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Ensaios de Economia do Meio Ambiente e do Desenvolvimento

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Essays on Environmental and Development Economics

Ensaios de Economia do Meio Ambiente e do Desenvolvimento

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Abstract

Paper 1: The causal impacts of local institutions on tropical deforestation are still little explored in the literature because they involve endogenous mechanisms that act, to a large extent, through socioeconomic and political channels that hinder identification. To fill such a gap, this paper contributes to the literature by exploring exogenous variations in local institutions to identify their effects on forest cover in Brazil, an ecologically and economically important country. To achieve this, we exploit exogenous geographical and historical variations to construct instruments for current institutions, assuming that initial conditions found by the country's settlers led to institutional designs that conditioned its subsequent development, explaining current institutions' differences. Our main results show that the local institutional quality change has positive statistically significant heterogeneous causal effects on deforestation in Brazil, even after several robustness checks. To further explore this evidence, we used a Causal Random Forest algorithm to estimate individual treatment effects without ad hoc hypotheses, which further supported significant heterogeneous positive causal effects. This empirical evidence is important because demonstrates that public policies that aim to improve local institutional quality must adequately consider the potential side effects of deforestation.

Keywords: Institutions; Deforestation; Brazil; Causal Random Forest.

Paper 2: The existence of a trade-off in the relationship between economic growth and environmental quality is still an open debate, especially when considering the deforestation of tropical forests. Part of the literature states that the negative environmental impacts are focused on the early stages of development, when institutional quality is low, up to a turning point in which the economy moves towards sustainable development. However, many critics have supported that this is only a snapshot of a complex process, requiring additional empirical assessments to shed light on this controversy. In this context, this paper aims to contribute to the debate with a new approach to model the relationship between economic growth, capture by income per capita, and deforestation in the Amazon by controlling for institutional changes, market conditions, dynamic interactions, leakages, and spatial spillovers. After several robustness checks, our results supported the hypothesis that higher economic well-being is associated with lower deforestation rates in the Amazon and this relationship seems to be mediated by structural transformations and market access. Therefore, empirical evidence suggests that higher economic well-being could be reconciled with forest preservation in the Amazon.

Keywords: Economic Growth; Deforestation; Amazon.

Paper 3: This paper maps palm oil plantations in the Eastern Amazon, the largest producer in Brazil, in 2014 and 2020, using machine learning algorithms, to estimate its causal effects on the trade-off between deforestation and economic activity. To achieve this goal, we combined optical spectral bands from Landsat-8, radar backscatter values from Sentinel-1, vegetation, and texture indices, and a linear spectral mixing model. The Random Forest algorithm presented the best classification with an overall accuracy of

94.53% and 95.53% for 2014 and 2020, respectively. Then, from a land use and land cover transition analysis, we identified an expansion of oil palm from 1,074 km^2 to 1,849 km^2; around 156.88 km^2 (20.24%) occurred directly over vegetation cover. To overcome potentially complex endogenous mechanisms that hinder a causal interpretation for prior estimates, we propose to instrumentalize palm oil expansion using the maximum agro-climatically attainable palm oil yield from the Global Agro-Ecological Zoning (GAEZ). Our main results support that palm oil expansion in the Eastern Amazon has a statistically significant and positive causal effect on deforestation and a negative impact on economic activity in the non-agricultural sectors. In other words, palm oil expansion is increasing the environmental impacts of the region while creating centripetal forces that reduce performance in the industrial and service sectors, raising concerns about the social and environmental sustainability of this crop.

Keywords: Oil Palm; Deforestation; Amazon; Remote Sensing.

Resumo

Artigo 1: O impacto causal das instituições locais no desmatamento tropical é ainda pouco explorado na literatura porque envolve mecanismos endógenos que atuam, em grande medida, por meio de canais socioeconômicos e políticos que dificultam sua identificação. Para preencher essa lacuna, esse artigo contrbui com a literatura ao explorar variações exógenas nas instituições locais para identificar seus efeitos na cobertura florestal do Brasil, um país ecologicamente e economicamente importante. Para atingir isso, explorou-se variações geográficas e históricas exógenas para construir instrumentos para as instituições correntes, assumindo que as condições iniciais encontradas pelos colonizadores do país levaram a desenhos institucionais que condicionaram seu desenvolvimento posterior, explicando diferencas atuais nas instituições. Os resultados principais confirmam que mudanças na qualidade institucional local possui um impacto positivo heterogêneo e estatisticamente significante no desmatamento do Brasil, mesmo após a realização de diversos testes de robustez. Com a finalidade de explorar mais essa evidência, utilizou-se um algoritmo de Random Forest Causal para estimar efeitos de tratamento individuais sem a necessidade de hipóteses *ad hoc*, o que confirmou a presença de significantes efeitos causais heterogêneos e positivos. Essa evidência empírica é importante no sentido de demonstrar que as políticas públicas que buscam melhorar a qualidade das instituições locais devem consderar adequadamente possíveis efeitos colaterais no desmatamento.

Palavras-chave: Instituições; Desmatamento; Brasil; Random Forest Causal.

Artigo 2: A existência de um *trade-off* na relação entre crescimento econômico e qualidade ambiental é ainda um debate em aberto, especialmente quando considerado o desmatamento de florestas tropicais. Parte da literatura afirma que os impactos negativos estão concentrados nos estágios iniciais de desenvolvimento, quando a qualidade institucional é baixa, até ocorrer um ponto de virada no qual a economia se move em direção a um desenvolvimento sustentável. Entretanto, muitos críticos afirmam que isso é apenas uma parte de um processo complexo, fato que querer evidências empíricas adicionais para lançar luz a essa controvérsia. Nesse contexto, esse artigo busca contribuir para o debate com uma nova abordagem para modelar a relação entre crescimento econômico, capturado pela renda *per capita*, e o desmatamento da Amazônia ao controlar por mudanças institucionais, condições de mercado, interações dinâmicas, vazamentos e transbordamentos espaciais. Após uma série de testes de robustez, os resultados suportaram a hipótese de que maior bem estar econômico é associado com menores taxas de desmatamento na Amazônia e que essa relação parece ser mediada por transformações estruturais e acesso a mercados. Portanto, essa evidência empírica sugere que maior bem estar econômico pode ser, *ceteris paribus*, conciliado com preservação florestal na Amazônia.

Palavras-chave: Crescimento Econômico; Desmatamento; Amazônia.

Artigo 3: Esse artigo mapeia plantações de óleo de palma na Amazônia Oriental, a maior produtora do Brasil, em 2014 e 2020, uusando algoritmos de aprendizado de máquina, para estimar seus efeitos causais no *trade-off* entre desmatamento e atividade econômica.

Para atigir esse objetivo, combinou-se bandas espectrais óticas do Landsat-8 com valores de retroespalhamento do Sentinel-1, índices de vegetação e textura, e um modelo linear de mistura espectral. O algoritmo Random Forest apresentou a melhor classificação com uma acurácia geral de 94.53% e 95.53% para 2014 e 2020, respectivamente. Então, a partir de uma análise de transição de uso e cobertura da terra, identificou-se uma expansão do óleo de palma de 1.074 km^2 para 1.849 km^2; com cerca de 156,88 km^2 (20.24%) ocorrendo diretamente sobre cobertura vegetal. Para evitar possíveis mecanismos endógenos complexos que impede uma interpretação causal para a estimação anterior, propo-se a instrumentalização da expansão do óleo de palma utilizando o seu potential agro-climático máximo obitido no Global Agro-Ecological Zoning (GAEZ). Os principais resultados atestam que a expansão do óleo de palma na Amazônia Oriental tem um efeito causal positivo e estisticamente significante no desmatamento e um impacto negativo na atividade econômica nos setores não-agrícolas. Em outras palavras, a expansão do óleo de palma está aumentando os impactos ambientais da região ao mesmo tempo que cria forças centrípetas que reduzem o desemepnho dos setores industrial e de serviço, o que levanta preocupações acerca da sustentabilidade social e ambiental dessa cultura.

Palavras-chave: Óleo de palma; Desmatamento; Amazônia; Sensoriamento Remoto.

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Parte I

Do local institutions impact the environment? Evidence from deforestation in Brazil

1 Introduction

Institutions are widely perceived as a major determinant of economic growth and development[1] More recently, the potential threats of global warming have placed environmental concerns at the center of the long-term economic development debate, and the need for new institutional arrangements has become increasingly important. For example, the success of the Paris Agreement relies on strong institutions to implement measures such as an international market for carbon credits and the intensification of forest protection efforts in the developing world.[2]. Despite the perceived importance of strong institutions, the interplay between the quality of institutions, economic development, and environmental protection is still poorly understood.

This paper takes steps toward the estimation of the causal impact of institutional changes on environmental quality. More specifically, we estimate the impact of institutional changes on deforestation in different biomes and municipalities in Brazil, taking into account the possibility of heterogeneous impacts of institutions on environmental outcomes. In addition to its strategic role in any global effort to curb deforestation, Brazil is a large country with significant variations in institutional quality and deforestation rates within its territory. Furthermore, as we concentrate on a single country, we avoid cross-country analyses that are subject to comparability concerns due to large cultural, historical, and economic differences.

In general, the literature supports that lower institutional quality increases deforestation rates (Barbier e Burgess 2001; Bhattarai e Hammig 2004; Culas 2007; Van e Azomahou 2007; Marchand 2016; Sohag, Gainetdinova e Mariev 2023). However, theory suggests that institutional improvements may either positively or negatively impact environmental protection and that these effects are likely heterogeneous, making the connection between institutions and the environment an empirical question. For example, Chimeli e Braden (2005) e Chimeli (2007) state that if institutions influence Total factor productivity (TFP) and other efficiency parameters such as return on investment in environmental protection and capital pollution intensity, then the final effect on the environment is unclear, which

[1] See for example, Acemoglu, Johnson e Robinson (2001), Engerman e Sokoloff (2002), Dell (2010) e Easterly e Levine (2016), etc.

[2] Article 6 of the Paris agreement sets the grounds for the international trade of carbon credits conditional on transparent governance of carbon markets. Many of these credits could originate from forest protection efforts that take center stage in Article 5 of the same agreement (Paris 2015)

should be investigated empirically. In fact, Koop e Tole (1999), List e Gallet (1999) e Van e Azomahou (2007) empirically confirm that the relationship between institutions and environmental quality has heterogeneous results according to geographical, historical, and environmental differences. For this reason, more reliable estimates of how institutions shift human behavior toward a forest are needed.

To address the likely endogeneity of institutional change, we use an IV approach by exploring exogenous variations in local institutional development to attempt to isolate its impact on forest cover in Brazil, an ecologically and economically important country. In practice, we propose to exploit geographical and historical variations to construct instruments for current institutions, hypothesizing that the initial conditions found by the country's settlers led to institutional designs that conditioned its subsequent development, explaining current institutions disparities (Acemoglu, Johnson e Robinson 2001; Engerman e Sokoloff 2002; Dell 2010; Naritomi, Soares e Assunção 2012; Marchand 2016; Easterly e Levine 2016). Based on this, we used distance to the Metropolis (Portugal), distance to the coast, and distance to former colonial villages to capture the true level of interference dictated by the metropolis; colonial economic booms - sugarcane and gold episodes; socioeconomic characteristics from the first Brazilian population census of 1872: proportion in the population of literate, slaves, white and foreigners. Menezes-Filho et al. (2006), Naritomi, Soares e Assunção (2012) e Nakabashi, Pereira e Sachsida (2013) show that these characteristics were important in shaping current institutions so that they are likely correlated with institutional development due to historical inertia. We also use our IV approach to explore the potential heterogeneous impacts of institutional changes on different biomes in the country.

Finally, we explore the heterogeneous impacts of institutions on environmental protection by estimating an instrumental causal random forest model at the municipal level. To avoid ad hoc hypotheses and specifications and estimate potential heterogeneous effects, that could bias our results, we estimated an instrumental Causal Random Forest, which allows us to estimate individual treatment effects without ad hoc hypotheses. The algorithm estimates a local Conditional Average Treatment Effect (CATE) that is robust in out-of-sample validation for each observational unit (Athey e Imbens 2016; Wager e Athey 2018; Athey, Tibshirani e Wager 2019). Our main results show that the change in local institutional quality has statistically significant heterogeneous causal effects on deforestation in Brazil. Forest conservation is particularly sensitive to heterogeneous outcomes, so moving beyond the average effects helped to better understand its relationship with local institutions and how it varies spatially.

However, to further support that our results are not driven by omitted factors and to eliminate potentially hidden bias, common in nonexperimental designs, we conducted a series of additional robustness checks to provide further evidence that the effects we estimate are indeed causal. First, we control for additional differences that potentially are correlated with institutional development and deforestation. In summary, our results are also robust when we control for geographical differences, demographic density, rural population, income inequality, openness to trade, Bolsa Família,[3] human capital and economic scale. Therefore, these geographic, social, economic, and macro-institutional variables do not confound the results, further validating our initial results.

Second, neighbors' interactions may influence local institutional quality, leading to an indirect spatial effect and spatial autocorrelation that could invalidate our estimates. In addition, deforestation decisions are affected by spatially correlated unobservables, which may invalidate our exclusion restriction that the instruments affect deforestation only through the institutional channel, also biasing the estimates. However, measuring such between-municipalities spatial interactions and correlations is difficult since neighbors simultaneously affect each other (Robalino e Pfaff 2012; Choumert, Combes-Motel e Dakpo 2013; Baylis et al. 2016; Pfaff e Robalino 2017; Busch e Ferretti-Gallon 2017; Amin et al. 2019). To overcome this, we directly model these spatial effects by estimating a Spatial Autoregressive Model (SAR) as proposed by the spatial econometric literature[4]. The results confirmed the importance of significant spatial effects and autocorrelation and further supported the robustness of our main results.[5]

Third, we test whether the standardization used for the dependent variable, the forest change percentage, drives the results. First, we adopt alternative standardization procedures: (i) normalized forest change[6]; (ii) forest change (ha) divided by the municipality area in km^2 (ha/km^2); and (iii) forest change (ha) divided by forest stock (ha). The results for standardization (i) and (ii) further supported our empirical findings, but for (iii) the

[3] Bolsa Família is a conditional cash transfer program that aims to alleviate poverty in Brazil.
[4] See Elhorst (2014) for more details
[5] Following Robalino e Pfaff (2012), we also model spatial effects by instrumentalizing average deforestation in neighboring municipalities using neighbors' slopes and neighbors' slopes since they affect deforestation decisions but are not influenced by confounder variables. However, the slope instruments were not statistically significant, which rendered the estimates invalid for further analysis.
[6] We subtracted the municipality forest change from the country's mean and divided it by the standard deviation.

institutional variable is not statistically significant, indicating that our results may be driven by the remaining forest stock at the municipality level.

Fourth, we test two alternative proxies for institutional quality change: (i) land concentration, captured by a land Gini index, and (ii) property rights insecurity, represented by the proportion of squatters. The concentration of land aims to proxy *de facto* political and economic power, which could be concentrated in a small elite within the municipalities and, therefore, be correlated with extractive institutions (Naritomi, Soares e Assunção 2012) and deforestation. On the other hand, the insecurity of property rights captures weak enforcement institutions that could lead to greater land use conflicts and expropriations, reducing incentives for forest conservation (Araujo et al. 2009). Our results indicated that higher land concentration and property rights insecurity are related to higher rates of forest clearings. However, the results also suggest that this relationship may hide potential heterogeneous outcomes because higher property rights insecurity is related to lower deforestation rates in the Cerrado biome.

Finally, the Causal Random Forest resulted in 1398, 3975, and 594 statistically significant and positive coefficients and only 77, 18, and 0 negative coefficients for the institutional quality indicator, land gini index, and property rights insecurity, respectively; which indicate that increases in those institutional proxies lead to deforestation in a significant sample of Brazilian municipalities. Furthermore, all variables had a higher standard deviation compared to the mean Conditional Average Treatment Effect (CATE), confirming the presence of significant heterogeneity for the effects of institutional change on forest clearings. This result stresses the importance of paying attention to heterogeneity and that the other average effects might have been misleading. Therefore, this empirical evidence is important for a better understanding, design, and targeting of public policies that aim to control and curb deforestation.

In this context, we propose heterogeneity tests to further explore our results. First, we constructed samples based on the county's remaining forest percentage. The results indicated that the forest threshold chosen made the institution coefficient unstable and was not statistically significant for samples with 20% remaining forest or more. This empirical evidence shows that our results are driven by the remaining forest stock in the initial period. In addition, the institutional quality interaction with the biomes indicators also changed, indicating that even the biomes heterogeneity is driven by the remaining forest stock at the municipality level.

Therefore, our overall results support the hypothesis that local institutional change does have a significant and robust heterogeneous causal impact on deforestation in Brazil. Our work contributes to the literature in three directions. First, it is related to a growing literature that addresses the relationship between institutions and the environment (Ostrom 1990; Fredriksson, Matschke e Minier 2010; Cabrales e Hauk 2010). Second, it is also associated with papers that specifically assess the impacts of local governments on forest conservation (Lemos e Agrawal 2006; Ribot, Agrawal e Larson 2006; Sills et al. 2015; Marchand 2016; Larcom, van Gevelt e Zabala 2016; Wehkamp et al. 2018; Fischer et al. 2021). Finally, it relates to the tropical deforestation literature that aimed to further understand the causes of forest clearings in Brazil (Arima et al. 2014; Cisneros, Zhou e Börner 2015).

The remainder of this project is organized as follows. Section 2 describes the theoretical framework between institutions and the environment, especially deforestation, in addition to its possible spatial interactions and heterogeneous patterns. Section 3 details the proposed methodologies and database, while the research results are outlined in Section 4. Finally, the robustness checks, heterogeneity tests, and conclusions are given in Sections 5, 6, and 7, respectively.

2 Theoretical Background

2.1 Institutions and the environment

Despite its relevance, the relationship between institutions and deforestation remains an open debate (Choumert, Combes-Motel e Dakpo 2013; Greenstone e Jack 2015; Busch e Ferretti-Gallon 2017; Wehkamp et al. 2018; Polasky et al. 2019; Fischer, Giessen e Günter 2020), in particular, because it involves endogenous mechanisms that act, to a large extent, through socioeconomic and political channels that hinder identification (Cropper e Griffiths 1994; Arrow et al. 1995; Pamayotou 1997; Bhattarai e Hammig 2001, 2004; Dasgupta et al. 2002; Chimeli e Braden 2005; Van e Azomahou 2007; Chimeli 2007; Culas 2007, 2012; Busch e Ferretti-Gallon 2017).

However, institutional improvements have been seen as an important way to reduce deforestation, especially in tropical forests (Fischer et al. 2021). In general, weak institutions make it difficult for local governments to enforce laws and implement conservation policies effectively. In this context of the absence of the government and lower institutional quality, illegal activities and informational asymmetry are greater, which can lead to forest clearings Sohag, Gainetdinova e Mariev 2023. In other words, local institutions shape the impact of conservation policies (Bonilla-Mejía e Higuera-Mendieta 2019). In this context, institutions are an underlying cause of deforestation, a fundamental force that underlies the proximate determinants by creating incentives for the behavior of agents (Larcom, van Gevelt e Zabala 2016; Fischer et al. 2021). However, the relationship between local institutions and deforestation is complex and context-specific (Wehkamp et al. 2018; Bonilla-Mejía e Higuera-Mendieta 2019). It often involves complex feedback mechanisms that act to a large extent through socioeconomic, historical, and political channels, making it difficult to infer causal effects.

Marchand (2016) supports that colonial heritage led to institutional persistence that shaped current institutions, creating different patterns and incentives for deforestation. In practice, institutional quality often plays a key role in smoothing out potential trade-offs of the structural transformation process, especially in the early stages of development when the impact of economic growth is greatest (Cropper e Griffiths 1994; Arrow et al. 1995; Pamayotou 1997; Bhattarai e Hammig 2001, 2004; Dasgupta et al. 2002; Chimeli e Braden 2005; Van e Azomahou 2007; Chimeli 2007; Culas 2007). However, it is important to highlight that the impact of institutions on environmental quality is unclear. According to Chimeli e Braden (2005) e Chimeli (2007) show that environmental quality may increase or decrease with institutional improvements, especially in early stages of economic development, because it may affect Total factor productivity (TFP), the efficiency of spending on environmental protection or pollution intensity of capital

The evidence for deforestation is mixed and varies between regions and countries (Marchand 2016. Furthermore, forest conversion has many irreversible components, such as loss of biodiversity and species extinction, so institutional development may be insufficient to achieve environmental restoration. Therefore, the relationship between institutions and deforestation is difficult to generalize, which reinforces the need for specific investigations (Bhattarai e Hammig 2001, 2004; Van e Azomahou 2007; Jusys 2016). In developing countries, in particular, forest clearings usually follow a boom and boost pattern if institutions do not create incentives for the preservation of the environment. Without the right incentives, the extraction of wood and forest products and land use conversion to agricultural and cattle production allows rapid economic growth, but, after a period, with the growing scarcity of forest areas and decreased soil fertility, the pace of economic development may slow down or even reverse (Hartwick 1977; Weinhold, Reis e Vale 2015; Caviglia-Harris et al. 2016).

Spatial spillovers and heterogeneous patterns usually change the relationship between institutions, economic development, and environmental quality. For example, increased economic activity, especially in agricultural frontier regions where law enforcement is weak, generates agglomeration and externalities effects that attract labor and capital, which could boost environmental degradation (Choumert, Combes-Motel e Dakpo 2013; Pfaff e Robalino 2017). Deforestation, in particular, is affected both directly and indirectly by the decision of neighbors and by spatially correlated unobservables, altering the balance between economic development and forest conservation (Robalino e Pfaff 2012). This process occurs mainly through three channels: i) Input Reallocation: economic agents, when faced with restrictions on land use, can reallocate capital and labor; ii) Market Prices: leakage effects arising directly from market conditions for agricultural and forestry products along with capital assets and labor. iii) Learning: Technology learning and adoption are affected by information networks (Pfaff e Robalino 2017).

In addition, the relationship between institutions and environmental quality can vary with historical, economic, and environmental differences, highlighting the need to consider heterogeneous responses and non-linearities (Koop e Tole 1999; List e Gallet 1999; Van e Azomahou 2007). In deforestation, this phenomenon potentially reflects differences in historic experiences, intrinsic environmental characteristics, and/or dynamics among the regions with forest clearings reflecting local conditions (Barbier e Burgess 2001).

2.2 Brazilian regions, biomes, and institutions

Brazil is one of the largest countries in the world with a territory of approximately 851 Mha and is also one of the richest countries in biodiversity in the world. It holds a significant portion of the planet's natural resources and plays an important role in regulating the global climate. The country has six biomes: Amazon 419 Mha (49,29%), Cerrado 203 Mha (23,92%), Atlantic Forest 111 Mha (13,04%), Caatinga 84 Mha (9,92%), Pampa 17 Mha (2,07%) e Pantanal 17 Mha (1,76%). These biomes have large stocks of carbon, biodiversity, and the largest reserve of fresh water in the world.

However, deforestation, forest fires, and environmental degradation, especially in the Amazon, have caused concern due to irreversible losses of its natural resources, biodiversity, emission of greenhouse gases, and the emergence of diseases (Ferrante e Fearnside 2019). For example, the forest area covered approximately 70.5% of the Brazilian territory in 1985 but was reduced to just over 60% in 2017, with the Amazon concentrating 41.8% of deforestation and the Cerrado 33.8%. The Atlantic Forest, in turn, is the biome that has undergone the most changes in land use and cover due to its older occupation (Souza et al. 2020).

The expansion of the agricultural frontier in Brazil is an important driver of deforestation, resulting from an increase in the demand for agricultural and forest products. However, it often promotes local economic growth and poverty alleviation in regions with lower development, such as the Amazon and Matopiba[1], highlighting potential trade-offs. The decision of land users to convert forest areas to farmlands is usually driven by cattle and high-value crops, such as soybeans and corn (Assuncao, Gandour e Rocha 2015; Bustos, Caprettini e Ponticelli 2016; Araújo et al. 2019). In this context, the implementation of protected areas is often adopted as a conservation policy to inhibit deforestation, although with mixed results, especially due to leakage, spatial spillovers, and location bias (Ferraro

[1] Matopiba is the agricultural frontier in the Cerrado biome located in Maranhão, Tocantins, Piauí, and Bahia.

e Hanauer 2014; Amin et al. 2019). Command and control policies were also important to curb Brazilian deforestation by increasing enforcement of conservation laws (Hargrave e Kis-Katos 2013; Assuncao, Gandour e Rocha 2015). Finally, it is important to mention that the literature, in general, supports heterogeneous patterns and spatial spillovers in Brazilian deforestation (Jusys 2016; Faria e Almeida 2016; Amin et al. 2019).

It is also important to note that a significant part of Brazil's land is public and faces land tenure insecurity, especially in the Amazon biome, which frequently drives higher rates of deforestation, illegal occupations, expropriations, and violence (Alston, Libecap e Mueller 2000; Araujo et al. 2009; Hargrave e Kis-Katos 2013). To make matters worse, in this context, international trade plays an important and ambiguous role in determining deforestation patterns, because, on the one hand, it creates incentives for agricultural frontier expansion (Faria e Almeida 2016) while, on the other hand, can contribute to forest conservation by generating alternative economic opportunities (Lopez e Galinato 2005). In this context, national and local institutions play a key role in environmental sustainability, primarily for common property resources such as forests by creating incentives for conservation and law enforcement (Polasky et al. 2019).

Despite the existence of common macro-institutions, many components vary significantly across the country due to colonization heritages and geographical differences. There were no complex societies before colonization in Brazil, which made institutional arrangements strongly associated with the colonization process along with climate and geographical conditions. The country was a Portugal colony from 1500 to 1822 and its colonization took place mainly through different extractive economic cycles, such as the sugarcane and gold cycles, which varied in their institutional characteristics. The sugarcane was the first major economic boom cycle in Brazil; occurred mainly on the Northeast coast side and was characterized by monoculture plantations based on slave labor. In this context, economic and political power was concentrated in a small elite with the Metropolis focusing on establishing rules to extract revenue from the colony, making institutions unequal and extractive (Menezes-Filho et al. 2006; Naritomi, Soares e Assunção 2012; Nakabashi, Pereira e Sachsida 2013).

Next, in the gold economic boom, Portugal also established a series of regulations to extract income from mining activity. However, despite their efforts, fraud was constant, which induced the Metropolis to adopt increasingly aggressive regulations and control mechanisms, resulting in a highly antagonistic environment between the public institutions and civil society. On the other hand, despite the widespread use of slaves, society was not as polarized as in the sugar cycle, because technologies and the scale of production allowed slaves to gain bargaining power due to the informational asymmetries present in the mining activity. Therefore, the disparities in institutional development between Brazilian municipalities can be traced back to these colonial origins and differences, which, in turn, are not related to the current deforestation Naritomi, Soares e Assunção 2012.

3 Empirical Design

3.1 Identification strategy

We propose to estimate the causal effects of institutional quality change on deforestation. However, there are some challenges to achieving this goal. The simultaneity and endogeneity problems associated with institutions and deforestation make it difficult to assess a causal relationship, prompting the need for a source of exogenous variation to instrumentalize institutional quality change. In this context, since institutional inertia perpetuates initial differences in institution development (Acemoglu, Johnson e Robinson 2001; Engerman e Sokoloff 2002; Dell 2010; Marchand 2016; Easterly e Levine 2016), we use different experiences of colonization as a source of exogenous variation in institutional quality to estimate its impact on deforestation.

We support the hypothesis that institutional differences between Brazilian municipalities are based on two basic assumptions: (i) colonization policies among Brazilian regions largely reflected different economic cycles and geographic characteristics that, in turn, resulted in institutional quality differences at the municipal level; (ii) institutional quality inertia so that initial differences in institutional quality perpetuate over time, impacting current changes. In addition, it is worth mentioning that municipalities are the smallest political and administrative units in Brazil and despite having a homogeneous formal role, there are still significant differences in institutional quality between them, both in terms of administrative quality and public goods provision. For example, municipalities have administrative autonomy, can collect some taxes, and decide on specific spending on education, health, and infrastructure.

Therefore, since land use changes, market conditions, and governance can impact both institutional development and clearings, this paper considers institutions as endogenous and, therefore, proposes a two-stage estimation, using different experiences of colonization as a source of exogenous variation to instrumentalize current institutions' quality growth differences. In this sense, we exploit differences at the municipality level related to colonial experience and geographical differences. As suggested by Menezes-Filho et al. (2006), Naritomi, Soares e Assunção (2012) e Nakabashi, Pereira e Sachsida (2013)), we use distance (in kilometers) to the coast, to the metropolis (Portugal), and to colonial villages to capture effective colonial interference. These variables reflect the higher administrative and trade costs that ultimately determined the degree of Metropolis intervention in the colony. Next, we constructed a binary variable that indicates if the county was founded during the sugar and gold booms to capture different institutional heritages that arise from these extractive economic cycles. We also used socioeconomic differences from the first Brazilian Census of 1872 at the state level: proportion in the population of literate, slaves, white, foreigners, and liberal professionals. We expect these baseline variables to be related to the evolution of institutions but not the current deforestation. Our first-stage equation is the following,

$$\Delta Institutions_i = \beta_0 + \beta_1 Z_i + \delta Controls_i + u_i \tag{1}$$

where Z_i is the instruments listed above; $\Delta Institutions_i$ is the change in the local institutional quality indicator between 2005 and 2015, and u_i is the error term. Our second stage equation is given by:

$$\Delta Deforestation_i = \beta_0 + \beta_1 \Delta Institutions_i + \delta Controls_i + \varepsilon_i \tag{2}$$

where $\Delta Deforestation_i$ is the forest cleared at municipality i between 2005 and 2015; ε is the error term. Therefore, we also eliminate the potential fixed effects that could compromise our exclusion restriction by estimating a first difference model between 2005 and 2015[1] at the municipality level. In other words, we propose to exploit differences in settlers' experiences to isolate the causal relationship between local institutional change and deforestation in Brazil.

To further support our exclusion assumption, we control for possible geographic confounders that may affect both deforestation and instruments. The geographic controls are composed of temperature, precipitation, soil quality, altitude, and forest stock, which capture remaining geographical differences that may affect local institutional development and clearing patterns. For example, these variables can affect road construction and maintenance, along with the potential for agricultural productivity, affecting both deforestation and colonization patterns (Chomitz e Thomas 2003), which would invalidate

[1] We limited the empirical analysis for 2005 and 2015 due to data incompatibilities for other years to construct the local institutional quality indicator,

our exclusion hypothesis. The identifying assumption is that conditional on these local characteristics, instruments have no other effect on the deforestation patterns than through the institutional quality channel.

3.2 Data

To estimate the effect of local institutions on forest clearings, we used data at the municipality level covering the country's 5,570 municipalities. Our outcome variable is forest change in the 2005-2015 period from the annual maps of land cover and land use released by MapBiomas, which uses images from Landsat satellites with 30 meters pixel resolution to estimate land use changes. The initiative was formed in 2015 and covers all the Brazilian biomes.

However, municipalities in Brazil are very different in terms of their area, which could bias our results. Therefore, to overcome this, we divided our variable of interest by the municipality area, which resulted in the percentage of forest change in the period. In addition, we propose two robustness checks: (i) alternative normalization for our outcome variable; (ii) restrict our sample to municipalities with at least 10% and 20% of remaining forest. In addition, we explored potential heterogeneity in forest dynamics by considering forest gain and loss separately. In other words, this paper seeks to contribute to the conservation debate by including dynamics beyond primary forest loss, since the literature has few papers on forest regrowth (Busch e Ferretti-Gallon 2017; Ferraro e Simorangkir 2020).

To measure institutional quality change, we created an institutional quality indicator with Principal Component Analysis (PCA) based on Leão et al. (2020) for 2005 and 2015, which seeks to represent the quality of the public administration in the municipalities. The information used comes from the *Pesquisa de Informações Básicas Municipais (MUNIC)* from the Brazilian Institute of Geography and Statistics (IBGE). It is worth mentioning that the variables that make up the indicator are based on the municipalities' normative attributions granted by the Federal Constitution of 1988. However, many Brazilian municipalities have not yet been able to comply with these requirements, or have done so with poor quality, which creates cross-section variation that can be explored. The indicator reflects the municipalities' administrative capacity, ranging from tax collection to administrative and planning instruments. Additional information and the results are presented in Appendix A.

To construct our distance instruments, we used spatial vector data to build specific variables to this empirical design. First, we used the municipalities centroids to measure the linear distance to (i) the metropolis, which we considered the Lisbon centroid, the capital of Portugal, and (i) to the coast. The shapefiles of the municipalities, the Lisbon and the Brazilian are available in the *Instituto de Geografia e Estatística (IBGE)*. Next, we constructed a variable that measure the linear distance from the municipalities centroid to the nearest colonial villages, which are the urban districts created in the colonial period (between 1500 and 1822). The data come from the Digital Atlas of America Lusa built by the University of Brasilia (UnB). The socioeconomic variables from the first Brazilian census of 1872 at the state level are also from IBGE. Finally, for the sugar and gold booms, we created two binary variables that assigned one for municipalities founded in regions affected by the economic cycles before its end; and zero otherwise.

The rainfall and temperature data are the average values from the 1961 to 1990 period, available in the Climate Research Unit from the University of East Anglia (CRU-UEA). For soil quality, we constructed a variable using the Map of Brazilian Agricultural Potential compiled by the Brazilian Institute of Geography and Statistics (IBGE) and made available by the Ministry of the Environment. The Brazilian territory was classified according to the agricultural potential of its soils, considering: fertility, physical and morphological characteristics, main limitations, and topography. The altitude and neighbors' slopes are constructed with the Land Elevation Data from NASA's Shuttle Radar Topography Mission (SRTM). The forest stock is the remaining forest percentage in 2005, previous to our considered period to avoid endogeneity and simultaneity problems. It is worth mentioning that we used raster and vector spatial models in R to construct the variables for each municipality in the country.

4 Results

4.1 First Stage

To check our hypothesis that different colonial heritages resulted in distinct long-run institutional development along the Brazilian regions, we considered the first stage estimation, in Table 1. To further support our results and exclude threats to our exclusion restriction, we control for geographical variables that may be related to both deforestation and local institutions: soil quality, altitude, annual precipitation, remaining forest area, and dummies for the main biomes in Brazil; Amazon, Cerrado, and Atlantic Forest. To check the robustness of our instruments, we added controls gradually, which resulted in six specifications.

All instruments are statistically significant in specifications (1) to (6), except the Sugar Boom and its interaction with distance to Portugal. This result supports our main hypothesis that different historical heritages resulted in different local institutions in Brazil. In addition, the F statistic is statistically significant in all specifications, confirming the relevance of the instruments and reinforcing the validity of our empirical approach. In general, as the distance between Portugal and colonial villages increases, institutional quality became better, which supports our hypothesis that a higher control from the Metropolis and the colonial authorities resulted in forces that did not favor local institutions in the long run, leading to lower institutional quality growth today. In addition, the literate population proportion in 1872 also led to higher current local institutional quality development, indicating that education had an important long-run impact in Brazil.

On the other hand, higher distance to the coast is negatively correlated with institutional quality growth today. This evidence supports the hypothesis that institutions located in regions distant from the coast are relatively weaker, which may reflect differences in the colonial experiences, institutional heritages, and occupation of the territory. For example, the coast concentrated most of the Brazilian population until the construction of Brasília, the country's new federal capital in the 1950s. The proportion of slaves in the

Tabela 1 – First Stage

	Dependent variable: Δ Institutions					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance Portugal	0.0012***	0.0013***	0.0014***	0.0015***	0.0017***	0.0017***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)
Distance Coast	−0.0099***	−0.0098***	−0.0098***	−0.0097***	−0.0104***	−0.0108***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0014)
Distance Villages	0.0113***	0.0118***	0.0115***	0.0117***	0.0130***	0.0089**
	(0.0040)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0043)
Literate	0.2649***	0.2725***	0.2555***	0.2610***	0.2487***	0.2509***
	(0.0808)	(0.0808)	(0.0841)	(0.0838)	(0.0837)	(0.0868)
Slaves	−0.2537***	−0.2508***	−0.2515***	−0.2483***	−0.2344***	−0.3294***
	(0.0565)	(0.0567)	(0.0567)	(0.0573)	(0.0575)	(0.0623)
Gold Boom	225.4281***	226.9660***	228.0565***	224.9500***	211.1647***	224.1026***
	(69.8180)	(69.3591)	(69.6307)	(69.4652)	(67.9565)	(68.8793)
Sugar Boom	10.4868	10.3572	11.9811	12.3860	17.0026	20.3352
	(36.2810)	(36.3886)	(36.4314)	(36.4084)	(36.4381)	(36.4924)
D.Portugal.Gold	−0.0312***	−0.0314***	−0.0315***	−0.0311***	−0.0293***	−0.0311***
	(0.0097)	(0.0096)	(0.0096)	(0.0096)	(0.0094)	(0.0096)
D.Portugal.Sugar	−0.0020	−0.0020	−0.0023	−0.0023	−0.0030	−0.0036
	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0058)	(0.0059)
Soil		−1.7275	−1.6327	−1.7023	−1.0625	−0.9226
		(1.3524)	(1.3552)	(1.3605)	(1.3759)	(1.3830)
Altitude			−0.0009	−0.0010	−0.0006	−0.0007
			(0.0011)	(0.0011)	(0.0011)	(0.0012)
Precipitation				−0.0015	−0.0019	−0.0095***
				(0.0027)	(0.0027)	(0.0032)
Forest					4.5895***	6.0276***
					(1.5008)	(1.5707)
Amazon						5.4294***
						(1.5922)
Cerrado						3.2288***
						(0.9663)
Atlantic Forest						4.1989***
						(1.0854)
Constant	−3.1222	−3.1443	−3.3163	−3.2030	−6.8504***	−5.0547*
	(2.1365)	(2.1370)	(2.1533)	(2.1692)	(2.5355)	(2.8236)
Observations	5,027	5,027	5,027	5,027	5,027	5,027
F Statistic	21.469***	21.238***	21.265***	21.047***	22.411***	17.048***

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

population in 1872 is also negatively correlated with the institutional development today. Considering that Brazil received the largest number of slaves from Africa and was the last in the West to ban slavery, our results support the long-standing negative impacts of enslavement on the institutions.

4.2 Second Stage

Considering the consistency of our results and the empirical support provided to our exclusion hypothesis in the first stage, we used a Two Stage Least Square (2SLS) approach to identify the causal impact of local institutional quality change on deforestation at the municipality level (Table 2). Similar to the first stage, we included geographical controls to further support our findings. In addition, since deforestation may be sensitive to heterogeneous outcomes, the average effect from the two-stage estimation may not be equal across different ecosystems, varying for different biomes. In this context, we exploit our empirical design to access these potential sources of heterogeneity and test whether local institutional quality growth has differential effects across different ecosystems.

We explicitly consider the three biggest biomes in Brazil; Amazon, Cerrado, and Atlantic Forest, respectively. The Amazon, for example, still has most of its territory occupied by native vegetation and is facing intensive agriculture-related land use occupation. On the other hand, the Atlantic Forest is the most degraded biome and densely populated in Brazil. Those factors may create underlying forces that could generate heterogeneous outcomes (Assuncao, Gandour e Rocha 2015; Araújo et al. 2019). In practice, we include binary variables to control for those ecosystem differences and interact with our variable of interest to decompose potential heterogeneous outcomes of institutional change.

Tabela 2 – Two-Stage Least-Squares Regression

	Dependent variable: ΔDeforestation				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
ΔInstitutions	0.0001	0.0012	0.0015*	0.0006	0.0034**
	(0.0002)	(0.0008)	(0.0008)	(0.0010)	(0.0014)
Amazon	−0.0004			−0.0012	0.0101
	(0.0084)			(0.0087)	(0.0107)
Cerrado	−0.0062			−0.0068	0.0112
	(0.0067)			(0.0073)	(0.0071)
Atlantic Forest	0.0122			0.0097	0.0336**
	(0.0084)			(0.0111)	(0.0168)
ΔInstitutions*Amazon	−0.0001				−0.0020
	(0.0002)				(0.0015)
ΔInstitutions*Cerrado	−0.0003				−0.0049***
	(0.0002)				(0.0016)
ΔInstitutions*AtlanticForest	0.0001				−0.0039*
	(0.0003)				(0.0021)
Geographic	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Observations	5,027	5,027	5,027	5,027	5,027
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors				

Our main findings confirmed a positive and statistically significant coefficient for institutions, meaning that local institutional quality growth has a causal impact on deforestation. The results from column 5 suggest a positive impact of institutions on deforestation on average, but a negative impact on the Cerrado and Atlantic Forest biomes.

This reinforces the likely heterogeneous nature of the relationship between institutions and deforestation, which might have important implications for policy design.

Therefore, the Two-Stage Least Square (2SLS) estimation, which addressed the potential endogeneity problem arising from institutional development, led to different results when compared to the OLS estimation which does not account for possible confounders. However, to check the robustness of our results, search for additional insights, and overcome potential caveats with our empirical design, we realized several tests to further support our findings, which are presented in the next subsection.

5 Robustness Checks

5.1 Additional Controls

To search for potential sources of bias that could be compromising our estimations, we test the robustness of the results by controlling for additional variables that may be correlated with institutions and deforestation at the municipal level. Table 3 presents the results. We included additional controls associated with socioeconomic features, international markets, macroenvironmental institutions, human capital, and economic development. In summary, our results are stable due to the inclusion of these controls. In other words, the causal effects of the institutional quality change are not confounded by these variables, confirming the robustness of the results and further supporting our empirical design. In this context, we considered the most complete estimation (Column 7) as our new Benchmark model for the next robustness checks.

Tabela 3 – Robustness Check - Additional Controls

	Dependent variable: ΔDeforestation						
	OLS	Benchmark I	Social	Trade	Fines	HumanCap.	Development
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔInstitutions	0.0001	0.0034**	0.0027**	0.0027**	0.0030**	0.0030**	0.0033**
	(0.0002)	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Amazon	−0.0004	0.0101	0.0207	0.0207	0.0220	0.0220	0.0197
	(0.0084)	(0.0107)	(0.0155)	(0.0155)	(0.0166)	(0.0166)	(0.0157)
Cerrado	−0.0062	0.0112	0.0124	0.0125	0.0137	0.0137	0.0111
	(0.0067)	(0.0071)	(0.0098)	(0.0096)	(0.0088)	(0.0088)	(0.0096)
Atlantic Forest	0.0122	0.0336**	0.0274**	0.0272**	0.0285**	0.0285**	0.0294**
	(0.0084)	(0.0168)	(0.0108)	(0.0111)	(0.0117)	(0.0117)	(0.0120)
ΔInstitutions*Amazon	−0.0001	−0.0020	−0.0015	−0.0015	−0.0018	−0.0018	−0.0020
	(0.0002)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
ΔInstitutions*Cerrado	−0.0003	−0.0049***	−0.0044***	−0.0044***	−0.0047***	−0.0047***	−0.0047***
	(0.0002)	(0.0016)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
ΔInstitutions*AtlanticForest	0.0001	−0.0039*	−0.0035**	−0.0035**	−0.0038**	−0.0038**	−0.0040**
	(0.0003)	(0.0021)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0017)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*No*	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
Human Capital	*No*	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Nightlight	*No*	*No*	*No*	*No*	*No*	*No*	*Yes*
Observations	5,027	5,027	4,971	4,971	4,971	4,971	4,971

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

For socioeconomic characteristics, we considered population density, the proportion of individuals living in rural areas, income inequality, and the Bolsa Familia program. These variables seek to capture population and agglomeration effects, size of the labor and consumer markets, social inequality, and poverty. Next, we created an openness to trade indicator (sum of exports and imports divided by gross domestic product) to control for possible effects arising from international market forces. To control for macro-environmental institutions, we used environmental fines per km2 issued by IBAMA as a proxy. This measure reflects the extent that command and control policies from the federal government may affect deforestation at the municipality level. Then, we included a proxy for human capital, the average schooling as a proxy, to check if it is related to institutional development.

The data source for population density, rural population, inequality, and human capital comes from the 2000 demographic census carried out by *Instituto Brasileiro de Geografia e Estatística* (IBGE). It was conducted through direct interviews with the Brazilian population at the municipal level. The data from environmental fines comes from IBAMA (*Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis*). Finally, the data for Bolsa Familia and openness to trade comes from the Institute of Applied Economic Research (*Instituto de Pesquisa Econômica Aplicada*), IPEA.

Finally, we control for differences in the total visible night light emitted by the earth's surface, which is an important proxy for economic activity. This is supported by the fact that light is a normal good, that is, as income increases, the demand for lighting grows, reflecting a higher level of economic development (Henderson, Storeygard e Weil 2012). The data is from the 2005 DMSP-OLS Nighttime Lights Time Series, which is a cloud-free composite from the Operational Linescan System (OLS) of the Defense Meteorological Satellite Program (DMSP) satellites operated by the National Oceanic and Atmospheric Administration (NOAA). The pixels from the image are 1 km wide, therefore, we calculated the mean value for each municipality considering all pixels that fall within its borders. In the next subsection, we considered potential spatial interactions and spillovers from deforestation.

5.2 Spatial Interactions and Spillovers

Spatially correlated unobservables and neighbors' interactions in deforestation decisions may affect both clearings and institutional performance and lead to leakage effects, invalidating our exclusion restriction and impact valuation (Robalino e Pfaff 2012; Baylis et al. 2016; Pfaff e Robalino 2017; Busch e Ferretti-Gallon 2017). In this context, it is important to include the average deforestation in neighboring municipalities to control for these potential spatial effects. However, to measure such between-municipalities spatial effects, we need to consider the endogenous nature of the problem. To overcome this caveat, we estimated a Spatial Autoregressive Model (SAR) from the spatial econometric literature[1], which use the average of the neighbors' characteristics as instruments (WX). However, first, it is necessary to define a neighborhood criterion, which, in this paper, we used a k-nearest neighbor's spatial weight matrix W based on whether the municipalities share borders.[2]

In addition, we also instrumentalized neighborhood deforestation using neighbors' slopes and neighbors' neighbors' slopes, using the first stage in our identification strategy

$$WDeforest_i = \beta_0 + \beta_1 Neigh.Slopes_i + \beta_2 N.Neigh.Slopes_i + \delta Controls_i + u_i \qquad (3)$$

$Neigh.\ Slopes_i$ and $N.Neigh.\ Slopes_i$ are the neighbors' slopes and neighbors' neighbors' slopes; $WDeforest_i$ is the weighted neighbors' deforestation defined from a neighborhood criterion. However, the empirical results do not support that the deforestation in the neighborhood is correlated with its terrain slopes, which invalidates these instruments. In this context, although we considered an exogenous source of variation, we were not able to isolate the effect of spatial interactions and spillovers from concurrent confounders and endogenous mechanisms. On the other hand, the instruments for the SAR model were statistically significant, which makes this model more suitable to further consider the potential effects of spatial spillovers on the relationship between deforestation and institutions. Therefore, we use the SAR model as our benchmark spatial model for further analysis. The results are outlined in Table 4.

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1 For additional information about the spatial econometric literature, see (Elhorst 2014)

2 In this paper, we choose the k-neighborhood based on the Akaike Information Criterion.

Tabela 4 – Robustness Check - Spatial Models

	Dependent variable: ΔDeforestation				
	OLS	Benchmark I	Benchmark II	Spatial IV	SAR/IV
	(1)	(2)	(3)	(4)	(5)
ΔInstitutions	0.0001	0.0034**	0.0033**	0.0012	0.0026*
	(0.0002)	(0.0014)	(0.0013)	(0.0013)	(0.0015)
Amazon	−0.0004	0.0101	0.0197	0.0067	0.0146
	(0.0084)	(0.0107)	(0.0157)	(0.0095)	(0.0101)
Cerrado	−0.0062	0.0112	0.0111	0.0069	0.0100
	(0.0067)	(0.0071)	(0.0096)	(0.0073)	(0.0092)
Atlantic Forest	0.0122	0.0336**	0.0294**	0.0109	0.0164
	(0.0084)	(0.0168)	(0.0120)	(0.0143)	(0.0115)
ΔInstitutions*Amazon	−0.0001	−0.0020	−0.0020	−0.0006	−0.0011
	(0.0002)	(0.0015)	(0.0014)	(0.0013)	(0.0017)
ΔInstitutions*Cerrado	−0.0003	−0.0049***	−0.0047***	−0.0019	−0.0035**
	(0.0002)	(0.0016)	(0.0014)	(0.0014)	(0.0016)
ΔInstitutions*AtlanticForest	0.0001	−0.0039*	−0.0040**	−0.0007	−0.0024
	(0.0003)	(0.0021)	(0.0017)	(0.0019)	(0.0016)
WΔDeforestation				0.5947**	0.4967**
				(0.2540)	(0.2042)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*No*	*No*	*Yes*	*Yes*	*Yes*
International Trade	*No*	*No*	*Yes*	*Yes*	*Yes*
Environmental Fines	*No*	*No*	*Yes*	*Yes*	*Yes*
Human Capital	*No*	*No*	*Yes*	*Yes*	*Yes*
Nightlight	*No*	*No*	*Yes*	*Yes*	*Yes*
Observations	5,027	5,027	4,971	5,027	4,750

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

The benchmark SAR results confirmed that spatial interactions and spillovers, which presented a positive and statistically significant coefficient, are important in explaining forest clearing decisions at the municipality. Although we can not directly decompose the channels that the interactions and spillovers operate, it captures potential impacts from input reallocation, leakages, market prices, technology learning, and social interactions, which could confound our results. Our outcomes of interest, the local institutional indicator, remained statistically significant, further supporting that it has a heterogeneous causal impact on deforestation. In the next section, we exploit our empirical approach to search for potential biases arising from alternative standardization procedures that could be misleading our results.

5.3 Alternative Standardisation

The standardization technique that we chose for our outcome variable, forest change (ha) divided by the municipality area (ha), which resulted in the percentage of forest change in the 2005-2015 period, could also be driving our empirical results. Therefore, in Table 5, we re-estimated our benchmark results by using alternative standardization techniques. We considered three additional standardization procedures: (i) the normalized deforestation constructed by subtracting the municipality forest change from the country's mean and diving it its standard deviation; (ii) the hectares of forest change divided by the municipality area in km^2 (ha/km^2); and forest change (ha) divided by the remaining forest stock (ha) in the initial period (2005).

Tabela 5 – Robustness Check - Alternative Dependent Variables

	Dependent variable: ΔDeforestation			
	Percent (%)	Normalized	ha//km2	Forest Percent (%)
	(1)	(2)	(3)	(4)
ΔInstitutions	0.0033**	0.0119**	0.0014***	0.0010
	(0.0013)	(0.0046)	(0.0005)	(0.0012)
Amazon	0.0197	0.0701	0.0028	0.0231**
	(0.0157)	(0.0557)	(0.0034)	(0.0099)
Cerrado	0.0111	0.0395	0.0096***	0.0059
	(0.0096)	(0.0340)	(0.0027)	(0.0084)
Atlantic Forest	0.0294**	0.1043**	−0.0044	−0.0110
	(0.0120)	(0.0425)	(0.0029)	(0.0106)
ΔInstitutions*Amazon	−0.0020	−0.0073	−0.0002	0.0024*
	(0.0014)	(0.0049)	(0.0006)	(0.0014)
ΔInstitutions*Cerrado	−0.0047***	−0.0169***	−0.0014***	−0.0035***
	(0.0014)	(0.0051)	(0.0005)	(0.0014)
ΔInstitutions*AtlanticForest	−0.0040**	−0.0142**	−0.0013***	−0.0035**
	(0.0017)	(0.0061)	(0.0005)	(0.0015)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*Yes*	*Yes*	*Yes*	*Yes*
Human Capital	*Yes*	*Yes*	*Yes*	*Yes*
Nightlight	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,971	4,971	4,971	4,971

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

The results for Columns (1) to (3) support the robustness of our identification strategy since the institution's coefficient remains statistically significant. In other words, our main results are not driven by the method of standardization adopted and the sample used. However, the institution's coefficient is not robust when our dependent variable is the percentage of forest change; only its interactions with Cerrado and Atlantic Forest are statistically significant. These empirical results indicate that institutional quality change in the Cerrado and Atlantic Forest biomes has a consistently negative causal effect on deforestation. Meanwhile, in the Amazon and the remaining biomes of Brazil, the impact is positive or not robust. Therefore, the results further support that institutional quality change has a causal effect on forest clearings after considering heterogeneity in biomes characteristics. However, it is worth mentioning that column (4) indicate that our results may still hide potential heterogeneous outcomes arising from the different remaining proportion of forest stock in the municipality. Therefore, in the next section, we realized a heterogeneity test to explore if different sample compositions related to remaining forest stock change our main results.

5.4 Alternative Institutional Indicators

Finally, we used two different proxies for institutional quality change to test the robustness of our results: (i) land distribution and (ii) property rights insecurity. The distribution of land aims to proxy *de facto* political and economic power, which could be concentrated in a small elite within the municipalities and, therefore, be correlated with extractive institutions (Naritomi, Soares e Assunção 2012) and deforestation. On the other hand, the insecurity of property rights captures weak enforcement institutions that could lead to higher land use conflicts and expropriations, reducing incentives for forest conservation (Alston, Libecap e Mueller 2000; Araujo et al. 2009). We constructed a land Gini coefficient to represent the land distribution and the proportion of land occupied by squatters to capture insecurity in property rights. To construct both variables, we used the 2006 and 2017 Brazilian Agricultural Census. It is worth mentioning that all regressions were instrumentalized in a two-stage estimation as in the benchmark regressions for the institutional quality change indicator. The results are in Table 6

We can note that the proxies for institutional quality change, Land Gini (2) and Squatters (3) are positive and statistically significant, indicating that higher land concentration and propriety right insecurity lead to increasing rates of forest clearings. On the other hand, by considering biome heterogeneities on land concentration and property right insecurity, Land Gini (5) became statistically insignificant while Squatters (5) remained positive and statistically significant and its interaction with the Cerrado biome indicator was negative and statistically significant. Therefore, land concentration and property rights insecurity changes are in general associated with higher deforestation

Tabela 6 – Robustness Checks - Alternative Institutional Indicators

	Dependent variable: Δ Deforestation					
	Institutions	Land Gini	Squatters	Institutions	Land Gini	Squatters
	(1)	(2)	(3)	(4)	(5)	(6)
ΔInstitutions	0.0029			0.0030**		
	(0.0026)			(0.0013)		
ΔLand Gini		0.5184***			0.1221	
		(0.1767)			(0.0761)	
ΔSquatters			0.0106***			0.0027**
			(0.0035)			(0.0014)
Amazon	−0.0715**	−0.0351	−0.0857**	0.0181	0.0181	0.0118
	(0.0361)	(0.0322)	(0.0362)	(0.0142)	(0.0152)	(0.0209)
Cerrado	0.0717	0.0155	−0.0666**	0.0114	0.0044	−0.0281**
	(0.0572)	(0.0194)	(0.0292)	(0.0093)	(0.0071)	(0.0139)
Atlantic Forest	−0.0139	−0.0219	−0.0852***	0.0302**	0.0144*	−0.0075
	(0.0140)	(0.0147)	(0.0249)	(0.0126)	(0.0087)	(0.0149)
ΔInstitutions*Amazon				−0.0018		
				(0.0014)		
ΔInstitutions*Cerrado				−0.0047***		
				(0.0014)		
ΔInstitutions*AtlanticForest				−0.0038**		
				(0.0016)		
ΔLandGini*Amazon					0.0157	
					(0.1059)	
ΔLandGini*Cerrado					−0.4191	
					(0.2880)	
ΔLandGini*AtlanticForest					−0.3682**	
					(0.1671)	
ΔSquatters*Amazon						0.0030
						(0.0026)
ΔSquatters*Cerrado						−0.0039**
						(0.0018)
ΔSquatters*AtlanticForest						−0.0015
						(0.0037)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Human Capital	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Nightlight	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,971	4,971	4,971	4,971	4,971	4,971
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors.					

levels in Brazil, except property rights insecurity in Cerrado which is negatively associated with deforestation, suggesting potential heterogeneous outcomes for the causal effects of institutional quality changes on forest clearings in Brazil. In this context, we propose additional heterogeneity tests in the next section to further explore our results.

6 Heterogeneity Test

6.1 Alternative Sample Compositions

To show that the heterogeneous effects that we estimate for the percentage of forest change at the municipality level are indeed the causal impact of institutional quality change, we further estimate a series of regressions that considered the remaining forest stock to construct the samples used. The results are in Table 6.

Tabela 7 – Heterogeneity Test - Sample

	Dependent variable: ΔDeforestation				
	10%	20%	30%	40%	50%
	(1)	(2)	(3)	(4)	(5)
ΔInstitutions	0.0033**	0.0023*	0.0003	0.0003	−0.0004
	(0.0013)	(0.0014)	(0.0013)	(0.0013)	(0.0008)
Amazon	0.0197	0.0311	0.0051	0.0051	0.0027
	(0.0157)	(0.0242)	(0.0100)	(0.0100)	(0.0084)
Cerrado	0.0111	−0.0053	0.0085	0.0085	0.0190**
	(0.0096)	(0.0147)	(0.0082)	(0.0082)	(0.0074)
Atlantic Forest	0.0294**	0.0230*	0.0195*	0.0195*	0.0199
	(0.0120)	(0.0125)	(0.0113)	(0.0113)	(0.0215)
ΔInstitutions*Amazon	−0.0020	−0.0019	0.0003	0.0003	0.0018**
	(0.0014)	(0.0014)	(0.0011)	(0.0011)	(0.0008)
ΔInstitutions*Cerrado	−0.0047***	−0.0015	−0.0024***	−0.0024***	−0.0021**
	(0.0014)	(0.0018)	(0.0009)	(0.0009)	(0.0009)
ΔInstitutions*AtlanticForest	−0.0040**	−0.0030	−0.0007	−0.0007	−0.00003
	(0.0017)	(0.0018)	(0.0015)	(0.0015)	(0.0014)
Geographic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Socioeconomic	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
International Trade	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Environmental Fines	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Human Capital	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Nightlight	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,971	3,927	3,021	3,021	1,777
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors				

This test indicates that our results are driven by the remaining forest stock at the municipality in the initial period. In other words, the coefficients change according to the remaining forest stock threshold chosen to create the sample. In samples with municipalities with higher forest stock, the institutional quality coefficient turned to be unstable and not statistically significant, and even became negative for densely forested counties - more than 50% of forest area. Its interaction terms also changed with sample composition, indicating that the heterogeneous effects are also related to the forest stock.

6.2 Causal Random Forest

The search for potential heterogeneous treatment effects and for by what mechanisms it occurs are important in the formulation and design of public policies. However, the estimation of heterogeneous effects is an empirical challenge, as the most common methods usually require a pre-specification of how the effects occur either through variable interaction with a heterogeneity indicator, or through subgroups from the initial sample. Both approaches require ad hoc hypotheses, which can lead to biased inferences. In this context, advancements in the literature have been combining traditional causal inference methods with machine learning algorithms to disentangle heterogeneous outcomes. In this paper, we highlight Athey e Imbens (2016) e Wager e Athey (2018) who proposed a causal Random Forest that allows an estimation of the treatment effect for different subgroups and does not require ad hoc hypotheses, as it iteratively partitions the data based on the treatment effect. Therefore, the algorithm allows a parsimonious way to estimate sources of treatment effect heterogeneity that is robust in out-of-sample validation, while avoiding problems with multiple hypothesis tests. Athey, Tibshirani e Wager (2019) generalized the method which enabled the estimation of a local conditional treatment effect with instrumental variable.

The Causal Random Forest algorithm uses a modified version of regression trees, which are characterized by being flexible and non-parametric, for automated subgroup selection. The regression trees split the sample into subgroups in which treatment effects are estimated, however, in this causal context it is not possible to use the traditional mean squared error (MSE) metric to construct the tree leaves because the counterfactual value is not observed. The partition is chosen based on the minimization of the Expected Mean Squared Error (EMSE) between the estimated treatment effect and its true value. The authors propose an honest approach in which it separates the training sample into two; one to determine the tree splits and another to estimate the predicted value, avoiding model overfitting in which the predictions performed poorly out-of-sample. Then, it averages the predictive values over many causal trees to create a Causal Random Forest that is pointwise consistent for the true treatment effect and has an asymptotically Gaussian and centered sampling distribution.

In practice, the instrumental Causal Random Forest estimates a local Conditional Average Treatment Effect (CATE) for each unit in the sample, which, in our empirical approach, resulted in a coefficient for each municipality in Brazil. In summary, the estimations indicated that the mean CATE is 0,000499 with 0,002375 of standard deviation. Further exploring this result shows that 1,833 municipalities presented a negative coefficient and 3,199 positives, which confirmed a significant heterogeneity for the institutional quality change causal effect on deforestation in Brazil. However, it is worth mentioning that only 1,062 of those results were statistically significant; 1398 with a positive coefficient and 77 with a negative one.

To further explore our empirical design, we also estimated a local CATE for the alternative institutional indicators; Land Gini and Squatters. The first presented a mean CATE of 0,03126 and 0,09230 of standard deviation with 3975 being statistically positive and 18 negative. On the other hand, the squatters presented a mean CATE of 0,000682 and 2,924 of standard deviation with 594 positive statistically significant and 0 negative[1] The fact that we have a Conditional Average Treatment Effect for each municipality in Brazil allows us to plot the results in a map to further explore its spatial distribution in the country. The results are presented in Figure 1.

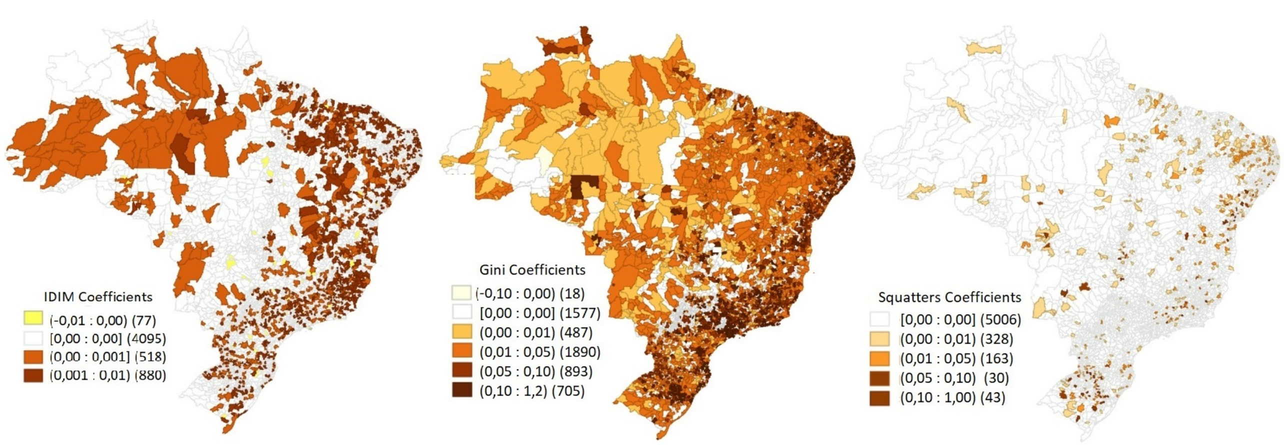

Figura 1 – Local Conditional Average Treatment Effect (CATE).

[1] When considering all coefficients (and not only the statistically significant ones), 4540 are positive and 492 negative for the Land Gini indicator; while 4825 are positive and 207 negative for the Squatters indicator.

It is worth mentioning that the coefficients that were not statistically significant are represented by zero in Figure 1 while the remaining ones are statistically significant with 95% confidence. In summary, we can note that positive changes in the three institutional indicators are generally associated with increases in deforestation rates; only 77 municipalities presented a negative coefficient for the institutions' indicator, 18 for the Gini indicator, and zero for Squatters.

7 Final Considerations

Tropical deforestation is a worldwide concern and Brazil is a significant player in this environmental scenario since it has the biggest active agriculture frontier and the highest tropical deforestation area in the world. The Brazilian Amazon and the Cerrado biomes, for example, are important biological ecosystems with high levels of forest stock and biodiversity, but they have been presenting significant forest clearings in the last decades. In this context, the literature points out that intuitions can play a key role in curbing or increasing deforestation because they create the incentives and rules that economic, social, and political agents operate. However, although it is expected that institutional changes have a significant causal effect on forest clearings, the subject is still an open debate and needs further empirical investigation, especially because the relationship embodies important endogenous and confounding factors that hinder identification.

In this context, this paper aimed to estimate the causal effect of local institutional change on deforestation in Brazil. For that, we specifically constructed an indicator using Principal Component Analysis (PCA) to proxy local institutional quality change and used geographical and historical features as exogenous variations to instrumentalize the relationship and, therefore, estimate a credible causal impact. In other words, we followed the economic development literature that hypothesized that current institutions reflect, to a great extent, geographical and historical events faced by the country's settlers which conditioned initial institutional arrangements and, due to institutional inertia, perpetuated it to the current period. In addition, we searched for potential heterogeneous effects since deforestation is particularly sensitive to local heterogeneity and used alternative institutional proxies, such as land concentration and property rights insecurity.

Our main results confirm that local institutional change has a heterogeneous statistically significant causal effect on Brazilian forest clearings. We also confirm the robustness of this empirical evidence after several tests that aimed to find potential confounding factors that could be biasing the results. We also confirm the causal effect for the alternative proxies tested, which indicate that forest clearings in Brazil are related to institutions in a broader sense. To further explore our identification strategy, we used a Causal Random Forest, an algorithm that estimates a local Conditional Average Treatment Effect (CATE) that is robust in out-of-sample validation. This novel empirical approach indicates that, although there are significant heterogeneous effects between local institutions and deforestation, the majority has a positive causal impact. In other words, increases in local institutional quality, land concentration, and property rights insecurity lead to higher deforestation rates for a significant part of municipalities.

It is worth mentioning that, despite the robustness of our results, our empirical estimates must be considered with caution and future empirical design should consider these potential flaws. First, we used just a few potential institutional features as proxies to estimate the causal effects; local institutions Institutions can take many forms, designs, and arrangements with some characteristics being harder to capture, especially the informal ones. Second, the results may reflect only a snapshot of the relationship since our database is limited temporally and regionally. In other words, by further considering different temporal and/or regional settings in future papers, the estimates could change due to changes in structural or local characteristics. Finally, our empirical design considered just a handful of empirical methods and approaches; future research could try additional or newer methods to corroborate or not the results. However, it is important to state the results found in this paper can contribute to the debate by supporting the hypothesis that institutions have a causal impact on deforestation, although with heterogeneous effects. This fact, in turn, is important to show that public policies and institution design must move beyond the average effects and adequately consider potential deforestation side effects and heterogeneous outcomes,

A Appendix

To construct the local institutional quality indicator, we used the Principal Component Analysis (PCA) in twenty variables that capture many dimensions of institutional quality for 2005 and 2015. We have chosen the variables based on the literature, especially Leão et al. (2020). The variables' descriptions are in Table A1.

Tabela A1 – Variables used in the local institutional quality indicator.

Variables
Plano diretor - existência
Legislação sobre solo criado ou outorga onerosa do direito de construir - existência
Legislação sobre área e/ou zona especial de interesse social - existência
Legislação sobre zona e/ou área de especial interesse - existência
Legislação sobre parcelamento do solo - existência
Legislação sobre zoneamento ou uso e ocupação do solo - existência
Legislação sobre operação urbana consorciada - existência
Legislação sobre estudo de impacto de vizinhança - existência
Legislação sobre regularização fundiária
Código de obras - existência
O município cobra IPTU
Consórcios de Educação
Consórcios de Assistência e desenvolvimento social - existência
Consórcios de Turismo - existência
Consórcios de Cultura - existência
Consórcios de Habitação - existência
Consórcios de Meio ambiente - existência
Consórcios de Transporte - existência
Consórcios de Desenvolvimento urbano - existência
Consórcios de Saneamento e/ou Manejo de Resíduos Sólidos - existência

Source: Prepared by the authors.

The PCA enabled the extraction of six factors with characteristic roots greater than one ($\lambda_i \geq 1$). The explained variance was approximately 60%. The Kaiser-Meyer-Olkin (KMO) test resulted in a 0.9384 value, corroborating that the variables used are sufficiently correlated to use the PCA approach.

To construct the indicator, we used the following equation: $Institutions_m = \sum_{j=1}^{k} \frac{\lambda_j}{tr(P_{nxn})} F_{jm}$, where $Institutions_m$ is the local institutional quality indicator for municipality m; λ_j is the j-th characteristic root of the correlation matrix; k is the number of factors with characteristic root greater than one; F_{jm} is the factorial load of municipality m from factor j; $tr\left(P_{nxn}\right)$ is the trace of the correlation matrix. Then, we transformed it so that the values are restricted to the 0-100 range.

Parte II

Economic growth and the preservation of the Amazon rainforest: Is it possible to reconcile?

B Introduction

The Amazon is the largest tropical forest in the world with high levels of biodiversity, water resources, and forest biomass. However, its deforestation has caused concern worldwide due to the irreparable loss of its natural wealth and emissions of greenhouse gases. The region is the most active agricultural frontier in the world in terms of forest loss and CO2 emissions (Assuncao, Gandour e Rocha 2015). At the same time, poverty is still a problem in the Amazon, prompting the need for economic growth. However, increases in the scale of production may lead to land use changes and structural transformation that put additional pressure on natural resources (Arrow et al. 1995; Bustos, Caprettini e Ponticelli 2016).

This paper examines the potential trade-offs between economic growth, especially of income per capita, and deforestation in the Brazilian Amazon. It aims to contribute to the debate with a new empirical approach to model the relationship between economic growth and deforestation by controlling for institutional improvements, market conditions, and population pressures that may change the relationship or shift its tipping point. In addition, we use satellite night light data as a proxy for economic growth to check the robustness of our results as this may be better suited to represent economic scale increases in remote and underdeveloped regions like the Amazon (Henderson, Storeygard e Weil 2012).

In general, economic growth leads to structural transformation, changes in demographic factors, and shifts in consumption patterns that create opposing pressures on the environment, especially in the presence of heterogeneous outcomes and spillovers. However, even though the increased scale of economic activity put additional pressure on natural resources, higher stages of development partially offset its adverse effects by improving the composition and techniques of production and abatement costs, on the supply side, and by increasing the marginal willingness to pay on the demand side. The net result of these contradictory forces is largely determined by the behavioral incentives generated by institutions (Selden e Song 1994; Grossman e Krueger 1995; Arrow et al. 1995; Dasgupta et al. 2002; Greenstone e Jack 2015; Polasky et al. 2019). The literature shows that institutional improvements can smooth the trade-off between economic growth and deforestation, especially in the early stages of development when the impact of economic growth is greatest, reducing the environmental costs of economic growth (Cropper e Griffiths 1994; Arrow et al. 1995; Pamayotou 1997; Bhattarai e Hammig 2001, 2004; Dasgupta et al. 2002; Van e Azomahou 2007; Culas 2007, 2012).

Therefore, the literature supports that several contradictory economic forces explain the relationship between economic growth and environmental quality like structural, technological, institutional, and demand composition changes. In this context, some authors argue that the negative impacts of economic growth are concentrated in the early stages of development up to a point where there is a turning point in which the economy moves towards sustainable development[1] (Arrow et al. 1995; Dasgupta et al. 2002). However, empirical exercises that test this hypothesis for deforestation do not always support it because the relationship may vary from region to region, largely due to regional and institutional differences (Bhattarai e Hammig 2001; Choumert, Combes-Motel e Dakpo 2013). Therefore, the relationship between economic growth and environmental preservation, in general, and the deforestation of tropical forests, in particular, are still an open debate (Choumert, Combes-Motel e Dakpo 2013; Greenstone e Jack 2015). Therefore, additional research and empirical assessments are needed to shed light on this controversy.

For Amazon, several empirical papers consider the relationship between economic growth and deforestation with mixed results (Araujo et al. 2009; Oliveira et al. 2011; Polome e Trotignon 2016; Tritsch e Arvor 2016; Jusys 2016). However, despite the importance of market conditions and institutional improvements for the conservation policies that aim to reduce deforestation in the Amazon, there is no paper in the literature that explicitly considers these factors in the same empirical framework. Given that the region's economic growth largely depends on activities that are sensitive to these changes, such as the agricultural sector, the mixed evidence found in the literature may be due to the non-consideration of these confounded factors.

Therefore, to further support our empirical approach and eliminate potentially hidden bias, common in nonexperimental designs, we control for confounding variables that could affect both economic performance and forest clearings: i) population pressure (Cropper e Griffiths 1994); ii) agricultural markets conditions (Hargrave e Kis-Katos 2013; Assuncao, Gandour e Rocha 2015); iii) technology (Barbier e Burgess 2001); iv) openness

[1] Sustainable development is an optimal allocation of the planet's resources in meeting the needs of the present, in terms of poverty alleviation and well-being, without compromising future generations and the planet's sustainability (Polasky et al. 2019).

to trade (Faria e Almeida 2016); v) property rights (Alston, Libecap e Mueller 2000; Araujo et al. 2009); vi) protected areas (Ferraro e Hanauer 2014); vii) rural credit (Chomitz e Thomas 2003); ix) spatial spillovers (Pfaff e Robalino 2017; Amin et al. 2019); x) indirect land use changes (ILUC) (Arima et al. 2011; Andrade de Sá, Palmer e di Falco 2013). We also control for possible spatial and dynamic interactions in deforestation, as well as leakages from conservation policies and externalities arising from market conditions and agricultural frontier expansion (Arima et al. 2011; Oliveira et al. 2011; Andrade de Sá, Palmer e di Falco 2013; Jusys 2016; Pfaff e Robalino 2017; Amin et al. 2019; Assuncao et al. 2019).

Our results show that higher income per capita is negatively associated with deforestation while its growth has a positive relationship. Both were statistically significant and robust to the inclusion of controls for population pressure, agricultural frontier expansion, market conditions, and institutional changes. Next, we realized several tests to further check the robustness of our results. First, we control for potential confounding variables that could bias our results: (i) - cattle, corn, and soybean productivities; (ii) - soybean and sugarcane indirect land use changes (ILUC); (iii) - time fixed effect. In other words, we seek to control potential effects arising from agricultural practices and technology adoption, indirect displacement effects for land use changes, and, finally, technological and macroeconomic shocks. Although both income per capita and growth drop their coefficient value in absolute terms, they remained statistically significant supporting the robustness of the initial benchmark estimates.

Second, to check if our results are being driven by the way our deforestation variable was measured and calculated (deforestation percentage rate), we used different units or calculations for our dependent variable: (i) logarithm of the deforestation area; (ii) deforestation area divided by the municipality area; (iii) time normalization[2]; (iv) deforestation in hectares. The results confirm the robustness of the estimates for income per capita because the coefficient kept its signal and statistical significance; except for the time normalization procedure that turned the coefficient not statistically significant. On the other hand, only the deforestation in hectares remained positive and statistically significant for income growth, with the remaining coefficients losing their significance or changing their signal. Therefore, in summary, our test confirms the robustness of income

[2] We subtracted the municipality deforestation percentage rate from Brazil mean deforestation percentage rate in the period; then divided by its standard deviation.

per capita but not its growth, which seems to be driven by the way that the dependent variable is calculated.

Third, we estimated several alternative models to check if our results are not being driven by spatial and dynamic effects, potential leakages from conservation policies, and spillovers arising from market conditions and agricultural activities. In summary, the estimates followed the same pattern described in the previous paragraph, with income per capita remaining statistically significant and negative in all alternative specifications, but its growth becoming not significant or even changing its coefficient signal. We also performed several restriction tests to find which dynamic/spacial specification is the best to capture the variation in our database. The tests pointed out that the Dynamic Spatial Autoregressive Model (DSAR), which captures both spatial and dynamic effects from deforestation, was the best specification. In other words, the results further supported the robustness of the relationship between income per capita and deforestation in the Amazon even in the presence of spillovers and dynamic effects. It is worth mentioning that the spatial effects may also control for potential confounding variables that are spatially autocorrelated in addition to spatial spillovers from deforestation, which reduces potential omitted variable bias; and the dynamic component controls for many common macro impacts, such as macroeconomic and technological shocks. Therefore, we further used the Dynamic Spatial Autoregressive Model (DSAR) as our new benchmark model for further analysis,

Forth, we check if our results are being driven by endogeneity problems following Amin et al. (2019) that proposed a test based on the re-estimation of the models using the residuals as a dependent variable. If our estimations do not suffer from endogeneity problems, it is expected that the explanatory variables would be not statistically significant. The estimations confirm that the explanatory variables were not statistically significant for our DSAR benchmark model, which reduce concerns arising from the fact that we are not using exogenous variation to estimate the relationship between economic growth and deforestation. In addition, it is worth mentioning that only the models that included the spatial interactions component did not present statistically significant explanatory variables, indicating that the control for this variable captured confounding variations that were biasing our results.

Fifth, our results may also hide significant heterogeneous outcomes since there are many regions in Amazon with different stages of economic development and levels of human occupation. In this context, we split our database considering the level of income per capita and how the agriculture frontier expanded in the municipality in the previous decade. These two features of the municipalities encompass important underlying characteristics that could lead to heterogeneous outcomes. To accomplish the test, we (i) ranked the municipalities using the income variable in three levels to proxy municipalities with relatively low, middle, and high relative income; (ii) considered two samples for agriculture frontier expansion, one with municipalities that presented expansion in its agricultural area in the previously decade, 1990-2000, and those that do not expand its area. In summary, our results presented heterogeneous outcomes, confirming our hypothesis. For example, higher income per capita is associated with lower deforestation rates in non-frontier agricultural areas and in high and middle-income municipalities; while having a lower negative coefficient for frontier regions and was not statistically significant in the low-income sample.

Sixth, we search for potential mechanisms by which income per capita could be acting to cause forest clearings since the relationship could be mediated by these mechanisms. In practice, we interact our variable of interest with six potential mechanisms: structural transformation, education, market access, migration, resources, rural population, and Bolsa Famılia (a poverty alleviation program). The income per capita coefficient remains statistically significant and even increases, in absolute terms, its magnitude in some estimations. In addition, the estimates resulted in a positive and statistically significant coefficient for the structural transformation arising from the industrial sector and the municipality market access. Therefore, deforestation is higher when the industrial sector increases its participation in the gross domestic product and when the municipality is farther from the state capital market.

Seventh, we used a different proxy for income per capita to rule out potential concerns arising from the choice of the variables to represent the phenomena of interest. First, we calculated municipal-level changes in per capita night light intensity from the DMSP-OLS Nighttime Lights Time Series database, which is a cloud-free composite from the Defense Meteorological Satellite Program (DMSP) operated by the National Oceanic and Atmospheric Administration (NOAA). According to Henderson, Storeygard e Weil 2012, this variable is a better proxy for economic performance for remote areas with poor economic statistics. Increases in night light reflect income gains since it captures the intensity of the use of outdoor lights and a portion of indoor lighting in human settlements.

The estimates support our benchmark results with higher night light intensity associated with lower deforestation rates.

Finally, we further explore our empirical design to search for potential environmental impacts beyond primary forest loss, using a novel database provided by the Mapbiomas project and remote sensing images from Landsat 7 to construct proxies for environmental quality. From Mapbiomas, we considered forest gain and loss and, from the Landsat 7 images, we calculated the NDVI (Normalized Difference Vegetation Index) and the EVI (Enhanced Vegetation Index) that measure above-ground biomass and are indirectly used to search for environmental degradation and regeneration. In summary, the results show that income per capita and growth were not statistically significant, indicating that it is not directly associated with environmental quality. However, when we interact the variables with an indicator that represents if the municipality is presenting environmental degradation or regeneration, some interesting heterogeneous outcomes emerge. After controlling for this heterogeneity, the income per capita presented a negative and statistically significant association with environmental loss in line with our previous results. In addition, income per capita in municipalities that presented gains in environmental quality was statistically significant and negatively associated with environmental loss while in municipalities with environmental loss, the relationship reverses. Therefore, our results indicate that it is important to consider potential heterogeneous outcomes in the relationship between economic performance and environmental quality.

We structured the paper into four sections, including this introduction. In the second section, we bring a debate about deforestation drives and economic development in the Brazilian Amazon and the Third section details the database and methodology adopted. The results are in the fourth section, followed by final considerations.

C Deforestation Drivers and Economic Development in the Brazilian Amazon

The deforestation decision is largely linked to various economic, social, and political forces that affect the cost-benefit of forest clearing. For example, higher agricultural commodity prices, market access, and an inadequate conservation policy create incentives for deforestation (Barbier e Burgess 2001). In developing countries, economic growth in rural areas is initially associated with land use changes and deforestation. Market absence for the forest ecosystem services such as biodiversity, climate and ecosystem stability, carbon storage, and environmental amenities leads to higher conversion rates than socially desirable. The agricultural frontier expansion that leads to considerable land use changes is one of the most important factors to explain deforestation in Legal Amazon (Igliori 2006).

Large-scale deforestation in the Brazilian Amazon began after the 1960s with the implementation of infrastructure and colonization projects aimed to develop and occupy the region. Among them, we highlight the construction of highways that integrate the Amazon with the rest of the country, subsidized credit, and colonization incentives. From the 1980s onwards, deforestation has been increasingly conditioned by the commodity market dynamics, especially for cattle ranching and soybean (Barbier e Burgess 2001; Hargrave e Kis-Katos 2013; Assuncao, Gandour e Rocha 2015).

Pasture expansion for cattle production is the main deforestation driver in the Amazon, comprising 65% of the total area. The production of soybeans and maize, often adopted jointly in crop rotation, also contribute to the Amazon rainforest occupation (Barona et al. 2010; Faria e Almeida 2016). However, the indirect impacts of soybean are possibly more important than the direct ones, which reflects considerable land use changes. Soy increased its production, for example, mainly on occupied land, especially by extensive livestock (Barona et al. 2010; Arima et al. 2011). This process induced the displacement of cattle rearing, due to the demand inelasticity for beef, to regions where the price of land is relatively lower, usually in the agricultural frontier (Andrade de Sá, Palmer e di Falco 2013).

The indirect impact of land use changes also extends to other crops that have recently gained market value, such as sugarcane and maize. The increase in the national and international demand for animal feed and biodiesel led to higher profits, inducing production growth; and indirectly displacing cattle to agricultural frontier regions in the Amazon. The empirical pieces of evidence support that the increase in sugarcane production for biodiesel in São Paulo state, and to a lesser extent in other regions, shifted livestock towards the agricultural frontier, together with other non-fuel crops. Between 2002 and 2012, the sugarcane displacement effect resulted in approximately 16,000 km^2 of cleared area in Amazon, corresponding to 12.2% of total deforestation in the period (Barona et al. 2010; Andrade de Sá, Palmer e di Falco 2013; Jusys 2016).

It is worth mentioning that spatial interactions in forest conversion and land use changes are also important to explain deforestation. Centripetal forces, generated by productivity differences, transport costs, climate, topography, and soil conditions cause significant regional differences; attracting productive activities, especially agricultural and livestock. Several papers found evidence of a strong positive spatial interaction impacting deforestation in the Legal Amazon (Igliori 2006; Pfaff et al. 2007; Oliveira et al. 2011; Jusys 2016; Amin et al. 2019). In addition, several determinants of deforestation have dynamic aspects since deforested areas facilitate the access of new economic agents, leading to new forest conversion (Amin et al. 2019).

In the Brazilian Amazon, deforestation reached a peak in 2004, with approximately 28,000 km^2 of forest clearings, reflecting increases in agricultural prices and the failure of the conservation policies (Hargrave e Kis-Katos 2013; Assuncao, Gandour e Rocha 2015). In this context, the Brazilian government implanted several changes to its conservation policy for the Amazon. Among them, we highlight the creation of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (*Plano de Ação para Prevenção e Controle do Desmatamento na Amazônia Legal - PPCDAm*)[1], the expansion of protected areas and indigenous lands, the List of Priority Municipalities and the environmental regularity for rural credit. In general, although leakages and spillovers from these policies shift forest clearing to other regions (Amin et al. 2019; Assuncao et al. 2019), they helped to reduce deforestation by 80% in 2012, to 4,500 km^2.

Among the main measures of the PPCDAm, we mention the creation of DETER (Real Time Deforestation Detection System) which created a remote monitoring of deforestation in the Amazon using satellite images with an interval of 15 days. DETER's main objective is to locate deforestation hot spots in near real-time and thus alert the

[1] The plan sought to integrate actions of territorial administration and environmental monitoring and control.

competent authorities, especially IBAMA so that they can focus their actions to control and stop deforestation. DETER was important for combating deforestation in Brazil by enabling deforestation control in almost real-time, especially in critical areas with high rates of forest clearings. Previously, effective action was difficult because illegal deforestation identification occurred through voluntary actions, with no remote sensing system for real-time monitoring.

In addition, from the mid-2000s onwards, protected areas and indigenous territories expanded rapidly, which resulted in approximately 43% of the Legal Amazon area being under protection by the end of the decade. In general, these protected areas hindered deforestation, especially in regions with significant human pressures, by making it difficult to obtain property rights and increasing the probability of punishment for illegal deforestation. However, the literature points to possible spillover effects, which shift forest clearing to other regions, reducing its net benefits (Cisneros, Zhou e Börner 2015; Amin et al. 2019).

In 2008, the Brazilian government created the List of Priority Municipalities to increase the focus on environmental conservation policies in the Amazon. In addition, Presidential Decree 6,514 of July 2008 provided legal support for more effective law enforcement. This decree increased the instruments for curbing environmental crimes, such as the increase in the amount and value of fines, as well as the seizure and destruction of assets used by offenders. In the same year, the National Monetary Council, through Resolution 3,545, turned the granting of rural credit in the Amazon biome conditional on compliance with environmental laws and ownership of a property title. Considering that most rural producers in the region either did not fully comply with environmental legislation or did not have definitive property titles, the resolution caused a significant drop in credit granted, especially among ranchers (Assuncao et al. 2019).

Despite these policies, Caviglia-Harris et al. (2016) e Silva, Prasad e Diniz-Filho (2017) empirical evidence supports that the deforestation reduction after 2004 did not have a significant impact on the pace of economic development in the Brazilian Amazon. According to the authors, after the policies implemented by the Brazilian government in 2004, a "decoupling" process emerged between development and environmental degradation. However, Celentano et al. (2012) highlights that the decoupling may be temporary, with the long-term economic development having as a necessary condition the region's deforestation.

In this context, several empirical papers estimated the relationship between economic growth and deforestation for the Amazon. Polome e Trotignon (2016) e Tritsch e Arvor

(2016) found evidence of an inverted "U"relationship, with growth-inducing deforestation reduction in the long run. On the other hand, Araujo et al. (2009) e Jusys (2016) captured a "U"relationship, with development initially decreasing degradation, but increasing it again after a certain income level. Finally, Oliveira et al. (2011) found an "N"format with environmental degradation returning to increase after high levels of development.

D Methodology

D.1 Empirical Design

The relationship between tropical deforestation and economic growth is a dynamic process that has important interconnections that must be considered in empirical estimates, therefore, a cross-section database is not able to adequately represent this relationship. A panel data approach is more suitable as it allows to control for structural, historical, physical, and institutional characteristics that are relatively fixed over time, in addition to temporal trends such as technological and macroeconomic shocks. Therefore, this paper uses panel data from 2002 to 2011 to measure the relationship between economic growth and tropical deforestation in the Brazilian Amazonian municipalities. In other words, we control for time and fixed effects such as weather, geography, culture, history, economic structure, etc. In addition, to further support our empirical design, we control for changes in institutions, market conditions, and other confounding variables that could be related to both economic performance and forest clearings. Therefore, we estimate the equation

$$Deforest_{i,t} = a_i + a_t + \beta_1 GDP_{i,t-1} + \beta_2 Growth_{i,t-1} + \beta_3 Popul.Pressure_{i,t} + \beta_4 Institutions_{i,t} + \beta_5 Commod.Prices_{i,t} + u_{i,t} \quad (4)$$

where $Deforest_{i,t}$ is the Deforestation percentage rate for the i-th municipality in period t; $GDP_{i,t-1}$ is the gross domestic product per capita in period $t-1$; $Growth_{i,t-1}$ is the growth in gross domestic product per capita between $t-1$ and t; $Popul.Pressure_{i,t}$ is the population growth; $Institutions_{i,t}$ is a institutional vector; $Commod.Prices_{i,t}$ is a price vector from the main agricultural commodities produced in the Amazon; a_i is the municipality fixed effect; a_t is the time fixed effect.

D.2 Database

The deforestation data comes from the *Instituto Nacional de Pesquisas Espaciais (INPE)*, consulted through the *Programa de Cálculo do Desflorestamento na Amazônia (PRODES)*. We compiled data for a sample of 760 municipalities during the 2002-2011 period and considered the annual percentage increment in deforestation as the forest area converted to a cleared area between the years t and t+1. It is worth mentioning that the data is measured from a Landsat satellite image, which is unable to scan through clouds which, therefore, could introduce bias in our estimations due to measurement error. To control for such a problem, we included the percentage of clouds in the municipalities at year t. In addition, to minimize potential heterogeneity problems and get the best fit for our estimation, we considered only municipalities that presented at least 10% of remaining forest, which resulted in 490 municipalities. The Gross Domestic Product (GDP), population, soybean, and corn productivity come from the IBGE (*Instituto Brasileiro de Geografia e Estatistica*). On the other hand, we used cattle productivity data from Cisneros, Zhou e Börner (2015).

Agricultural commodity prices can accelerate the pace of deforestation by increasing the profitability of activities located close to forested areas. However, considering that local prices are endogenous to agricultural production and economic activity in the region, it is necessary to use exogenous variations to capture these effects. Therefore, we used variations in soybean, corn, and cattle prices from a non-Amazonian state, Paraná, to construct the variables, as suggested by Assuncao, Gandour e Rocha (2015). These exogenous variations are weighted by the proportion of municipal area dedicated to that crop in the initial period, which allows, therefore, to control the impact of market conditions considering the importance of agricultural activity for the municipality. Finally, the Agricultural Price variable is an indicator composed of agricultural activities in Brazil, calculated using the Principal Component Analysis (PCA). We also consider timber prices made available by Cisneros, Zhou e Börner (2015).

The present empirical strategy also controls for changes in institutional characteristics, especially those linked to environmental conservation policies. In general, these policies, by prohibiting and/or changing the incentives, impact the pace of deforestation and also the economic agents' decisions regarding land use and land cover. During the period 2002-2011, the Brazilian government changed its environmental policy for the Amazon in several ways, which were controlled by the following variables: i) environmental fines and ii) proportion of embargoed areas, to represent strengthening in monitoring and compliance with environmental law; iii) protected areas; iv) the total amount of rural credit; v) dummy for priority municipalities defined from their inclusion in the list; vi) area of the municipality covered by the Rural Environmental Registry (CAR); vii) party diversity of political representatives.

E Results

Deforestation in Legal Amazon has significant negative impacts on the environment, affecting adjacent localities and potentially global climatic stability. Figure 1 shows the deforestation spatial distribution for the Amazon municipalities between 2002 and 2011. Comparing initial period (a) versus final (b), we identified similar spatial patterns, with the permanence of some municipalities that, a priori, had higher rates of deforestation, in a region known as the "Deforestation Arc", which is characterized by intense agricultural frontier expansion. Despite this, we can notice that this region reduced its dimension, highlighting the significant drop in deforestation rates in the period.

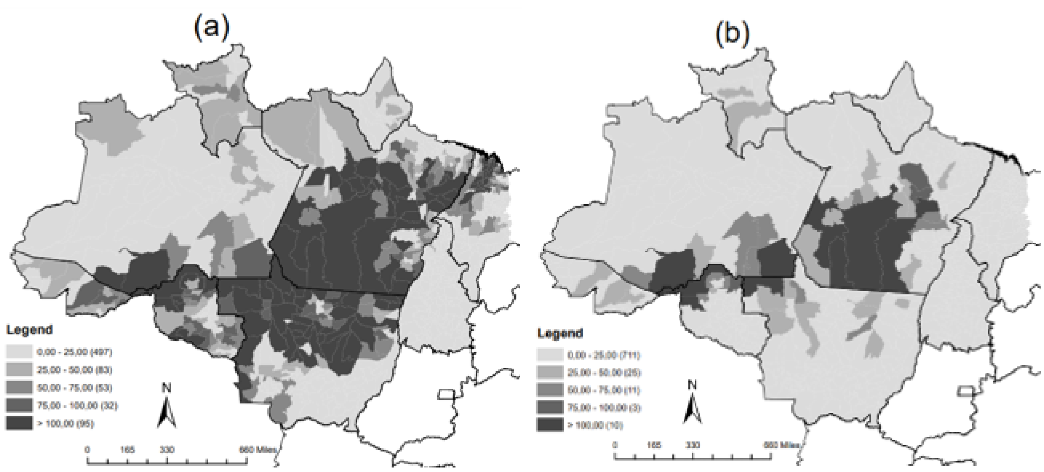

Figura 2 – Deforestation 2002 (a) and Deforestation 2011(b) in Legal Amazon.

Table A2 shows the empirical estimates for the panel data equation (1) from column (1) to (7) and for a pooled estimation in column (8). We gradually included the control variables to check the robustness of the results: population pressure, agricultural frontier expansion, market conditions, and institutional changes, respectively. The panel data approach resulted in better results when compared to the pooled estimation as expected. Therefore, we use the panel data results as the benchmark for the following analysis.

In short, we note that the estimates for GDP and Growth remained statistically significant and with the same signal even with the inclusion of the controls. The GDP, which captures the municipality's income per capita, is negatively associated with deforestation in the Amazon and its coefficient remains relatively stable, highlighting a potentially robust result. The Growth variable presented the same pattern but with a positive association with deforestation. Therefore, a higher economic scale is negatively associated with deforestation

Tabela A2 – Panel Data

	Dependent variable: Deforestation						
	GDP	Growth	Population	Agricultural	Market	Institutions	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP	−0.0749***	−0.0806***	−0.0905***	−0.0888***	−0.0798***	−0.0641***	−0.0123***
	(0.0141)	(0.0148)	(0.0177)	(0.0177)	(0.0168)	(0.0148)	(0.0019)
Growth		0.7086***	0.4163***	0.3953***	0.3767***	0.3540***	0.4409***
		(0.0880)	(0.1031)	(0.1016)	(0.0992)	(0.0928)	(0.0897)
Population			0.0075***	0.0071***	0.0063***	0.0047**	0.0054***
			(0.0022)	(0.0021)	(0.0021)	(0.0021)	(0.0018)
Corn				−0.00001***	−0.00001***	−0.00001***	0.000001
				(0.000003)	(0.000003)	(0.000003)	(0.000002)
Cattle				0.000003***	0.000003***	0.000003***	0.000004***
				(0.000001)	(0.000001)	(0.000001)	(0.000001)
Soybean				0.000004	0.00001	0.00001*	0.00002***
				(0.000004)	(0.000004)	(0.000004)	(0.000004)
Price Corn					−0.00001	−0.00001	−0.000003
					(0.00001)	(0.00001)	(0.00001)
Price Timber					−0.0022***	−0.0015***	−0.0005***
					(0.0004)	(0.0003)	(0.0001)
Price Soybean					0.000004	0.000003	−0.000001
					(0.00001)	(0.00001)	(0.00001)
Price Cattle					0.000002	0.000002	−0.000002
					(0.000002)	(0.000002)	(0.000002)
Party Affiliation						0.0032	0.0227
						(0.0685)	(0.0415)
CAR						−1.6849***	−2.1051***
						(0.2329)	(0.1243)
Protected Area						−0.7993***	−0.1170**
						(0.2579)	(0.0490)
Priority Mun.						−0.4668***	−0.4426***
						(0.0742)	(0.0528)
Embargoed Area						−0.1093**	−0.0557
						(0.0440)	(0.0360)
Rural Credit						6.9105	5.2792
						(9.4805)	(4.2943)
Environmental Fine						−0.00002**	−0.00001
						(0.00001)	(0.00001)
Observations	4,920	4,920	4,920	4,920	4,920	4,920	4,920
R^2	0.0963	0.1155	0.1241	0.1312	0.1440	0.1688	0.1034
Adjusted R^2	-0.0046	0.0166	0.0256	0.0328	0.0463	0.0725	0.0997

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

while its growth is positively associated with deforestation. In the next subsections, we check the robustness and potential mechanisms, and heterogeneity in our results.

E.1 Robustness Checks

In Table A3, we check the robustness of our results by including additional controls in the benchmark estimation (column (7), Table A2), which is reproduced in column (1) of Table A3 for comparison reasons. We included an interaction term between the proportion of forest in a previous period (2000) and a trend in column (2) to capture differences in deforestation among municipalities for different initial levels of forest cover. Next, we included in column (3) the cattle, corn, and soybean productivities to control for potential effects arising from different agricultural practices and technology adoption. We also control for deforestation effects coming from soybean and sugarcane indirect land use changes in column (4). These variables were constructed by interacting the soybean and sugarcane area expansion in the Brazilian regions that are not part of the Legal Amazon in $t-2$ with the cattle herd expansion in the Amazon municipalities in $t-1$. These variables control for displacement effects from soybean and sugarcane expansion over pasture areas in other regions of Brazil, which displaces cattle production to the agricultural frontier due to inelastic demand for beef, increasing pressure on forest areas (Barona et al. 2010; Andrade de Sá, Palmer e di Falco 2013; Jusys 2016). Finally, we included the time-fixed effect in column (5) to control for time effects such as technological and macroeconomic shocks.

Tabela A3 – Panel Data (Robustness Check)

	Dependent variable: Deforestation				
	Benchmark I	Forest Trend	Productivity	ILUC	Time Effect
	(1)	(2)	(3)	(4)	(5)
GDP	-0.0641^{***}	-0.0611^{***}	-0.0518^{***}	-0.0511^{***}	-0.0210^{***}
	(0.0148)	(0.0141)	(0.0120)	(0.0118)	(0.0049)
Growth	0.3540^{***}	0.3525^{***}	0.3529^{***}	0.3486^{***}	0.2115^{**}
	(0.0928)	(0.0920)	(0.0898)	(0.0894)	(0.0841)
Agriculture	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Institutions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Forest Trend	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Productivity	*No*	*No*	*Yes*	*Yes*	*Yes*
ILUC	*No*	*No*	*No*	*Yes*	*Yes*
Time Effect	*No*	*No*	*No*	*No*	*Yes*
Observations	4,920	4,920	4,920	4,920	4,920
R^2	0.1688	0.1754	0.1999	0.2019	0.3117
Adjusted R^2	0.0725	0.0796	0.1063	0.1082	0.2293

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

We can notice that the GDP and Growth variables remain statistically significant and with the same signal when compared with the benchmark result. However, it is worth mentioning that the GDP coefficient dropped in magnitude from -0.0641 to -0.0210 and the Growth coefficient dropped from 0.3540 to 0.2115. The biggest drop in both coefficients occurred with the time-fixed effect inclusion, indicating that both variables are, to some extent, correlated with temporal shocks. Considering that the additional controls improved our estimations, we considered the results of column (5) as our new benchmark (II) for the following analysis.

Then, we check the robustness of our results by considering different units or calculations for our dependent variable. In column (2), we used the deforestation logarithm; in column (3), the deforestation divided by the municipality area; in column (4), the time normalization; and in column (5), we used the deforestation in hectares. Despite the different normalization procedures, the GDP variable remains statistically significant and with the same signal, reinforcing the robustness of our results, except for time normalization. However, it is worth mentioning that the Growth variable was significant only for the deforestation in hectares and even changed signal for the deforestation divided by the municipality area, potentially reflecting a not robust empirical estimate.

Tabela A4 – Panel Data (Robustness Check - Dependent Variable)

	Dependent variable:				
	Benchmark II	ln	area	time norm.	hectares
	(1)	(2)	(3)	(4)	(5)
GDP	−0.0210***	−0.0335***	−0.0168***	−0.0076	−1.3625***
	(0.0091)	(0.0063)	(0.0045)	(0.0071)	(0.5145)
Growth	0.2115**	0.0854	−0.0598	0.1757	7.8529*
	(0.0875)	(0.0889)	(0.0798)	(0.1151)	(4.7357)
Agriculture	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Institutions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Forest Trend	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Productivity	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ILUC	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,920	4,920	4,920	4,920	4,920
R^2	0.2134	0.3618	0.2181	0.2041	0.3687
Adjusted R^2	0.1206	0.2851	0.1240	0.1084	0.2928
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors				

Next, we check the robustness of our results by controlling for spatial and dynamic effects, potential leakages from conservation policies, and spillovers arising from market conditions and agricultural activities. This procedure aims to control for potential confounding variables that could be correlated with both economic growth and deforestation. The results are in Table A5. The GDP remains statistically significant for all specifications, a fact that further supports the negative relationship between income per capita and deforestation in the Amazon rainforest. On the other hand, Growth became not statistically significant in the SAR (4), SEM (5), and SDM (6) specifications and even changed its signal in the SLX (3) model, highlighting a least robust result. To select the best dynamic/spacial specification, we started with a general model that includes both spatial and dynamic effects, the Dynamic Spatial Durbin Model (DSDM), and then compared it with simpler specifications. In addition, for the spatial models, we used a k-nearest neighbor criterion for the spatial weight matrices. Then, we tested spatial matrices ranging from 3 to 100 and define the best one based on an Akaike information criterion, an approach that resulted in a matrix with 5 neighbors. Then, we used this spatial weight matrix to estimate all the spatial models in Table A5.

Tabela A5 – Spatial Models

	Dependent variable: Deforestation							
	Benchmark	Dynamic	SLX	SAR	SEM	SDM	DSAR	DSDM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP	−0.0210***	−0.0299***	−0.0119***	−0.0120***	−0.0129***	−0.0122***	−0.0161***	−0.0163***
	(0.0049)	(0.0026)	(0.0050)	(0.0033)	(0.0034)	(0.033)	(0.0025)	(0.0030)
Growth	0.2115***	0.4239***	−0.2653*	0.0955	0.0553	0.0775	0.1918***	0.1740***
	(0.0841)	(0.0871)	(0.1550)	(0.0679)	(0.0670)	(0.0691)	(0.0652)	(0.0645)
WGDP			−0.198***			0.2097		0.0001
			(0.0075)			(0.0055)		(0.0067)
WGrowth			0.3913**			0.2097		0.2631*
			(0.1915)			(0.1397)		(0.1388)
L1.Deforest		−0.0507***					0.0143	0.0140
		(0.0357)					(0.0112)	(0.0113)
Rho (ρ)				0.6847***		0.6798***	0.7009***	0.6953***
				(0.0148)		(0.0147)	(0.0155)	(0.0157)
Lambda (λ)					0.6917***			
					(0.0148)			
Agriculture	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Institutions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Forest Trend	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ILUC	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Spillovers (WX)	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*Yes*
Observations	4,920	4,428	4,920	4,920	4,920	4,920	4,428	4,428
AIC	11670	10621	11633	9620	9628	9624	7846	7858

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors .

The first test compared the Dynamic Spatial Autoregressive Model (DSAR) against the DSDM, which in practice is the same as testing whether all the spatially lagged explanatory variables are jointly non-significant. We obtained a χ^2 statistic of 31.04 (p-value = 0.0729) for the test, so we cannot reject the null hypothesis that the DSAR model is worse than the DSDM model, which is the same as stating that the spatially lagged explanatory variables are jointly non-significant at 5% of statistical significance. Next, we test the dynamic component using a LR (Likelihood-Ratio) test and obtained a χ^2 statistic of 7.66 (p-value = 0.0056), i.e., the dynamic component is statistically significant at 1%. Then, to test if the SEM model is the best specification, we test if the spatially lagged independent variables could be represented by a multiplication of the explanatory variables with the spatial interactions parameter, i.e., $\rho\beta_i$, as suggested by Elhorst (2014). The test resulted in a χ^2 statistic of 112.10 (p-value = 0.0000), thus rejecting the null hypothesis with 1% of statistical significance. In summary, the best specification, considering the restriction tests, is the DSAR model, which we use as the new benchmark model (III) for the following analysis.

The GDP and Growth in the DSAR specification (column (7)) are statistically significant at 1%. In addition, the GDP remains relatively stable in its magnitude and is statistically significant at 1% in all specifications, highlighting the robustness of our results. In other others, even after controlling for spatial and dynamical effects, the relationship between income per capita and deforestation is statistically significant. It is worth mentioning that this evidence further supports our results because the Rho ρ also controls for potential confounding variables that are spatially autocorrelated in addition to spatial spillovers from deforestation, reducing potential omitted variable bias. These results highlight the importance of the indirect effects coming from spillovers to understand the relationship since spatial interactions reinforce initial impacts.

To get further evidence about the robustness of our results, we realized an endogeneity test, following Amin et al. (2019). This test was based on the model's residuals and specifications from Table A5; we re-estimated all models using the residuals as a dependent variable. The logic behind the test reflects the fact that should not be any significance in the model's explanatory variables if there is no endogeneity in the estimates. In other words, if the coefficients are not significant, it further supports the lack of endogeneity in the estimations. The results are in Table A6. The variables of interest are not statistically significant in the specifications that control for potential spatial interactions from deforestation, i.e., that include the Rho term. In particular, the coefficients in the DSAR model, which is the best specification, are not statistically significant, reducing potential endogeneity concerns arising from the fact that we are not using exogenous variation to estimate the relationship.

Tabela A6 – Endogeneity Test

	Dependent variable: Model residuals							
	Benchmark II	Dynamic	SLX	SAR	SEM	SDM	DSAR	DSDM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP	−0.0168***	−0.0242***	−0.0102***	−0.0010	0.0032	0.0006	0.0002	−0.0001
	(0.0020)	(0.0019)	(0.0050)	(0.0020)	(0.0020)	(0.0020)	(0.0021)	(0.0021)
Growth	−0.0165	−0.0039	−0.0127	−0.0188	−0.1503**	−0.0084	−0.0597	−0.0234
	(0.0841)	(0.0826)	(0.0763)	(0.0736)	(0.0740)	(0.0728)	(0.0835)	(0.0825)
Agriculture	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Institutions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Forest Trend	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ILUC	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Spillovers (WX)	*No*	*No*	*Yes*	*No*	*No*	*Yes*	*No*	*Yes*
L1.Deforest	*No*	*Yes*	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Rho (ρ)	*No*	*No*	*No*	*Yes*	*No*	*Yes*	*Yes*	*Yes*
Observations	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors .

Next, we performed a heterogeneity test to check if our results change for sub-samples that consider different underlying characteristics of the Amazonian municipalities. In practice, we considered two features to separate our sample. First, we test if the relationship changes between municipalities that presented agricultural frontier expansion and those that have a more consolidated agriculture, which we called Frontier and Non-Frontier, respectively. To define agricultural frontier regions, we considered those municipalities that presented expansion in their agricultural area in the previous decade, 1990-2000, to avoid endogeneity problems, with data from the Mapbiomas project. Then, we test if our results change with sub-samples of municipalities with different income levels. We ranked our sample by income and divided it into three parts. We called the poorest municipality as Low Income, the middle class as Middle Income, and the richest as High Income. The results are in Table A7.

Tabela A7 – Heterogeneity Test

	Dependent variable: Deforestation					
	Benchmark III	Frontier	Non-Frontier	High Income	Middle Income	Low Income
	(1)	(2)	(3)	(4)	(5)	(6)
GDP	−0.0161***	−0.0165***	−0.0222***	−0.0247***	−0.0231***	−0.0437
	(0.0025)	(0.0065)	(0.0026)	(0.0036)	(0.0040)	(0.0323)
Growth	0.1918***	0.1673	0.2478***	0.0387	0.1912*	0.6843**
	(0.0652)	(0.1292)	(0.0858)	(0.1195)	(0.1045)	(0.3463)
Agriculture	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Institutions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Forest Trend	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ILUC	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
L1.Deforest	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Rho (ρ)	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,428	1,062	3,366	1,476	1,476	1,476

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors .

In general, our benchmark results change for different sub-samples, which confirms a heterogeneous relationship, especially for income per capita and growth. For example, the GDP coefficient is smaller for Non-Frontier, High Income, and Middle Income; and is not statistically significant for Low-Income municipalities. In other words, higher income is associated with smaller rates of deforestation on the Amazon in consolidated agricultural areas and High and Middle-Income municipalities. This is consistent with the literature that relates higher economic development with lower environmental impacts. The Growth variable also presents heterogeneous outcomes; especially in Low-Income municipalities where economic growth has a strong statistical association with deforestation. In addition, for Frontier and High-Income municipalities, economic growth seems to be not related to deforestation. These results confirm that economic scale and growth have heterogeneous associations with deforestation for different income levels and land use stages; and, therefore, must be properly considered in the analyses.

Next, we check for possible mechanisms by which income per capita could be acting. We considered six mechanisms: structural transformation (proportion of industrial and services on the gross domestic product), education (average years of education), market access (distance to the capital state), migration (proportion of the population not born in the municipality), resources (extraction of natural resources), rural population (proportion) and Bolsa Família (a poverty alleviation program). In practice, the relationship between economic growth and deforestation could be mediated by these mechanisms; therefore, by interacting the variables of interest with these potential mechanisms, we can test if some of these variables mediate the economic development effect. The results are in Table A8. The GDP and Growth coefficients and statistical significance remain relatively stable and even increased in absolute terms for some estimations.

Among the interactions, only two are statistically significant: structural transformation arising from the industrial sector and the municipality market access. Although GDP is negatively associated with deforestation, its interaction with the industry share is positive and statistically significant, indicating that when higher income per capita leads to structural transformation in the industry sector it ends up reducing its negative association (in absolute terms) with deforestation on the Amazon. Similarly, economic growth in municipalities with restricted market access has a smaller association with deforestation when compared to regions located next to the state capital.

Tabela A8 – Mechanisms

	Dependent variable: Deforestation								
	Benchmark III	Structure	Education	Market Access	Migration	Resources	Rural Pop	Bolsa Família	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP	−0.0161***	−0.0182***	−0.0137***	−0.0211***	−0.0143***	−0.0161***	−0.0148***	−0.0135***	−0.0163***
	(0.0025)	(0.0025)	(0.0028)	(0.0032)	(0.0024)	(0.0250)	(0.0025)	(0.0025)	(0.0048)
Growth	0.1918***	0.2004***	0.1922***	0.2006***	0.1913***	0.1891***	0.1949***	0.1868***	0.2125***
	(0.0652)	(0.0658)	(0.0658)	(0.0649)	(0.0657)	(0.0654)	(0.0659)	(0.0653)	(0.0661)
GDP*Industry		$4.89e-08^{***}$							$6.42e-08^{*}$
		$(1.71e-08)$							$(3.77e-08)$
GDP*Services		$6.78e-08$							$7.89e-08$
		$(1.26e-07)$							$(1.09e-07)$
GDP*Education			$-1.08e-06$						$-4.99e-07$
			$(9.70e-07)$						$(1.41e-06)$
GDP*Distance				$1.46e-136^{***}$					$1.05e-13^{**}$
				$(4.12e-14)$					$(4.86e-14)$
GDP*Migration					$-1.14e-07$				$-7.50e-09$
					$(9.84e-08)$				$(1.27e-07)$
GDP*Extraction						$-1.88e-10$			$1.83e-10$
						$(6.08e-10)$			$(6.45e-10)$
GDP*Rural Pop							$-3.34e-07$		$-4.85e-07$
							$(2.74e-07)$		$(3.42e-07)$
GDP*Bolsa Família								−0.0001	−0.0001
								(0.0002)	(0.0002)
Agriculture	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Institutions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Forest Trend	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ILUC	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
L1.Deforest	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Rho (ρ)	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,428	4,428	4,428	4,428	4,428	4,428	4,428	4,428	4,428
AIC	7846	7847	7847	7843	7847	7846	7847	7847	7846

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors .

To further support our results, we used a different proxy for income per capita. In remote locations like Amazon, calculating nominal GDP is difficult because a significant portion of economic activities is conducted in the informal sector, economic integration and price equalization are low, and government infrastructure is weak. Furthermore, the calculation of real GDP growth over time also requires reliable price indices, which is also a difficulty for underdeveloped regions. In this context, following the literature suggestion, we used aggregated municipal-level changes in night light to proxy economic performance (Henderson, Storeygard e Weil 2012).

To measure the relationship between economic growth and deforestation in the Brazilian Amazon, we use night light from the DMSP-OLS Nighttime Lights Time Series database. The data is a cloud-free composite from the Defense Meteorological Satellite Program (DMSP) satellites operated by the National Oceanic and Atmospheric Administration (NOAA). DMSP satellites circle the earth 14 times a day to capture the night light intensity of the earth's surface with an Operational Linescan System (OLS) and have been in operation since the 1970s. The sensors were intended to detect "moonlight clouds", but had as a by-product the capture of night lights produced by human settlements. Satellites collect information from all over the earth between 8:30 and 10:00 pm local time.

The raw data is processed by NOAA at the National Geophysical Data Center (NGDC) and then made available to the public. In this pre-processing, information from the most luminous half of the lunar cycle, the summer months (when the sun sets later), auroras, and fires are eliminated, leaving a final product with only light data from human settlements. Finally, they calculate the average of the remaining data from all orbits to compose the annual data, which are then made available to the public. Each annual satellite data refers to a "grid" that shows the light intensity as a 6-bit digital number (from 0 to 63) for every 30 arc-second pixels between 65 degrees South and 75 degrees North latitude. Typically, there is only a small fraction of pixels with a value of 63 located in populated regions of developed countries.

It is worth noting that annual values vary between satellites and also due to sensor configurations, which is minimized by considering a fixed time effect in the panel data estimations. Night light intensity measures the use of outdoor lights and a portion of indoor lighting in human settlements, reflecting that as per capita income increases, so does the consumption of light per person (Henderson, Storeygard e Weil 2012). The results are in Table A9 (we used the DSAR model as the benchmark). The amount of per capita night lights captured by the satellite's sensors is statistically significant and negatively associated with deforestation, reinforcing the previous results for income per capita (GDP). In other words, our results are robust to the proxy used to represent economic performance. Finally, the Night Lights Growth is not statically significant, and Δ Night Lights is statistically significant and negatively associated with deforestation.

Tabela A9 – Night Lights (Robustness Check)

	Dependent variable: Deforestation	
	(1)	(2)
Night Lights	-1.329^{***}	-1.228^{***}
	(0.4090)	(0.4170)
Night Lights Growth		0.0172
		(0.0211)
Agriculture	*Yes*	*Yes*
Market	*Yes*	*Yes*
Institutions	*Yes*	*Yes*
Forest Trend	*Yes*	*Yes*
ILUC	*Yes*	*Yes*
Time Effect	*Yes*	*Yes*
L1.Deforest	*Yes*	*Yes*
Rho (ρ)	*Yes*	*Yes*
Observations	4,920	4,920

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors.

There are many papers in the literature that analyze the deforestation of primary forests, however, only a few consider forest recovery or environmental degradation in general (Busch e Ferretti-Gallon 2017). In this context, this paper uses a novel database provided by the Mapbiomas project and remote sensing images from Landsat 7 to construct environmental degradation indices to better understand forest dynamics on the Amazon. In addition, we check for potential heterogeneous outcomes for the relationship by interacting GDP and Growth with a dummy indicating if the municipality presented environmental regeneration or degradation in the previous period, 2000 to 2005. For forest gain and loss, we used data from the Mapbiomas project. For forest degradation, we used two alternative vegetation indexes derived from satellite images, the NDVI (Normalized Difference Vegetation Index) and the EVI (Enhanced Vegetation Index). Both indices measure above-ground biomass and are indirectly used to search for environmental degradation and regeneration.

In the economic literature, for example, Foster e Rosenzweig (2003) e Burger (2018) used NDVI to proxy deforestation in a context of lack of specific data. The NDVI combines spectral reflectance measurements acquired in the red (visible) and near-infrared regions in the electromagnetic spectrum to capture biomass from live green vegetation. However, NDVI is saturated in high biomass levels, which turn its use impossible for areas with a high concentration of biomass like primary forests in the Amazon rainforest. The EVI, on the other hand, is an enhanced vegetation index with better sensitivity to higher biomass levels because it considers canopy structure and potential atmospheric influences on the spectral reflectance measurements. The results are in Table A10.

Tabela A10 – Environmental Impacts

	Dependent variable:								
	Mapbiom	Mapbiom	Mapbiom	NDVI	NDVI	NDVI	EVI	EVI	EVI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP	−0.00003	0.0001	−0.0007***	−0.0003	0.0009*	−0.0027***	−0.0005	0.0016***	−0.0022***
	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0004)	(0.0007)	(0.0004)	(0.0005)	(0.0007)
Growth	−0.0036	0.0027	−0.0087***	−0.0021	0.0528***	−0.0585***	0.0016	0.0654***	−0.0664***
	(0.0022)	(0.0028)	(0.0027)	(0.0072)	(0.0103)	(0.0157)	(0.0072)	(0.0116)	(0.0157)
GDP*Regener.		−0.0009***			−0.0038***			−0.0040***	
		(0.0001)			(0.0008)			(0.0008)	
GDP*Degrad.			0.0009***			0.0037***			0.0040***
			(0.0001)			(0.0008)			(0.0008)
Growth*Regener..		−0.0120***			−0.1203***			−0.1433***	
		(0.0036)			(0.0182)			(0.0197)	
Growth*Degrad.			0.0114***			0.1215***			0.1436***
			(0.0036)			(0.0176)			(0.0189)
Agriculture	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Institutions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Forest Trend	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
ILUC	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
L1.Deforest	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Rho (ρ)	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920	4,920

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors .

The GDP and Growth are not statistically significant when we do not consider possible heterogeneities in their relationship with environmental degradation (columns (1), (4), and (7)). In other words, income per capita and its growth do not have a significant relationship with forest dynamics when heterogeneous outcomes are not considered. However, in the interaction of these variables with an indicator of environmental regeneration or degradation, a statistically significant relationship emerges. The GDP and Growth interaction with the regeneration indicator presented a statistically significant and negative coefficient for the three environmental quality proxies. This indicates that income per capita and its growth are negatively associated with environmental quality in municipalities that are presenting some form of regeneration. On the other hand, for municipalities that presented environmental degradation, the relationship reverses, as expected, i.e., income per capita and its growth are correlated with environmental degradation. Finally, the three indicators of environmental quality presented similar associations with GDP and Growth, supporting the robustness of these results.

F Final Considerations

Economic growth in the Amazon is a controversial topic because while it may allow regional economic development, it is also associated with several environmental problems. There are several contradictory forces in this trade-off between economic scale increases and the environment like changes in economic structure, technology, institutions, and demand composition, which create additional difficulties for the empirical exercises. In addition, the literature supports that this potential trade-off may vary spatially from region to region due to local idiosyncratic characteristics. Therefore, it is still an open debate if there is a relationship between economic activity and environmental quality, in general, and in the Amazon, in particular, and by which mechanisms it probably works.

In this context, this paper sought to contribute to the debate by estimating the potential trade-offs between economic activity, particularly per capita income and growth, and deforestation in the Amazon. We used a novel approach that controls for institutional improvements, market conditions, population pressures, agricultural practices, technology adoption, indirect displacement effects from land use changes, technological and macroeconomic shocks, spatial spillovers, and dynamic effects. After several robustness checks, we confirm that income per capita has a robust negative and statistically significant association with deforestation while growth did not. However, it is worth mentioning that our results presented significant heterogeneous outcomes with the higher economic scale being strongly associated with lower deforestation rates in non-frontier agriculture areas and municipalities with high and middle income.

Therefore, our results support the hypothesis that higher economic well-being is associated with lower deforestation rates in the Amazon. However, it is worth mentioning that, despite its nonstatistical significance in some robustness tests, income per capita growth presented a positive relationship with deforestation, which highlights environmental concerns. In other words, to achieve higher income, the municipality needs to grow economically, which, in practice, could boost deforestation. Thus, the empirical evidence supports that the negative environmental impacts are concentrated in the early stages of development when the income per capita is still small. Finally, we checked for potential mechanisms that may mediate the relationship; the results suggest that the effects from higher income per capita are lower when the industrial sector increases its participation in the gross domestic product and when the municipality has smaller market access.

Therefore, our results highlight the significance of properly considering the potential environmental impacts of market forces and public policies that lead to economic growth. Although the importance of the empirical evidence that the relationship between income per capita and deforestation is negative, heterogeneous effects and economic growth could hinder the positive environmental impacts and boost forest clearings. However, it is worth mentioning that the results must be seen with caution. Even though we check for several potential sources of bias, the paper did not rule out completely this concern since we do not find an exogenous source of variation for income per capita that would result in a causal effect without doubt, which is an important gap in the literature that must still be addressed in future research. Anyway, the results are important in the sense that fill some gaps in the literature on the relationship between economic growth and deforestation, particularly for the Amazon, and reinforce the importance of the topic and the need for further research.

Parte III

The Impacts of Palm Oil Expansion on Deforestation in the Eastern Amazon

A Introduction

Palm oil is the most consumed and exported vegetable oil in the world and it is used mainly as food and in biodiesel production (Villela et al. 2014; Chong et al. 2017). The growing world demand for this commodity reflects a high production potential, low production cost, and incentives to replace fossil fuels with biofuels, which resulted in a rapid expansion in its production area (Xu et al. 2021).

Palm oil production is mainly located in tropical Asian countries such as Indonesia and Malaysia. Brazil is the 10th largest producer in the world, with most production concentrated in the state of Pará, which has, in particular, shown expressive growth in its cultivated area. For example, in the period between 2004 and 2014, Pará increased its cultivated area by more than 200%, reaching 2190 km^2 in extension and 900,000 tons per year of production, consolidating the state as the main producer in the country with 95% of the national production (Villela et al. 2014; Carvalho et al. 2015; Benami et al. 2018; Nahum, Santos e Santos 2020; Almeida, Vieira e Ferraz 2020). In any case, the cultivated area is still small compared to the country's productive potential. This fact is mainly due to economic restrictions such as high production costs, lack of knowledge about oil palm cultivation, and problems in the sector's governance model (Englund et al. 2015; Benami et al. 2018; Brandão et al. 2021).

Recognizing the importance of palm oil for the country, Brazil has created several programs that encourage the advancement of palm oil production, highlighting the National Program for the Production and Use of Biodiesel (*Programa Nacional de Produção e uso do Biodiesel* - PNPB), the Agroecological Zoning of the Culture of Palm Oil (*Zoneamento Agroecológico da Cultura de Palma de Óleo* - ZAE), the Sustainable Palm Oil Production Program (*Programa de Produção Sustentável de Óleo de Palma* - PPSP) and the Pronaf Eco Palm Oil (*Pronaf Eco Dendê*) (Carvalho et al. 2015; Englund et al. 2015; Lameira, Vieira e Toledo 2016; Nahum, Santos e Santos 2020; Brandão et al. 2021). However, despite the several economic gains that palm oil expansion creates, it has also caused concern due to its potentially negative environmental impacts, especially the deforestation of tropical forests (Koh e Wilcove 2008; Englund et al. 2015; Xu et al. 2021; Brandão et al. 2021).

The recent oil palm expansion in the Eastern Amazon has raised significant environmental concerns due to the existence of highly biodiverse forests in the region, which can be converted into plantation areas (Carvalho et al. 2015). Although the literature confirmed that oil palm cultivation has been replacing forest areas in the Brazilian Amazon (Carvalho et al. 2015; Lameira, Vieira e Toledo 2016; Furumo e Aide 2017; Benami et al. 2018; Almeida, Vieira e Ferraz 2020; Dias e Lima 2021), there are no papers that estimate the causal impacts of palm oil expansion on the trade-off between economic activity and deforestation in the region. This reflects the fact that the expansion of crops is normally associated with several economic, political, and social factors that make it difficult to measure their causal effects (Edwards 2018; Kubitza e Gehrke 2018; Cisneros, Kis-Katos e Nuryartono 2021) and because there is no spatially disaggregated data publicly available about the recent expansion of palm oil in Brazil.

In other words, the identification of the palm oil expansion causal effects on this trade-off, in addition to controlling the endogeneity problem, needs a previous mapping of its cultivation area in two different periods. In this context, this paper first follows the pioneering works of Foster e Rosenzweig (2003) e Burgess et al. (2012) and uses a novel database from Landsat-8 and Sentinel-1 satellite images to track palm oil expansion and forest loss in the Eastern Amazon. Then, it uses satellite data from the NASA/NOAA Visible Infrared Imaging Radiometer Suite (VIIRS) on Nighttime lights to proxy economic activity following Henderson, Storeygard e Weil (2012). Finally, it adopts an identification strategy that explores exogenous variation from geographical differences in the oil palm agro-climatically suitability to estimate its expansion causal impacts on the trade-off between economic activity and deforestation.

In practice, this paper used Machine Learning algorithms to map from satellite images the palm oil expansion and deforestation in the Eastern Amazon in the 2014-2020 period. The choice of the initial year for mapping is due to the limitation of satellite images from Sentinel-1, which was launched and started its operation only in 2014. It is also worth mentioning that this method has been showing satisfactory results for palm oil mapping especially when optical and radar satellites are combined (Chong et al. 2017; Xu et al. 2021), an approach not yet adopted for the Brazilian Amazon. Therefore, to overcome this caveat, we mapped oil palm expansion by combining optical spectral bands from Landsat-8 and radar backscatter values from Sentinel-1 considering a spatial resolution of 30 meters by 30 meters for the images pixels.

This effort resulted in overall classification accuracy for the Random Forest algorithm of 94.53% and 95.53% for 2014 and 2020, respectively, which is far superior to the accuracy presented by the oil palm literature for Amazon. Then, from a land use and land cover transition analysis, we identified that palm oil expanded from 1,074 km^2 to 1,849 km^2 in the region, a growth of 72.16%, and that 156.88 km^2 (20.24%) of this occurred directly over vegetation cover pixels. However, this expansion may involve complex endogenous mechanisms that hinder a causal interpretation for that estimate. Next, we use the NASA/NOAA Visible Infrared Imaging Radiometer Suite (VIIRS) on Nighttime lights satellite data to proxy economic activity considering a one-kilometer radius centered in the pixel[1].

To overcome the endogeneity problem associated with palm oil expansion, this paper explored the fact that the pixels differ exogenously in their productive potential for oil palm cultivation. In particular, we instrumentalize palm oil expansion using the maximum agro-climatically attainable palm oil yield from the Global Agro-Ecological Zoning (GAEZ) calculated by The Food and Agriculture Organization of the United Nations (FAO). Therefore, we compared pixels that were converted to palm oil with those that were not to estimate its causal impact on economic activity and deforestation. First, our results indicated that palm oil expansion is strongly associated with the maximum attainable yield even after controlling for many potential confounders that could compromise our exclusion restriction hypothesis. In other words, we confirmed that our identification strategy is suitable to estimate the causal effects of palm oil expansion in the trade-off between deforestation and economic performance.

Then, we used the instrumentalized palm oil expansion to further estimate, in a second stage logit regression, its causal effects on forest clearing and nightlight. The main results indicated that palm oil expansion has a positive and statistically significant causal effect on deforestation and a negative and statistically significant effect on the nightlight. It is worth mentioning that we control for geographical, maximum attainable yield from potential competing crops, initial economic scale, and infrastructure variables that could be confounded with palm oil expansion, which further supported the robustness of the estimates. Finally, we re-estimated our main results using a Skewed logistic regression (Scobit) approach to check its robustness, since this method is more flexible[2] and better

[1] We considered one-kilometer radius to proxy economic activity for two reasons: (i) there are not greater spatial resolution for night light data; (ii) the economic impacts of palm oil proxy by night light do not occur directly in the pixel, since agricultural activity does not directly emit light.

[2] The Scobit model introduces an additional shape parameter into the link function and encompasses the logit model as a special case. Therefore, the scobit model is a more general and flexible approach than the logit model.

suited to rare-events type outcomes. Since only 11% and 3,36% of the pixels that composed our database presented deforestation and palm oil expansion, respectively, the scobit model could be more suitable to model the palm oil expansion effects. In summary, the estimates further supported our main results, indicating that palm oil expansion has a positive causal effect on deforestation and a negative impact on the nightlight.

Therefore, our results confirm the hypothesis that palm oil expansion in the Eastern Amazon is rising deforestation rates, possibly causing several environmental impacts in the region. In addition, this scenario is worsened by the fact that this expansion is not being followed by rising economic activity that could ease economic and social problems for the local population. However, it is worth mentioning that the results must be seen with caution because our economic proxy is more suitable to capture light from the industrial and service sectors since agriculture does not emit light directly. Therefore, palm oil expansion may be increasing the region's economic performance in the agriculture sector, but this is not being captured by our proxy. Anyway, the negative causal effect of the palm oil expansion on non-agricultural economic activity may be reflecting a centripetal force that attracts labor and inputs to palm oil production, which raises competition and costs for industrial and service sectors, curbing their expansion.

This paper relates to the economic literature that seeks to measure the causal impacts of palm oil expansion in tropical development countries (Edwards 2018; Kubitza e Gehrke 2018; Cisneros, Kis-Katos e Nuryartono 2021) and to the economic literature that uses remote sensing data from satellites to map deforestation and economic activity (Foster e Rosenzweig 2003; Burgess et al. 2012; Henderson, Storeygard e Weil 2012) or to understand economic phenomena in general (Donaldson e Storeygard 2016). This paper also relates to a large literature on the environmental consequences of oil palm expansion in general (Koh e Wilcove 2008), particularly in Brazil (Villela et al. 2014; Englund et al. 2015; Carvalho et al. 2015; Benami et al. 2018; Brandão et al. 2021). Finally, it also contributes to the literature on oil palm mapping in Brazil (Lameira, Vieira e Toledo 2016; Furumo e Aide 2017; Almeida, Vieira e Ferraz 2020) by adopting an innovative methodology that combines optical and radar satellites.

To achieve the proposed objectives, the article is structured in four sections, in addition to this introduction. In section two, we present a literature review on palm oil while in section three we detail the methodology. In sections four and five, we present the results and the final considerations, respectively.

B Theoretical Background

Oil palm comes from Africa and is characterized by being a tree with a life cycle of 25 years, reaching up to 20 meters in height, therefore, it is a perennial crop more similar to a forest than to other agricultural activities. Palm oil is normally grown in monocultures with well-defined uniform geometric features when observed by satellite imagery. In general, palm oil is adapted to a humid tropical climate with high rainfall and solar radiation, as well as temperatures of 24-32ºC (Corley e Tinker 2008).

The production of vegetable oil from palm oil has great potential, especially due to its high productivity, which can reach up to 368 tons/km^2. Comparatively, soy has a productive potential of only 42 tons/km^2 (Carvalho et al. 2015; Englund et al. 2015). This productive capacity, associated with low production costs, largely explains the exponential growth of its demand in the international market (Xu et al. 2021). In Brazil, oil palm production began in the 1970s and accelerated especially in the 2000s to meet its growing demand in the food, cosmetics, and biofuel sectors (Villela et al. 2014; Carvalho et al. 2015; Almeida, Vieira e Ferraz 2020). Oil palm is well adapted to the conditions of the Amazon, especially Pará, due to its favorable soil and climate conditions and the availability of suitable areas for its expansion.

The production growth was especially stimulated from the 2000s onwards with the creation of the National Plan for the Production and Use of Biodiesel (*Plano Nacional de Produção e uso do Biodiesel* - PNB) in 2004, the Agroecological Zoning of the Culture of Palm Oil (*Zoneamento Agroecológico da Cultura de Palma de Óleo* - ZAE) with Decree nº 7.172/2010 and the Palm Oil Sustainable Production Program (*Programa de Produção Sustentável de Óleo de Palma* - PPSP) in 2010 (Lameira, Vieira e Toledo 2016; Nahum, Santos e Santos 2020; Brandão et al. 2021). The National Biodiesel Production and Use Program (PNPB) was launched in 2004 by the Brazilian government to increase biodiesel production, reduce greenhouse gas emissions and encourage regional development. Palm oil has the potential to be an important source for the growth of national biodiesel production due to its high productivity (Carvalho et al. 2015; Nahum, Santos e Santos 2020).

The ZAE and PPSP, in turn, were created to regulate the oil palm expansion to guarantee its social and environmental sustainability. The ZAE indicated the most suitable areas for its cultivation, resulting in approximately 130,000 km^2 of deforested areas with potential expansion, approximately 300 times the size of the current planted area. Its main objective is to ensure inclusive and sustainable regional economic development and encourage the substitution of fossil fuels towards renewable sources. Then, the PPSP was launched, based on the ZAE, to regulate the expansion of palm oil, restricting it to degraded and deforested areas before 2008. In this sense, the program creates incentives for the recovery of degraded areas, which generates social and environmental gains (Carvalho et al. 2015; Benami et al. 2018; Brandão et al. 2021).

Reflecting these institutional stimuli, from 2010 onwards, a new frontier of oil palm expansion was created in Pará, mainly with the replacement of degraded pastures in the Northeast of the state, a region that presents one of the best conditions for its cultivation in Brazil (Almeida, Vieira e Ferraz 2020). The expansion in cultivated areas showed a growth of approximately 200% in the period 2010-2014. However, it is worth mentioning that around 60% of this expansion took place near forested areas, raising environmental concerns, as the deforestation patterns induced by oil palm occurs mainly over adjacent forest areas (Benami et al. 2018).

C Oil Palm Mapping

C.1 Study Area

We selected the Acará, Moju, Tailândia, and Tomé-Açu municipalities, known as the oil palm pole in Brazil, as the spatial units of analysis. Together, they cover an area of 23,014.36 km^2, a significant portion of which is located in the Agroecological Zoning of the Culture of Palm Oil (ZAE). These municipalities are the main producers of palm oil in Brazil, standing out for their socioeconomic dynamism in the Northeast of Pará.

In general, the region has an average rainfall of 2,500 millimeters, with a minimum value of 60 mm for every month - necessary for oil palm cultivation without irrigation. The terrain is relatively flat with an altitude of 50 to 100 meters and an average temperature of 26º C. The region was historically occupied by cattle ranching, which began in 1960 with the conclusion of the BR-010 (Belém-Brasília). Other agricultural activities such as black pepper, açaí, wood (eucalyptus), cassava, and rice are also economically important. (Almeida, Vieira e Ferraz 2020). The region is close to the Belém Endemism Center, characterized by high endemism, fragmentation, and fire risk, being one of the most deforested and ecologically threatened in the Amazon (Almeida e Vieira 2010).

C.2 Remote Sensing

The increasing availability of satellite images with high spatial, temporal, and spectral resolution, and in low-cost monitoring techniques, have facilitated their application in economic and environmental analysis (Donaldson e Storeygard 2016; Weiss, Jacob e Duveiller 2020). Remote sensing allows you to analyze objects on the Earth's surface without physical contact. In this context, it is common to couple these sensors to orbital platforms, such as satellites. Remote sensors are basically of two types: active and passive. Passive sensors are normally optical, capturing the electromagnetic reflectance of targets while active sensors, such as radar and LIDAR, emit their signals and capture the backscatter effects.

Remote sensing data has three types of resolution: (i) – spatial (pixel size); (ii) – temporal (image frequency); and (iii) – spectral (electromagnetic spectrum bands). The best temporal, spatial and spectral resolution largely depends on the object and objective of the study, highlighting that the higher the temporal resolution, the lower the spatial resolution. Orbital remote sensing data contains useful information that can be used to estimate aboveground biomass as well as agricultural productivity and land use and land cover information.

In this paper, we combined optical images from Landsat-8 and radar images from Sentinel-1 from which we extract features to perform the classification. We then collect training and testing samples, with the most relevant variables selected in the training stage. Finally, we validated the model on the test sample and used it for classification and mapping. In the next subsections, we describe each methodological step used to map oil palm cultivation.

C.2.1 Images Selection and Composition from Landsat-8 and Sentinel-1

Initially, we selected Landsat-8 and Sentinel-1 images to compose the database and then mask the clouds based on the "pixel_qa" quality band, whose pixel value (322) has no such interference. Next, we composite the annual images with the median pixels from the image collection on the Google Earth Engine (GEE) platform (Gorelick et al. 2017).

With the annual composite and cloud-free images, we combined the Landsat-8 and Sentinel-1 images. Despite the spatial resolution of Landsat-8 being 30 m and Sentinel-1 being 10 m, we chose to combine the images at 30 m resolution to avoid artificially introducing spatial autocorrelation. It is worth noting that the GEE images were properly pre-processed by the image's proprietary repositories, suitable for final use (Gorelick et al. 2017).

C.2.2 Feature Selection and Extraction

From Landsat-8, this article used the following spectral bands: (i) – blue; (ii) – green; (iii) – red; (iv) – infra-red. There are important biophysical relationships in the spectral information derived from satellite images. For example, the vegetation biomass is related to the red band - which captures photosynthetic efficiency - and the near-infrared band - which identifies the accumulation of biomass. In this context, it is common to use vegetation indices that relate the spectral information captured by the sensors to the health, development, and phenological stage of the vegetation.

From Sentinel-1[1] we use information captured from its dual-polarized C-band: (i) – VV single co-polarization (vertical transmit/vertical receive) and (ii) – dual cross polarization VH (vertical transmit/horizontal receive).Sentinel-1 captures information from the Earth's surface at a time-frequency of 6 days considering the equator and at decreasing intervals as it moves towards the poles. In addition, it provides dual-polarized backscatter coefficients in the C-band at the level of 10 meters spatial resolution.

Vegetation backscatter values are largely determined by leaf angle and size and water content. For soil, the value reflects its moisture and roughness. The indices reflect the aboveground biomass and the three-dimensional structure of the soil-canopy complex. Therefore, Sentinel-1's Synthetic Aperture Radar (SAR) observations provide important complementary information by identifying alternative crop development characteristics and making it possible to obtain data even in the presence of clouds. Therefore, the combination of both optical and radar sensors significantly improves classification accuracy (Meroni et al. 2021).

Then, we used the Landsat images to generate a linear spectral model of the bared soil fraction and the oil palm fraction to reduce the confusion between these two classes and between oil palm and forest areas. The spectral mixing model separates the spectral signatures of different materials contained in a pixel. The resulting components are called *endmembers*, which in practice are pure pixels of a target on the earth's surface (Somers et al. 2011).

Next, we calculated vegetation and texture indices for the bands of the Landsat-8 images in R, using the Rtoolbox and GLCM packages, respectively. Vegetation indices are obtained from arithmetic operations between the different bands of remote sensing images to capture vegetation growth and structure, as well as soil characteristics and other information related to vegetation development and health. In particular, we calculated the following vegetation indices: (i) – Difference Vegetation Index (DVI); (ii) – Ratio Vegetation Index (RVI); (iii) – Greenness Index (GI); (iv) – Normalized Difference Vegetation Index (EVI); (v) – Enhanced Vegetation Index (EVI); (vi) – Soil-Adjusted Vegetation Index (SAVI). Among them, it is worth mentioning: (i) – NDVI, combines information from the red

[1] For more information about the state of the art on radar images and their applications, see Sano, Matricardi e Camargo (2020).

and infrared bands to capture the biomass, however, it presents saturation from a certain level; (ii) – EVI, combines blue, red, and infrared to correct atmospheric interference and thus reduce NDVI saturation; (iii) – GCVI, near-infrared and green to capture chlorophyll concentration to identify nutritional deficit.

Texture indices, in turn, reflect important geometric features for correct class discrimination. In this article, we derived the median of various texture characteristics of the spectral bands of Lansat-8, based on the gray-level co-occurrence matrix (GLCM). In particular, we calculated the following characteristics of GLCM with a 7x7 moving window: (i) – Contrast; (ii) – Angular Second Moment (ASM); (iii) – Correlation; (iv) – Entropy. According to Xu et al. (2021), this information is essential to improve the classification of oil palm, in particular, due to its unique geometric characteristics. We also used Sentinel-1 images to calculate three indicators from the SAR backscattering values : (i) – ratio (VV/H); (ii) – difference (VV-VH); (iii) normalized difference (NDI) – (VV-VH)/(VV+VH). Finally, the effort resulted in 19 variables that will be used to train the classification algorithms.

C.2.3 Sampling Process

To detect and map oil palm plantations in Northeast Pará, we collected a training sample with 6,194 observations with the visual interpretation of Landsat-8 images. We defined the samples in 3 classes: Vegetal Formation; Bare Soil and Palm Oil. The Vegetal Formation class corresponds to areas of primary forests and secondary vegetation. Bare Soil is a land use class and refers to the different types of transformations imposed on the environment by society such as urban infrastructure, agricultural areas, and roads, among others. Palm oil, despite having an arboreal stratum, is a land use class because the emphasis is on its economic and environmental scope.

We based the collection on a random sampling criterion, which resulted in the following distribution for each class (in pixels): Vegetal Formation (3330), Oil Palm (1564), and Bare Soil (1300). Then, we performed a validation of the sample with the visual interpretation of high-resolution images from Google Earth. Finally, we randomly subdivided the sample into 80% for training and 20% for testing.

C.3 Machine Learning

The main goal of Machine Learning[2] is to construct a model to predict or classify some outcome or class of interest. Statistical models are the basis of Machine Learning algorithms; especially regression, classification, and mixed models. Differently from standard statistics, that focus on asymptotic theory and casual relationships, the machine learning literature focus on the model's predictive or classification power. In practice, there are two basic algorithms: supervised and unsupervised. In this paper, we use different algorithms based on supervised models to classify the remote sensing information, that is, assign a class to each pixel in the images. To access the best machine learning algorithm for this paper, we used five complementary methods: K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF).

To implement such an approach, the first step is to train the model to minimize misclassification and avoid overfitting. In practice, we need to split our data sample in two: one for training and another for testing. In other words, this seeks to test the validity of our model by using the testing sample to access the classification power of the estimated model. To minimize potential bias, we used sampling techniques to construct the training and test samples, which comprise 80% and 20% of the total sample, respectively.

To check the robustness of the results, we use a k-fold cross-validation method, with 5-fold, to ensure that the testing data represents our data sample. This technique splits the data sample into k chunks and creates, for each chunk, a training and testing sample and estimates the model. Then, it takes the average of the k predicted errors from each chunk. In other words, the k-fold cross-validation enables to access the potential classification variation due to sampling. In addition, we adopted a recursive feature elimination method, which, in practice, is an optimization algorithm that selects the best combination of variables to use in the model training.

Then, after eliminating the non-relevant variables and with the model trained, it is important to compare the classification results. This is done by applying the trained model to the test sample to obtain the performance of the estimations in a sample that

[2] See Burger (2018) for a general explanation of Machine learning algorithms. For remote sensing image classification, in particular, see Kamusoko (2019) and, for agriculture and environmental applications, see Holloway e Mengersen (2018)

was not used in the training. Finally, we compared each classification algorithm based on the classification's overall accuracy level and the Kappa coefficient.

C.4 Post-classification processing

C.4.1 Spatial Filter and Manual Reclassification

After classification, we used a spatial mode filter with a 7x7 window on the images to minimize the salt and pepper effect, common in pixel-based classifications. This effect occurs because the classification by pixel does not consider spatial dependence, classifying independently of the neighborhood relationship. (Liang, Li e Zhao 2021). Therefore, the spatial mode filter, performed with the *raster* package in R, aims to reduce this effect and improve the final classification. Finally, we performed a manual reclassification of palm oil areas based on the visual interpretation of their geometric characteristics, color, texture, etc. Next, we identify the transitions between land use and land cover classes.

C.4.2 Land Use and Land Cover Transition

Then, with the final oil palm mapping, we performed an analysis of land use and land cover transitions at the pixel level. This effort is important to identify the dynamics of oil palm and how its expansion is taking place in the region, which makes it possible to check whether it is occurring over deforested areas or through the deforestation of natural areas. In other words, based on the transition results, it is possible to infer whether the advance of oil palm in the Eastern Amazon is sustainable. Finally, it is worth noting that the transition analyzes were performed in R with the OpenLand package.

D Empirical Strategy

Identifying the causal impacts of palm oil on the trade-off between economic activity and deforestation is difficult due to the endogeneity of its expansion. The high potential costs and benefits of investments in oil palm plantations make their location often endogenous with regional characteristics. Estimating the causal effects of palm oil expansion involves two main challenges: (i) – unobservable variables that may be correlated with palm oil expansion and the economy/deforestation; (ii) – reverse causality, as a higher rate of deforestation and/or economic activity could also encourage the expansion of palm oil.

This paper explores an exogenous variation, the maximum potential agro-climatically attainable palm oil yield, to instrumentalize its expansion in the Eastern Amazon and thus estimate its causal impact on deforestation and economic gains. In practice, the empirical strategy uses a two-stage estimation with an instrumental variable (IV) that explores geographic differences in potential palm oil yield. The instrument is measured as the agro-climatically attainable palm oil yield at the pixel level. It is calculated by FAO-GAEZ based on agronomic models and provides data on agroclimatic potential yield for different crops and levels of input and management at 30 arc-second (0.9 x 0.9 km) resolution. In this paper, we use the maximum potential yield of palm oil under non-irrigated, low-input, and low-management conditions for an average climate for the period 1961-1990.

Therefore, the first-stage estimation is,

$$Oil\_Palm_i = \alpha + \gamma Yield_i + \delta Controls_i + u_i \tag{5}$$

where Oil_Palm_i is a binary variable with value 1 when the pixel i is converted to the palm oil class, that is, it is the instrumented variable; $Yield_i$ is the maximum agro-climatically attainable palm oil yield for pixel i. The first stage intuition is that higher potential yields increase the probability of crop expansion. given that palm oil firms decide to expand production based on their expected productivity in addition to potential profitability (Edwards 2018).

Then, we estimate the following two second-stage equations to measure the trade-off,

$$Deforestation_i = \alpha + \beta Oil\_Palm_i + \delta Controls_i + \varepsilon_i \tag{6}$$

$$Nightlight_i = \alpha + \beta Oil\_Palm_i + \delta Controls_i + \varepsilon_i \tag{7}$$

where $Deforestation_i$ is a binary variable that receives 1 when the pixel i changes from the vegetation class to any other class; $Nightlight_i$ is the nighttime lights change in the period; Oil_Palm_i is the instrumentalized variable in the first stage that captures the pixel i change for the palm oil class; is the error term. In summary, the empirical strategy estimates the causal impact of oil palm expansion on the trade-off at the pixel level. It is worth mentioning that for $Nightlight_i$ we used the intensity of night light emitted change between 2014-2020 within a radius of 1 km from the pixel i.

D.1 Identification

The crucial identification hypothesis is that the maximum agro-climatically attainable palm oil yield affects deforestation and economic activity only through the expansion channel. According to Kubitza e Gehrke (2018), the instrument is highly correlated with the expansion of oil palm, as, together with access to land and markets, yield potential is the main determinant of land use patterns. Despite this, there are still some threats to the identification strategy that deserves to be highlighted.

Among them, it is worth mentioning that other crops have agroclimatic conditions and expansion patterns that may be similar to palm oil. Therefore, the instrument may be capturing potential agricultural productivity in general, which would not allow causal interpretations for the estimated effects. For example, an important input for GAEZ palm oil productivity is precipitation, which in addition to affecting the outcome for alternative tropical crops, also impacts deforestation and economic activity (Chomitz e Thomas 2003). Although the instrument is specific for oil palm, it is important to exclude this threat from the identification strategy. Therefore, we include in the estimations the potential yields for other competing agricultural activities such as soybean, maize, rice, and cassava.

Another possible threat to the identification strategy is that the instrument may be capturing general geographic features that may be correlated with deforestation and economic activity, making it necessary to eliminate fixed pixel effects in the estimations. The empirical strategy, by using a change between two time periods, 2014-2020, eliminates this concern, as the fixed effect is eliminated in the differentiation. In addition, we include the latitude and longitude to control for potential geographically distributed omitted variables.

It also seems plausible that initial differences in infrastructure and economic scale could induce different trends in crop expansion, forest loss, and economic activity. Therefore, we control the distance of pixel i to the nearest road, waterways, ports, cities, and mills to capture the availability of infrastructure and market access.

E Results

E.1 Classification

To access the best results, we compared each machine learning algorithm using its overall accuracy and Kappa coefficient, estimated in the test sample. In addition, we validated all models with the 5-fold cross-validation method for both feature selection and final classification. Finally, the results are in TableA11 and the information reflects the statistics after applying the recursive feature elimination method.

To check whether the algorithms performed well, we considered the overall accuracy and the Kappa coefficient for the years mapped. In 2014, Random Forest (RF) was the best-performing algorithm (accuracy of 94.45% and Kappa of 0.0975) followed by the Support Vector Machine (SVM) (accuracy of 94.03% and Kappa of 0.8993). In 2017, on the other hand, K-Nearest Neighbor (KNN) was the best algorithm (Accuracy of 94.61% and Kappa of 0.9088) followed by RF (Accuracy of 94.28% and Kappa of 0.9031). Finally, in 2020, RF was again the best algorithm (Accuracy of 95.53% and Kappa of 0.9239) followed by KNN (Accuracy of 93.87% and Kappa of 0.8956).In summary, it is possible to state that the RF classifier had the best performance for mapping palm oil in the selected region and period. Despite this, it is worth noting that the KNN and SVM algorithms also obtained good classification results, with KNN having the best performance for 2017.

Tabela A11 – Machine Learning Algorithms Results.

	Overall Accuracy		
	2014	2017	2020
	(1)	(2)	(3)
K-Nearest Neighbor	$92,54\%$	$94,61\%$	$93,87\%$
Artificial Neural Network	$89,84\%$	$83,51\%$	$78,44\%$
Decision Tree	$86,50\%$	$84,34\%$	$86,74\%$
Support Vector Machine	$94,03\%$	$94,20\%$	$93,29\%$
Random Forest	$94,53\%$	$94,28\%$	$95,53\%$
	Kappa Coefficient		
	2014	2017	2020
	(1)	(2)	(3)
K-Nearest Neighbor	$0,8737$	$0,9088$	$0,8956$
Artificial Neural Network	$0,8284$	$0,7201$	$0,6313$
Decision Tree	$0,7678$	$0,7305$	$0,7707$
Support Vector Machine	$0,8993$	$0,9022$	$0,8867$
Random Forest	$0,9075$	$0,9031$	$0,9239$

Source: Prepared by the authors.

Such empirical evidence is in line with Xu et al. (2021), which also compared several algorithms and identified that RF presented the best classification performance. On the other hand, Shaharum et al. (2020) obtained a better overall accuracy and Kappa for the SVM, but they emphasize that the RF was the one that best delimited the oil palm areas. Specifically for the Eastern Amazon, Almeida, Vieira e Ferraz (2020) also performed a classification using Random Forest and obtained an overall accuracy of 88.06% and a Kappa of 0.85, using Landsat images. The superior results presented by this paper may be due to the combination of optical and radar images. Radar images capture additional geometric information, which allows for better discrimination of targets with unique geometric characteristics such as oil palm. In this context, we present only the classification results for the RF algorithm due to its better performance and to maintain the consistency of the next analyses. Finally, we calculate the confusion matrices based on the test samples. The results are in Figure 3.

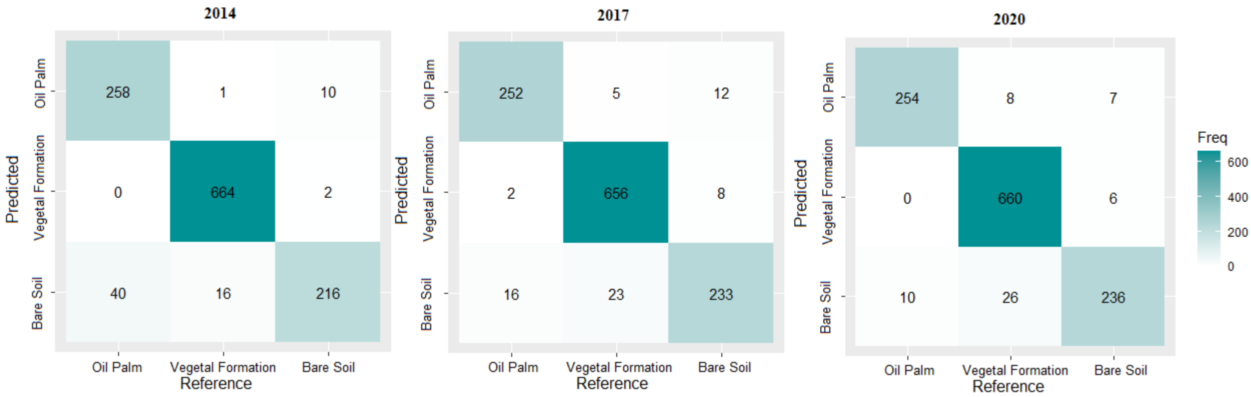

Figura 3 – Confusion matrices for the test sample.

Figure 4 shows the selected features with the recursive feature elimination method for the Random Forest algorithm. In practice, this method selects the best combination of features for the final classification. The relevant characteristics for oil palm mapping differ depending on the year and may reflect different climatic, phenological, and stage of maturation conditions. For 2014, the method selected 12 features: Landsat.4, Landsat.2, EVI, Endmember_2, DVI, Landsat.3, Landsat.1, Entropy, Setinel_VV, GI e Sentinel_VH. For 2017, 15 features: EVI, Landsat.2, Landsat.4, Sentinel_VH—VV, DVI, Endmember_1, Sentinel_NDI, Landsat.1, Sentinel_VH-VV, Sentinel_VV, Sentinel_VH, Entropy, GI, Endmember_2, Contrast. Finally, for 2020, 14 features were selected: EVI, Sentinel_VH—VV, Landsat.2, Landsat.3, Sentinel_NDI, Sentinel_VH-VV, Landsat.4, Sentinel_VH, Landsat.1, DVI, GI, Endmember_2, Endmember_1, Sentinel_VV.

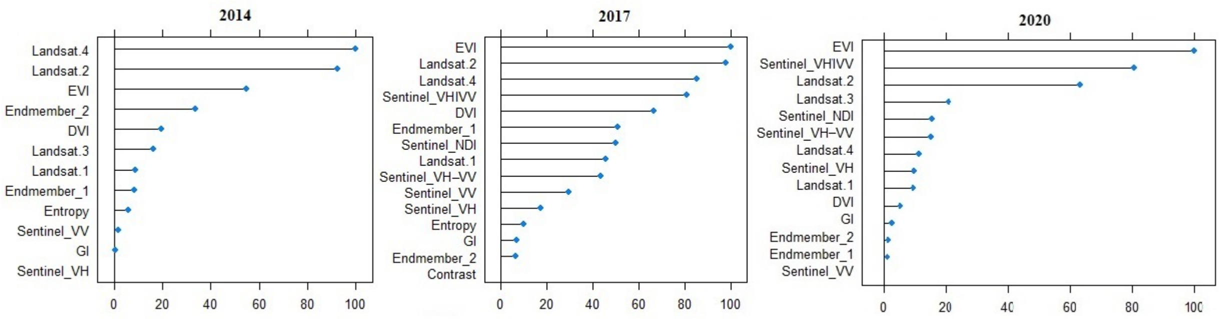

Figura 4 – Features importance for the RF classification.

In particular, features related to Landsat-8 reflectance surface information were more important for classifying oil palm areas, especially the Enhanced vegetation index (EVI). However, Sentinel-1 features were also important, with the difference and the ratio between VV and VH being the most relevant, respectively. The order of importance differs from those obtained by Xu et al. (2021), which used Top of Atmospheric (TOA) data from Landsat-8 and Sentinel-1.

E.2 Land Use and Land Cover Transition

Figure 5 presents land use and land cover maps for the study area and years 2014, 2017, and 2020, classified with the Random Forest algorithm. Note that oil palm areas are mainly concentrated roads and in the north-central region of the Tailândia municipality.

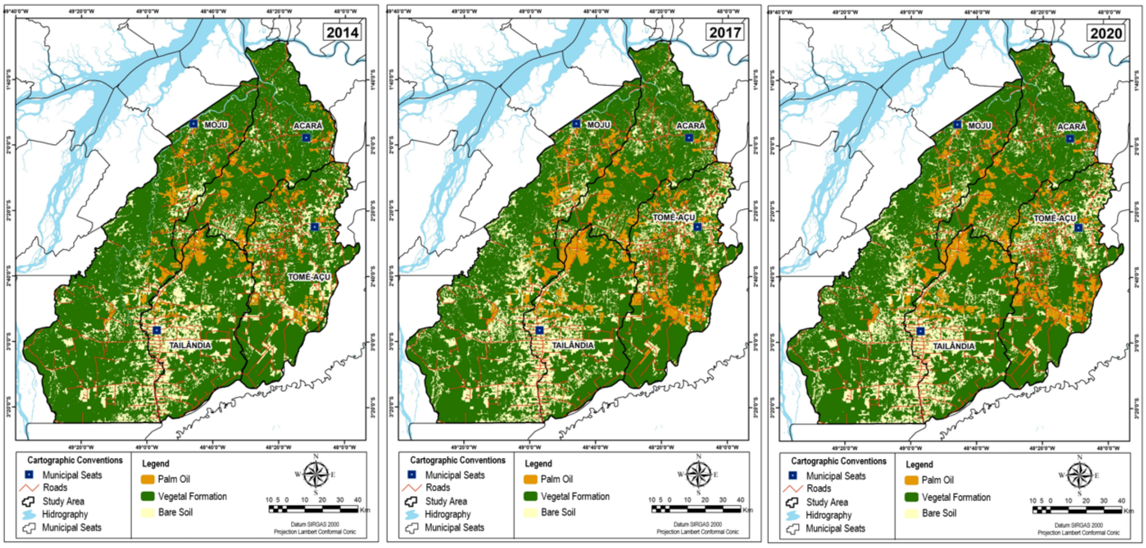

Figura 5 – Land use and land cover maps.

On the other hand, the expansion of palm oil occurs mainly in the administrative limits of Tomé-Açu, especially in the southeastern region of the municipality. Figure 6 shows the total amount of each class in the study area. The Vegetation Formation class had an area of 17,529.57 km² (76.37% of the total) in 2014 to 16,436.8 km² (71.61%) in 2017 and 16,289.13 km² in 2020 (70,96%). The oil palm class, in turn, had an area of 1,074.93 km² (4.68%) in 2014, increasing to 1,703.27 km² (7.42%) in 2017 and 1,849.89 km² (8.06%) in 2020. Finally, the Bare Soil class had an area of 4,349.72 km² (18.95%) in 2014, growing to 4,814.15 km² (20.97%) in 2017 and to 4,815.2 km² in 2020 (20 .98%).

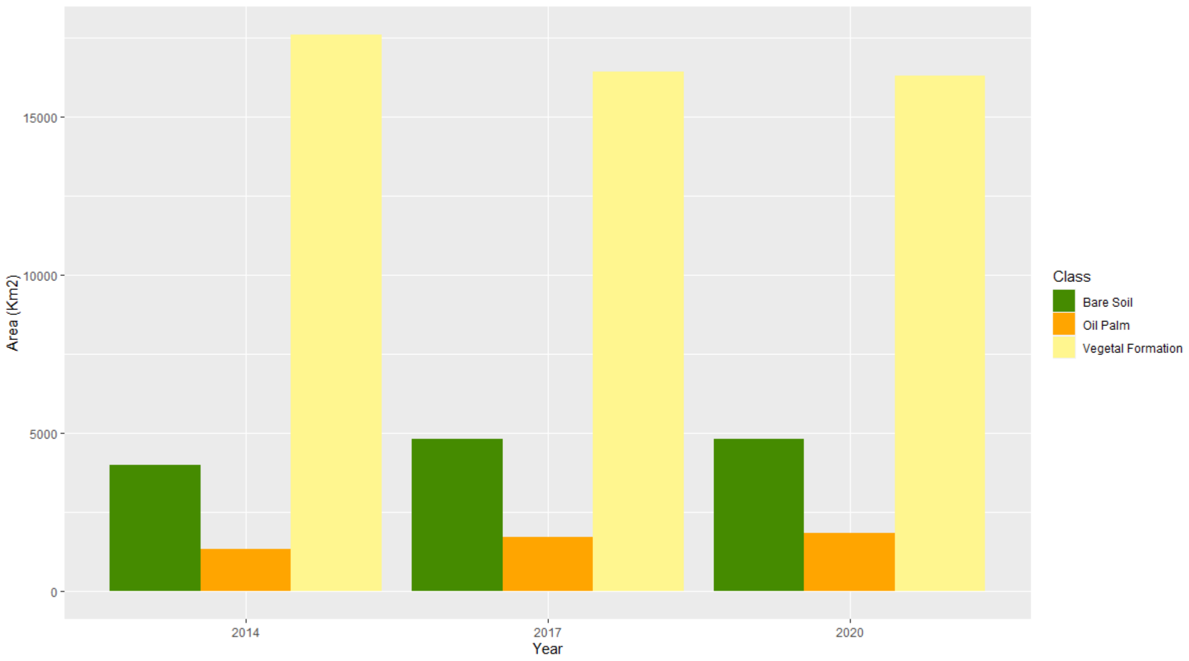

Figura 6 – Classes total area in km².

The joint analysis of the Figures 5 and 6 shows an increase in palm oil and bare soil classes, as well as a decrease in vegetation formation. In addition, the growth of land use classes was greater between 2014-2017 than in 2017-2020. For example, between 2014-2017, palm oil and bare soil had an area growth of 628.34 km² and 464.43 km² (growth of 58.45% and 10.684%), respectively, and vegetation formation areas decreased by 1,092.77km² (down 6.23%). On the other hand, in the 2017-2020 period, the transitions followed the previous period pattern, but at a slower pace, with palm oil and bare soil increasing the area by 146.62 km² and 1.05 km² (growth of 8.61% and 0.02 %), respectively, and the vegetation formation decreasing by 147.67 km² (fall of 0.90%). Therefore, the empirical evidence supports gains in the use classes and losses in the cover class.

It is worth noting that the results are in terms of net gains and losses, a fact that can hide significant transitions in land use and land cover change. In addition, understanding land use and land cover transitions is important to define strategies that curb illegal deforestation and optimize public policies for land use planning. In this context, Figure 7 presents the transitions of land use and land cover in the study area in the years 2014, 2017, and 2020.

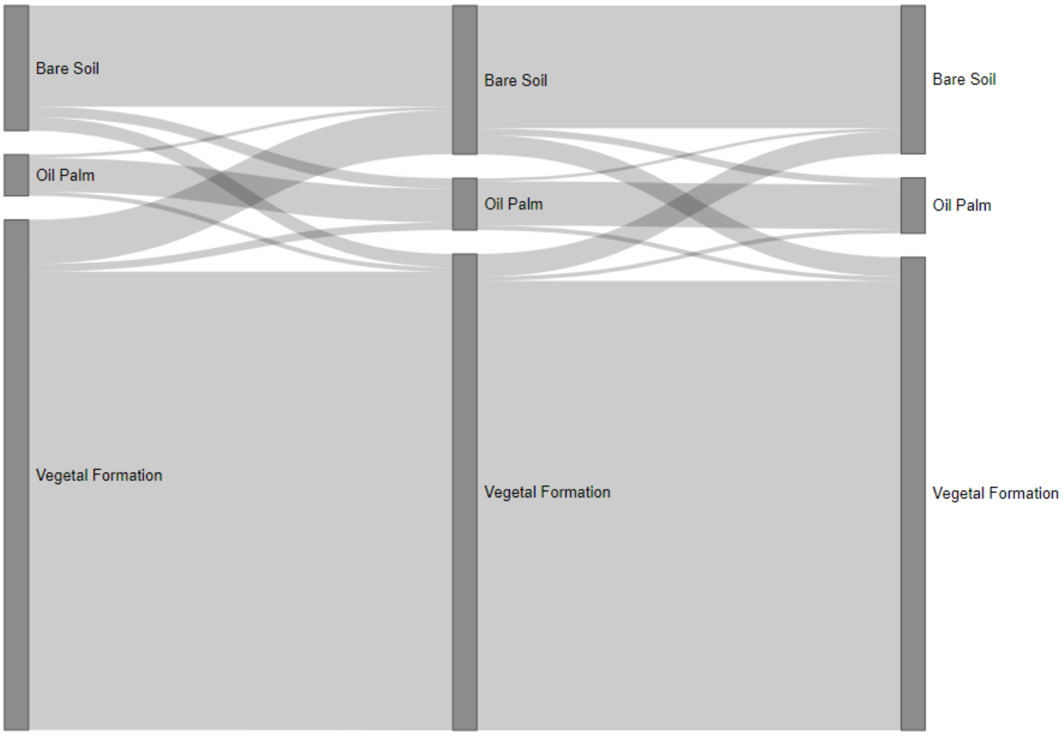

Figura 7 – Land use and land cover transitions between 2014-2017 and 2017-2020.

In general, the results demonstrate that the greatest transition occurs between the classes of vegetation formation and bare soil. This scenario may reflect that the main deforestation drivers in the Amazon are grouped in the bare soil class, especially agricultural activities. In the next section, we use an empirical strategy to estimate the causal impacts of palm oil expansion on the trade-off between economic benefits and deforestation.

E.3 Casual Effects Of Palm Oil Expansion

To test our hypothesis that palm oil expansion has a causal effect on the trade-off between economic activity and forest clearing, we use an empirical approach based on a two-stage logit regression. The results for the first stage regression, which considered the relationship between palm oil expansion and palm oil potential yield, are presented in Table A12. First, to check the robustness of our instrument, we control gradually for potential geographic confounders that could compromise our exclusion restriction hypothesis: forest[1], altitude, slope, and precipitation. We can note that the instrument, Palm Oil Yield, is

[1] A binary variable indicating if the pixel were classified as forest in the initial period (2014).

positive, statistically significant, and robust to the inclusion of the geographic controls in all specifications. Therefore, the results support the hypothesis that higher palm oil yield potential is associated with higher palm oil expansion as suggested by the literature.

Tabela A12 – First Stage Regression

	Dependent variable: Palm Oil Expansion				
	Logit IV	Logit IV	Logit IV	Logit IV	Logit IV
	(1)	(2)	(3)	(4)	(5)
Palm Oil Yield	0.0011***	0.0008***	0.0010***	0.0010***	0.0011***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
Forest		−0.7773***	−0.7713***	−0.7721***	−0.7738***
		(0.0255)	(0.0261)	(0.0261)	(0.0262)
Altitude			−0.0020***	−0.0021***	−0.0005
			(0.0007)	(0.0007)	(0.0008)
Slope				−5.5279	−4.1337
				(3.4569)	(3.4656)
Precipitation					0.0010***
					(0.0002)
Constant	−2.9937***	−2.2607***	−2.2951***	−2.2885***	−4.8151***
	(0.1502)	(0.1440)	(0.1573)	(0.1596)	(0.5653)
Observations	39,497	39,497	39,497	39,497	39,497
F statistic	124.36***	124.05***	100.24***	97.369***	94.319***
Note:	*** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors				

Next, we estimated the second stage regression that uses the instrumentalized variable to estimate the causal effects of palm oil expansion on forest clearing (Column (1) to (3)) and Nightlight (Column (4) to (6)). Palm oil expansion has a positive causal impact on both deforestation and Nightlight in the benchmark regressions (Columns (3) and (6)). To further check the robustness of our results, we control for potential confounding variables that could bias the estimates. First, we control for a maximum attainable yield of soybean, maize, rice, and cassava because they have agroclimatic conditions and expansion patterns that may be similar to palm oil. Therefore, this robustness check would exclude the hypothesis that the instrument is capturing potential agricultural productivity in general which would compromise our exclusion restriction.

Tabela A13 – Second Stage Regression

	Deforestation			*Nightlight*		
	OLS	Logit IV	Logit IV	OLS	Logit IV	Logit IV
	(1)	(2)	(3)	(4)	(5)	(6)
Palm Oil Expansion	0.9512***	11.5183***	14.7325***	0.0167***	0.1194	0.5311***
	(0.0015)	(0.9321)	(1.3274)	(0.0063)	(0.0954)	(0.1245)
Geographic	Yes	No	Yes	Yes	No	Yes
Observations	39,497	39,497	39,497	39,497	39,497	39,497

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

Then, we included latitude and longitude to control for potential geographically distributed omitted variables which could be correlated with palm oil expansion. We also included the night light in 2014 to control for potential effects arising from initial economic activity. For example, pixels with the presence of some night light could have different trend dynamics which would bias our results. Finally, we calculated the nearest distance to roads, waterways, ports, cities, and mills presented in the baseline to control for differences in infrastructure and market access that could create different trends in crop expansion, forest loss, and nightlight. The results are in Table A14. In summary, we confirmed the robustness of our results for the effects of palm oil expansion on deforestation. Despite the coefficient reduction, the causal effects remained statistically significant and positive, indicating that palm oil expansion increases deforestation even in a counterfactual scenario.

Tabela A14 – Robustness check: additional controls

	Deforestation			*Nightlight*		
	OLS	Logit IV	Logit IV	OLS	Logit IV	Logit IV
	(1)	(2)	(3)	(4)	(5)	(6)
Palm Oil Expansion	0.9543***	14.7325***	7.2408***	−0.0161**	0.5311***	−0.3086***
	(0.0024)	(1.3274)	(0.2395)	(0.0066)	(0.1245)	(0.0454)
Geographic	Yes	Yes	Yes	Yes	Yes	Yes
Yield	Yes	No	Yes	Yes	No	Yes
Coordinates	Yes	No	Yes	Yes	No	Yes
Night Light	Yes	No	Yes	Yes	No	Yes
Infrastructure	Yes	No	Yes	Yes	No	Yes
Observations	39,497	39,497	39,497	39,497	39,497	39,497

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

On the other hand, our robustness check showed that the economic nightlight is correlated with the controls, which was biasing our previous results. After including the additional controls, the nightlight shifted its statistically significant coefficient, from positive to negative, corroborating that the palm oil expansion has a negative causal effect on the nightlight emitted. One possible explanation for this negative impact is that Night light is mostly associated with the industrial and services sector and increases in oil palm production are related mainly to the agricultural sector. In addition, palm oil expansion could lead to higher overall production, increasing the demand for additional productive inputs. Higher competition for labor and inputs may lead to increasing costs for the industrial and services; therefore, reducing its production and participation in the economic structure.

It is worth mentioning that the distribution of our database is not uniformly distributed; only 11% and 3,36% of the pixels presented deforestation and palm oil expansion, respectively. In addition, it may not be reasonable to assume that pixels with 50% deforestation probability are more sensitive than other pixels, which is an important assumption in the logit model. In this context, to further check the robustness of our results, we re-estimated our logit model using a more flexible approach proposed by Nagler 1994, known as Skewed logistic regression (Scobit). The scobit model has the logit as a special case, which introduces more flexibility, and, according to Alix-Garcia e Millimet 2021, is better suited to rare-events type outcomes; as the deforestation and palm oil expansion in this paper. The results are in Table A15.

We can note that the scobit model further supported the robustness of our results; the coefficients remained statistically significant and with the same signal, only its magnitude changed, for both outcome variables. The causal effects of palm oil expansion on deforestation increased while the negative effect on nightlight was reduced. In other words, the results support the hypothesis that the expansion of palm oil culture in the region is impacting the trade-off between deforestation and economic activity in a pervasive way

Tabela A15 – Robustness Check - Scobit

	Deforestation			*Nightlight*		
	OLS	Logit IV	Scobit IV	OLS	Logit IV	Scobit IV
	(1)	(2)	(3)	(4)	(5)	(6)
Palm Oil Expansion	0.9543***	7.2408***	12.4200***	−0.0161**	−0.3086***	−0.1941***
	(0.0024)	(0.2395)	(1.2225)	(0.0066)	(0.0454)	(0.0294)
Geographic	Yes	Yes	Yes	Yes	Yes	Yes
Yield	Yes	No	Yes	Yes	No	Yes
Coordinates	Yes	No	Yes	Yes	No	Yes
Night Light	Yes	No	Yes	Yes	No	Yes
Infrastructure	Yes	No	Yes	Yes	No	Yes
Observations	39,497	39,497	39,497	39,497	39,497	39,497

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors

since it is increasing the region's environmental impacts while creating centripetal forces that reduce the performance in the industrial and service sector.

F Final Considerations

Palm oil is the most consumed vegetable oil in the world and it is used in a vast variety of products in the pharmaceutical, biofuel, and food industries. Many tropical countries have been developing specific policies and incentives to expand palm oil production, seeking potential economic benefits. However, previous palm oil expansion in tropical countries in Asia, such as Indonesia and Malaysia (the two biggest producers), was associated with significant environmental impacts, especially deforestation of tropical forests. This scenario raises environmental concerns about future expansion elsewhere since its biggest producers face significant restrictions to further increase its production area. According to the literature, the expansion of palm oil production will occur mostly in other tropical countries' competitors, mostly in Latin America and Africa. The Amazon, especially in Brazil, has the most suitable area for palm oil expansion, which is already occurring at a fast rate in the first two decades of the 21st century. For example, the biggest state producer in Brazil, Pará, expanded its cultivated area by more than 200% between 2004 and 2014 with a significant part of this replacing primary forests.

Despite the importance of the theme, there are no papers in the literature that seeks to estimate the causal impacts of palm oil expansion on the trade-off between economic activity and deforestation in the Eastern Amazon, the biggest producer in the country. Therefore, papers that aim to further understand this potential trade-off are important to identify critical drivers and to develop policies to curb deforestation; in other words, to create incentives and conditions for a sustainable palm oil expansion. In this context, this paper aims to contribute to the literature by mapping the recent palm oil expansion in the Pará state, Brazil, between 2014 and 2020 with optical and radar satellite images and, then, by estimating its causal effect on deforestation and nightlight. This is important because, to our best knowledge, there are no papers in the literature that map palm oil expansion using radar satellite images, despite its proven significant contribution in discriminating palm oil trees, or estimate its causal impact on the trade-off between deforestation and economic activity by using an exogenous source of variation.

To map palm oil expansion between 2014 and 2020, we adopted an innovative methodology by combining optical images from Landsat-8 and radar images from Sentinel-1, along with Machine Learning algorithms. In summary, the classification of palm oil areas presented an accuracy of 94.53%, and 95.53% and a Kappa coefficient of 0.9075 and 0.9239 for 2014 and 2020, respectively. It is worth mentioning that these results are superior to similar papers that also aimed to map oil palm in the Eastern Amazon, a fact that further support the importance of combining the usual optical satellite images with radar images.

Next, we carried out a land use and land cover changes analysis at the pixel level to calculate the expansion of palm oil and deforestation in the region between 2014-2020. Although this effort allowed us to confirm that it expanded especially over deforested areas, a significant portion, around 156.88 km^2 (20.24%), still took place directly over areas with vegetation cover, a fact that raises doubts about the sustainability of this expansion. It is worth noting that this occurred despite public policies aimed at inhibiting deforestation and encouraging sustainable palm oil expansion. However, this expansion cannot be causally assigned to palm oil since many potential confounders could be related to both expansion and deforestation. To overcome this caveat, we used the maximum agro-climatically attainable palm oil yield from the Global Agro-Ecological Zoning (GAEZ) calculated by The Food and Agriculture Organization of the United Nations (FAO) as an exogenous variation to instrumentalize palm oil expansion.

In summary, our main results support that the oil palm expansion in the Eastern Amazon has a statistically significant and positive causal effect on deforestation and a negative impact on economic activity in the non-agricultural sectors. In other words, our empirical estimates support the hypothesis that the expansion is increasing the region's environmental impacts while creating centripetal forces that reduces the performance in the industrial and service sector. Therefore, the evidence that its expansion is taking place over vegetation cover, with a direct causal effect, raises concerns about the sustainability of this crop, due to its potential direct and indirect impacts on deforestation. In addition, this is not leading to essential structural transformations that could boost economic development and, then, raise economic and social well-being.

However, it is important to highlight that there are still important issues to be addressed to better understand the benefits and costs of the palm oil expansion in the Oriental Amazon. For example, many environmental, social, and economic impacts were not directly captured or considered by our empirical strategy like biodiversity loss, labor issues, etc. Therefore, further research is essential to better understand these trade-offs, and their drivers and to design adequate policies that guarantee a sustainable expansion of palm oil in the Amazon region, environmentally, socially, and economically. However, in practice, the palm oil mapping, the land use and land cover change analysis, and the estimate of its causal impact on deforestation and economic activity at the pixel level carried out in this paper could be used to identify areas of greatest environmental and economic risk and thus support the design of policies and the improvement of palm oil production chain governance.

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