 5

```
> print(gtwr_model)
   ***********************************************************************
   *                       Package   GWmodel                             *
   ***********************************************************************
   Program starts at: 2025-01-25 23:07:56.286307
   Call:
   gtwr(formula = forest_variation ~ deforestation + vl_fob_cattle +
    vl_fob_others + vl_fob_soya + vl_fob_wood, data = combined_data_sf,
    obs.tv = combined_data_sf$year, st.bw = bw_gtwr, kernel = "bisquare",
    adaptive = TRUE, t.units = "year", st.dMat = expanded_spatial_distance)

   Dependent (y) variable:  forest_variation
   Independent variables:  deforestation vl_fob_cattle vl_fob_others vl_fob_soya vl_fob_wood
   Number of data points: 3640
   ***********************************************************************
   *                    Results of Global Regression                     *
   ***********************************************************************

   Call:
    lm(formula = formula, data = data)

   Residuals:
     Min       1Q   Median       3Q      Max
-5855817  -334454  -239778    -4921 14106795

   Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
   (Intercept)     2.897e+05  2.348e+04  12.339  < 2e-16 ***
   deforestation   1.273e+02  3.666e+00  34.723  < 2e-16 ***
   vl_fob_cattle  -1.090e-05  3.871e-06  -2.816 0.004882 **
   vl_fob_others   9.002e-05  8.101e-05   1.111 0.266572
   vl_fob_soya    -3.308e-05  8.212e-06  -4.028 5.73e-05 ***
   vl_fob_wood     1.348e-05  3.857e-06   3.493 0.000483 ***
```

```
   ---Significance stars
   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
   Residual standard error: 1202000 on 3634 degrees of freedom
   Multiple R-squared: 0.2586
   Adjusted R-squared: 0.2576
   F-statistic: 253.5 on 5 and 3634 DF,  p-value: < 2.2e-16
   ***Extra Diagnostic information
   Residual sum of squares: 5.25377e+15
   Sigma(hat): 1201722
   AIC:  112256.5
   AICc:  112256.6
   ***********************************************************************
   *    Results of Geographically and Temporally Weighted Regression     *
   ***********************************************************************

   *********************Model calibration information*********************
   Kernel function for geographically and temporally weighting: bisquare
   Adaptive bandwidth for geographically and temporally  weighting: 548 (number of nearest neig
hbours)
   Regression points: the same locations as observations are used.
   Distance metric for geographically and temporally  weighting: A distance matrix is specified
for this model calibration.

   ****************Summary of GTWR coefficient estimates:*****************
                       Min.     1st Qu.      Median     3rd Qu.       Max.
   Intercept      9.7500e+02  6.4661e+04  1.6938e+05  3.3901e+05 2.1720e+06
   deforestation -5.5775e+01  3.2375e+01  5.9960e+01  1.0674e+02 2.3290e+02
   vl_fob_cattle -5.8419e-04 -1.3661e-05 -2.7563e-06 -2.7867e-07 1.0000e-04
   vl_fob_others -5.9801e-04 -9.8077e-05 -5.6266e-06  9.9032e-05 2.8219e+00
   vl_fob_soya   -2.6605e-04 -7.3426e-06  4.6007e-06  3.8767e-05 6.0000e-04
   vl_fob_wood   -2.2441e-04 -5.2989e-06  4.1263e-07  2.3412e-05 1.1000e-03
   ************************Diagnostic information*************************
   Number of data points: 3640
   Effective number of parameters (2trace(S) - trace(S'S)): 84.11919
   Effective degrees of freedom (n-2trace(S) + trace(S'S)): 3555.881
   AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 110640
   AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 110568.2
   Residual sum of squares: 3.256052e+15
   R-square value:  0.5405229
   Adjusted R-square value:  0.5296502
```

MODEL 4

```
   ***********************************************************************
   *                       Package   GWmodel                             *
   ***********************************************************************
   Program starts at: 2025-01-14 08:55:45.628111
   Call:
   gtwr(formula = forest_variation_norm ~ deforestation_norm + vl_fob_total_norm +
    kg_liquido_total_norm, data = combined_data_sf, obs.tv = combined_data_sf$year,
    st.bw = bw_gtwr, kernel = "bisquare", adaptive = TRUE, t.units = "year",
    st.dMat = expanded_spatial_distance)

   Dependent (y) variable:  forest_variation_norm
   Independent variables:  deforestation_norm vl_fob_total_norm kg_liquido_total_norm
   Number of data points: 2083
   ***********************************************************************
   *                    Results of Global Regression                     *
   ***********************************************************************

   Call:
    lm(formula = formula, data = data)

   Residuals:
     Min       1Q   Median       3Q      Max
-0.42457 -0.01972 -0.01139  0.00068  0.77522

   Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
   (Intercept)            0.012784   0.002004   6.380 2.18e-10 ***
   deforestation_norm     0.719258   0.020178  35.646  < 2e-16 ***
   vl_fob_total_norm      0.021737   0.025021   0.869    0.385
   kg_liquido_total_norm -0.012070   0.025995  -0.464    0.642
```

```
---Significance stars
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1126000 on 2079 degrees of freedom
Multiple R-squared: 0.3795
Adjusted R-squared: 0.3786
F-statistic: 423.8 on 3 and 2079 DF,  p-value: < 2.2e-16
***Extra Diagnostic information
Residual sum of squares: 2.634144e+15
Sigma(hat): 1125081
AIC:  63965.7
AICc:  63965.73
***********************************************************************
*    Results of Geographically and Temporally Weighted Regression     *
***********************************************************************

*********************Model calibration information*********************
Kernel function for geographically and temporally weighting: bisquare
Adaptive bandwidth for geographically and temporally  weighting: 27 (number of nearest neighbours)
Regression points: the same locations as observations are used.
Distance metric for geographically and temporally  weighting: A distance matrix is specified for this
model calibration.

****************Summary of GTWR coefficient estimates:*****************
                            Min.     1st Qu.      Median     3rd Qu.       Max.
Intercept              -3.3343e+03  4.2389e+04  1.4452e+05  4.1282e+05   11254756
deforestation_norm     -4.6139e+08 -4.7964e+04  2.7232e+05  2.5339e+06  195668579
vl_fob_total_norm      -2.4759e+09 -6.1156e+05  2.2031e+03  9.9199e+05  111973025
kg_liquido_total_norm -1.9657e+08 -7.4147e+05  2.7869e+03  1.4613e+06 3577318912
************************Diagnostic information*************************
Number of data points: 2083
Effective number of parameters (2trace(S) - trace(S'S)): 605.5508
Effective degrees of freedom (n-2trace(S) + trace(S'S)): 1477.449
AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 58589.99
AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 57641.41
Residual sum of squares: 9.761804e+13
R-square value:  0.977004
Adjusted R-square value:  0.9675724
```

MODEL 3

```
***********************************************************************
*                       Package   GWmodel                             *
***********************************************************************
Program starts at: 2025-01-14 12:30:09.10466
Call:
gtwr(formula = forest_variation ~ deforestation_norm + vl_fob_total_norm +
 kg_liquido_total_norm, data = combined_data_sf, obs.tv = combined_data_sf$year,
 st.bw = bw_gtwr, kernel = "bisquare", adaptive = TRUE, t.units = "year",
 st.dMat = expanded_spatial_distance)

Dependent (y) variable:  forest_variation
Independent variables:  deforestation_norm vl_fob_total_norm kg_liquido_total_norm
Number of data points: 2083
***********************************************************************
*                    Results of Global Regression                     *
***********************************************************************

Call:
 lm(formula = formula, data = data)

Residuals:
    Min       1Q   Median       3Q      Max
-6376886  -296235  -171058    10282 11643494

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)              193703      30097   6.436 1.52e-10 ***
deforestation_norm     10803021     303067  35.646  < 2e-16 ***
vl_fob_total_norm        326483     375812   0.869    0.385
kg_liquido_total_norm   -181283     390436  -0.464    0.642
```

```
---Significance stars
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1126000 on 2079 degrees of freedom
Multiple R-squared: 0.3795
Adjusted R-squared: 0.3786
F-statistic: 423.8 on 3 and 2079 DF,  p-value: < 2.2e-16
***Extra Diagnostic information
Residual sum of squares: 2.634144e+15
Sigma(hat): 1125081
AIC:  63965.7
AICc:  63965.73
***********************************************************************
*    Results of Geographically and Temporally Weighted Regression     *
***********************************************************************

*********************Model calibration information*********************
Kernel function for geographically and temporally weighting: bisquare
Adaptive bandwidth for geographically and temporally  weighting: 27 (number of nearest neighbours)
Regression points: the same locations as observations are used.
Distance metric for geographically and temporally  weighting: A distance matrix is specified for this
model calibration.

****************Summary of GTWR coefficient estimates:*****************
                             Min.     1st Qu.      Median     3rd Qu.       Max.
Intercept              -3.3343e+03  4.2389e+04  1.4452e+05  4.1282e+05   11254756
deforestation_norm     -4.6139e+08 -4.7964e+04  2.7232e+05  2.5339e+06  195668579
vl_fob_total_norm      -2.4759e+09 -6.1156e+05  2.2031e+03  9.9199e+05  111973025
kg_liquido_total_norm -1.9657e+08 -7.4147e+05  2.7869e+03  1.4613e+06 3577318912
************************Diagnostic information*************************
Number of data points: 2083
Effective number of parameters (2trace(S) - trace(S'S)): 605.5508
Effective degrees of freedom (n-2trace(S) + trace(S'S)): 1477.449
AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 58589.99
AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 57641.41
Residual sum of squares: 9.761804e+13
R-square value:  0.977004
Adjusted R-square value:  0.9675724
```

MODEL 2

```
***********************************************************************
*                       Package   GWmodel                             *
***********************************************************************
Program starts at: 2025-01-08 21:11:13.001746
Call:
gtwr(formula = forest_variation ~ trade_variation + deforestation,
 data = combined_data_sf, obs.tv = combined_data_sf$year,
 st.bw = bw_gtwr, kernel = "bisquare", adaptive = TRUE, t.units = "year",
 st.dMat = expanded_spatial_distance)

Dependent (y) variable:  forest_variation
Independent variables:  trade_variation deforestation
Number of data points: 2083
***********************************************************************
*                    Results of Global Regression                     *
***********************************************************************

Call:
 lm(formula = formula, data = data)

Residuals:
    Min       1Q   Median       3Q      Max
-6384007  -294736  -170259    12391 11645431

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.914e+05  2.969e+04   6.447 1.42e-10 ***
trade_variation 2.024e-06  2.645e-06   0.765    0.444
deforestation   1.354e+02  3.797e+00  35.656  < 2e-16 ***

---Significance stars
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1125000 on 2080 degrees of freedom
Multiple R-squared: 0.3794
Adjusted R-squared: 0.3788
F-statistic: 635.8 on 2 and 2080 DF,  p-value: < 2.2e-16
***Extra Diagnostic information
Residual sum of squares: 2.634417e+15
Sigma(hat): 1125139
AIC:  63963.91
AICc:  63963.93
***********************************************************************
*    Results of Geographically and Temporally Weighted Regression     *
***********************************************************************

*********************Model calibration information*********************
Kernel function for geographically and temporally weighting: bisquare
Adaptive bandwidth for geographically and temporally  weighting: 22 (number of nearest neighbours)
Regression points: the same locations as observations are used.
Distance metric for geographically and temporally  weighting: A distance matrix is specified for this model calibration.

****************Summary of GTWR coefficient estimates:*****************
                      Min.     1st Qu.      Median     3rd Qu.      Max.
Intercept       -4.1983e+04  4.6470e+04  1.6241e+05  5.6492e+05 1.345e+07
trade_variation -2.6254e-03 -1.8237e-06  3.8767e-08  3.1507e-06 8.300e-03
deforestation   -5.7473e+03 -2.7728e+00  1.2800e-02  5.7542e+00 2.271e+03
************************Diagnostic information*************************
Number of data points: 2083
Effective number of parameters (2trace(S) - trace(S'S)): 575.8433
Effective degrees of freedom (n-2trace(S) + trace(S'S)): 1507.157
AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 58344.48
AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 57405.09
Residual sum of squares: 8.729104e+13
R-square value:  0.9794368
Adjusted R-square value:  0.9715749

***********************************************************************
Program stops at: 2025-01-08 21:12:35.267069
```

MODEL 1

```
   ***********************************************************************
   *                       Package   GWmodel                             *
   ***********************************************************************
   Program starts at: 2025-01-12 18:49:51.025711
   Call:
   gtwr(formula = forest ~ vl_fob_total + kg_liquido_total, data = combined_data_sf,
    obs.tv = combined_data_sf$year, st.bw = bw_gtwr, kernel = "bisquare",
    adaptive = TRUE, t.units = "year", st.dMat = expanded_spatial_distance)

   Dependent (y) variable:  forest
   Independent variables:  vl_fob_total kg_liquido_total
   Number of data points: 2404
   ***********************************************************************
   *                    Results of Global Regression                     *
   ***********************************************************************

   Call:
    lm(formula = formula, data = data)

   Residuals:
     Min       1Q   Median       3Q      Max
 -628107  -537511  -419877   -66080 14432837

   Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
   (Intercept)       5.885e+05  3.166e+04  18.587   <2e-16 ***
   vl_fob_total      1.183e-06  3.999e-06   0.296    0.767
   kg_liquido_total -2.086e-06  2.828e-06  -0.738    0.461

    ---Significance stars
    Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
    Residual standard error: 1384000 on 2401 degrees of freedom
    Multiple R-squared: 0.000267
    Adjusted R-squared: -0.0005657
    F-statistic: 0.3207 on 2 and 2401 DF,  p-value: 0.7257
    ***Extra Diagnostic information
    Residual sum of squares: 4.598685e+15
    Sigma(hat): 1383663
    AIC:  74814.55
    AICc:  74814.57
    ***********************************************************************
    *   Results of Geographically and Temporally Weighted Regression      *
    ***********************************************************************

    *********************Model calibration information*********************
    Kernel function for geographically and temporally weighting: bisquare
    Adaptive bandwidth for geographically and temporally  weighting: 29 (number of
 nearest neighbours)
    Regression points: the same locations as observations are used.
    Distance metric for geographically and temporally  weighting: A distance matrix
 is specified for this model calibration.

    ****************Summary of GTWR coefficient estimates:*****************
                           Min.     1st Qu.      Median     3rd Qu.       Max.
    Intercept          2.3242e+03  4.4056e+04  1.4714e+05  4.0471e+05 1.3825e+07
    vl_fob_total      -1.3182e-02 -2.7172e-06  1.3767e-07  1.3159e-05 1.3000e-02
    kg_liquido_total -4.9396e-02 -7.2771e-06  6.2363e-09  6.2046e-06 1.5000e-02
    ************************Diagnostic information*************************
    Number of data points: 2404
    Effective number of parameters (2trace(S) - trace(S'S)): 482.3635
    Effective degrees of freedom (n-2trace(S) + trace(S'S)): 1921.637
    AICc (GWR book, Fotheringham, et al. 2002, p. 61, eq 2.33): 67584.87
    AIC (GWR book, Fotheringham, et al. 2002,GWR p. 96, eq. 4.22): 66947.28
    Residual sum of squares: 1.457507e+14
    R-square value:  0.9683145
    Adjusted R-square value:  0.9603567
```

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