

# Deforestation in Legal Amazon: A Panel Data Analysis of Potential Interferers

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## Abstract

The knowledge on the significant factors that lead to environmental changes can be an attractive tool for directing priority actions of management, sustainability and impact minimization. In this regard, this work suggests the use of panel data analysis in environmental assessments, proposing a panel data regression model for the context of the Amazon forest, aiming to evaluate the role of primary activities over deforestation in Legal Amazon between 1988 and 2018. For this, the deforested areas in Legal Amazon were assessed regarding the potential explanatory variables: (i) area intended for soybean cultivation; (ii) area intended for palm oil cultivation; (iii) cattle ranching; and (iv) firewood and wood extraction. The model developed in this work evidenced cattle ranching and palm oil cultivation as significant factors for the increase of deforested areas, as well as the contribution of other factors besides primary activities in Amazon deforestation from 1988 to 2018. These results are in accordance with the literature, evidencing the applicability and assertiveness of the proposed method. This approach can help decision-makers of several other fields of environmental management. Additionally, this work also assessed the evolution of deforestation rates from 1988 to 2018, as well as possible regionalities and temporal trends in Legal Amazon deforestation. Statistically significant upward trends in deforestation rates in Amazonas, Mato Grosso, Pará, and Rondônia since 2012 were noticed. The spatial homogeneity in deforestation reinforces the need for effective oversight in Amazon.

**Keywords:** Amazon rainforest, cattle, livestock, palm oil, regression analysis, soybean

## 1. Introduction

### 1.1 Legal Amazon

Legal Amazon comprises the Brazilian states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO), and part of Maranhão (MA). Instituted by Federal Law nº 1.806/53 (Brasil, 1953), it has an approximated area of 5.1 million km<sup>2</sup>, which corresponds to 59.1% of Brazilian territory. This region is characterized by low socioeconomic development and high agriculture, extractivism, and livestock activity (SUDAM, 2019).

Amazon is the largest tropical forest in the world. With forest-covered areas larger than 3.3 million km<sup>2</sup> (Brasil, 2019), it is estimated that Amazon houses more than 40,000 plant species (Silva et al., 2005). Only in 2016, approximately 3.0 million m<sup>3</sup> of wood products from native species were extracted from the Amazon forest and destined for the Brazilian market. Among the main marketable woody native species are *Manilkara huberi* (trade name: maçaranduba), *Goupia glabra* (trade name: cupiuba), and *Erismia uncinatum* (trade name: cedrinho). Furthermore, about 10,000 km<sup>2</sup> of Legal Amazon is occupied by planted forests and 80% of such area is destined for eucalyptus monoculture (Brasil, 2019). Agriculture and livestock are also one of the major economic activities of the Amazon biome. In 2018, soybean cultivation represented 51% of the agricultural production value of the states which comprises Legal Amazon, corresponding to an amount of approximately US\$ 7.0 billion. In the same period, cattle ranching was responsible for a gross production of about US\$ 5.0 billion in such states (Brasil, 2018).

### *1.2 Role of Brazilian Government to Monitor Deforestation in Legal Amazon*

Amazon deforestation, with the intent of land use and occupation, is not directly related to a single aspect (Alencar et al., 2004). Its motivation and dynamics are interconnected to several factors, mainly those of environmental and economic control. The latter reached a peak in 1995, due to the Real Plan—a Brazilian governmental plan for economic stability. Among the causes that potentially led to deforestation of this biome are: road constructions, land occupation surrounding highways, expansion of agriculture and livestock, family farming, wood extraction, and land speculation by land grabbers (Alencar et al., 2004; Fearnside, 2003; Fearnside, 2006; Ferreira et al., 2005; Laurance et al., 2004; Soares-Filho et al., 2004; Soares-Filho et al., 2005).

Currently, to improve control over the situation, the Brazilian Government relies on projects, tools, and methodologies to monitor deforestation in Legal Amazon. The Amazon Deforestation Monitoring Project (PRODES) monitor clear-cuts in Legal Amazon using LANDSAT satellites (INPE, 2020a). DETER is a real-time system to detect changes in vegetation cover, serving as a basis for inspection (INPE, 2020b). DEGRAD maps degraded and vulnerable areas to deforestation (INPE, 2020c). TerraClass project qualifies deforestation in Legal Amazon based on changes in land use and land cover (INPE, 2020d). Additionally, the National System for the Control of the Origin of Forest Products (IBAMA, 2020) aims to promote the control of forestry products in Brazil.

Besides, there are several other important controlling, regulatory, and protective tools in Brazil, such as:

- the Environmental Rural Registry (CAR), mandatory since 2012, according to Law n° 12.651/12 (Brasil, 2012),
- the Annual Report on Potentially Polluting Activities and Users of Environmental Resources (RAPP), whose obligation has foreseen since 1981, in Brazil's National Environmental Policy advent (Brasil, 1981), and
- the Conservation Units (UC), which enable conservation, preservation, and reforestation of green areas since Law n° 9.985/00 (Brasil, 2000).

Nevertheless, only in 2019, more than 10,000 km<sup>2</sup> of was deforested in Legal Amazon (INPE, 2020a), evidencing the need to improve the effectiveness of the oversight.

### *1.3 Review of Econometric Models Towards Decision-Making Processes for Environmental Management and Conservation*

Econometric models have been increasingly used with the aim of assessing the impacts of anthropic activities on the environment (Arraes et al., 2012; Diniz et al., 2009; Chiu, 2012; Scricciu, 2007; Cheng et al., 2018; Salame et al., 2016; Zhang et al., 2017; Amare et al., 2017; Schmook & Vance, 2009). Through such approaches, it is possible to identify the factors that significantly contribute to the environmental changes, being extremely useful for management purposes, enabling simulations of possible future scenarios, and guiding priority efforts.

In the deforestation context, relevant findings from econometric models can be cited. Amare et al. (2017) exposed the role played by the smallholder farmers on deforestation in Northern Ethiopia. Schmook and Vance (2009) evidenced the importance of agricultural policies for halting deforestation in Southern Mexico. Chiu (2012) and Scricciu (2007) evidenced the influence of real income on deforestation. Furthermore, Arraes et al. (2012) proposed a linear regression model to predict the factors that contributed to diminishing the deforestation in Brazil between 1988 and 2002. The authors evidenced that the presence of environmental agencies in the municipalities, socioeconomic development, and the advent of regulatory laws for the delimitation of the expansion of the agricultural frontier were determinant factors to reduce deforestation. Diniz et al. (2009) pointed out a two-way Granger causality between deforestation and agricultural and socioeconomic variables—cattle herd size, cattle density, permanent and temporary crops, areas destined for agriculture, education, demographic density, and agricultural credits—during 1997 to 2006. Thus, demonstrating the effective influence of agriculture and livestock raising Amazon deforestation during these years, also the crucial role played by the environmental management agencies to reduce and prevent deforestation.

Compared to correlation and usual regression methods, panel data regression analysis can provide a broader approach, since the evaluation of the effects of different factors under a phenomenon contemplates transversal and longitudinal variations (Gujarati & Porter, 2011). Thus, being able to account the spatio-temporal heterogeneity of environmental phenomena. Due to its methodological stringency, such analyses can potentially offer more reliable and assertive results (Duarte et al., 2007). There is an extensive application of this type of regression in the conception of econometric models in socioeconomic studies. However, the use of panel data regression models in environmental researches is still modest. Thus, there is a broad field to be explored in this context. It is expected that the methodology applied in this work contribute to the decision-making process

guiding priority actions on environmental management and conservation.

In this sense, this work aimed to demonstrate the applicability of panel data regression models in environmental assessments, by means of the conception of a model for verifying the role of primary activities over deforestation in Legal Amazon. Additionally, we also discussed the evolution of deforestation rates from 1988 to 2018, as well as possible regionalities, and temporal trends in Legal Amazon deforestation.

## 2. Method

### 2.1 Study Area

Legal Amazon is characterized by considerable economic, political, and social heterogeneity. The state of AC had a native forest of about 144,065 km<sup>2</sup> in 2018 (MapBiomass, 2020), corresponding to approximately 88% of its size. In the state, cattle ranching has a strong influence in the primary sector of AC's economy (Ronivaldo, Steingraber, & Caetano, 2018), with an average herd increase of 8% per year from 1988 to 2018 (IBGE, 2020a). AM is the largest state of Legal Amazon, comprising an area of 1,559,167.889 km<sup>2</sup> (IBGE, 2020b), with an estimated native forest of 1,466,745.400 km<sup>2</sup> in 2018 (MapBiomass, 2020). Wood extraction and livestock are among the main profitable activities of the primary sector in AM. These sectors were increased, respectively, by an average of 207% and 3% per year between 1988 and 2018 (IBGE, 2020c; IBGE, 2020a). AP is the smallest state of the region, with almost 84% of its extension covered by native forest (MapBiomass, 2020). Traditionally, vegetal extraction is the main primary activity in the region (Milheiras & Mace, 2018). But, since 2013, both wood extraction and soybean cultivation has been crescent (IBGE, 2020c; IBGE, 2020d).

With the smallest Gross Domestic Product (GDP) per capita of the Legal Amazon region, of about US\$ 2,302 per inhabitant in 2017 (IBGE, 2020b; IBGE, 2020e), MA is also the state with the second smallest native area (approximately 46,620 km<sup>2</sup> in 2018) (MapBiomass, 2020), which corresponds to 0.01% of its size. Agriculture and cattle ranching are pointed out as precursors for reducing the native forest of MA (Celentano et al., 2017). In the last years, cattle ranching has shown a considerable expansion in the state, increasing by an annual average of 3% from 1988 to 2018 (IBGE, 2020a). On the other hand, MT has GDP per capita of about US\$ 6,710 in 2017 (IBGE, 2020b; IBGE, 2020e), the highest between the states of Legal Amazon. In addition to present the highest area intended for soybean cultivation and the highest cattle herds (IBGE, 2020d; IBGE, 2020a), in MT, cattle ranching expanded by an average of approximately 5% per year from 1988 to 2018 (IBGE, 2020a), whereas the soybean cultivation increased 7.5% per year (IBGE, 2020d).

Historically, PA was marked by an expansion of cattle ranching and soybean (Sauer, 2018; Barona, 2010). In the state, cattle ranching and soybean cultivation increased by 5% and 43% per year on average from 1988 to 2018. Additionally, the economy of PA is also great influenced by palm oil cultivation (Benami et al., 2018; Sauer, 2018), which increased by an annual average of 8% from 1988 to 2018 (IBGE, 2020d). Currently, PA has about 99% of the área intended for palm oil cultivation in Legal Amazon. RO has the second-highest GDP per capita of Legal Amazon (US\$ 4,503 per inhabitant in 2017) (IBGE, 2020b; IBGE, 2020e). This fact may be associated with a great expansion of soybean cultivation, wood extraction, and cattle ranching (IBGE, 2020d; IBGE, 2020c; IBGE, 2020a), with increases rates in cattle herd of about 59%, and in soybean cultivation and vegetal extraction of 9% per year on average between 1988 and 2018.

In RR, family farming is the major land use and slash-and-burn practice, to open new areas for crops or pasture, are pointed out as one of the main causes for deforestation in the state (Xaud et al., 2013). In TO, soybean cultivation expanded by an average of 28% per year during the period from 1988 to 2018 (IBGE, 2020d). TO has the smallest portion of Amazon forest between the states of the region, with only about 6.0 km<sup>2</sup> in 2018 (MapBiomass, 2020).

### 2.2 Data Collection

Annual data on deforested areas (AD) in the states of Legal Amazon, as well as on primary activities conducted in the Legal Amazon extension, were collected as described in Table 1.

Table 1. Description of the assessed data

Data	Data source	Measure unit	Time period	Territorial unit
Deforested areas (AD)	PRODES (INPE, 2020a)	km <sup>2</sup>	1988–2018	Each state of
Soybean cultivation area (SOY)	Municipal Agricultural Production survey (IBGE, 2020d)	km <sup>2</sup>		Legal Amazon
Palm oil cultivation area (POC)	Municipal Agricultural Production survey (IBGE, 2020d)	km <sup>2</sup>		(AC, AM, AP,
Production of firewood and wood extraction (FWE)	Vegetal Extraction and Silviculture Production survey (IBGE, 2020c)	m <sup>3</sup>		MA, MT, PA, RO, RR, and TO)
Cattle heads (CAT)	Municipal Livestock Survey (IBGE, 2020a)	-		

### 2.3 Data Treatment: Descriptive, Statistic, and Graphical Analysis

Initially, a descriptive analysis of deforested areas (AD) in Legal Amazon was computed. Then, the Pearson's Chi-square test (Pearson, 1900) was applied for validating the non-normality of the distributions. The Kruskal-Wallis (Kruskal & Wallis, 1952) test with multiple comparisons and a cluster analysis (Byrne & Uprichard, 2012) of the deforested areas in the distinct states were performed, aiming to identify states with similarities in their deforestation dynamics. These analyses, with the respective graphical results, were conducted in STATISTICA 10.0 software at 95% confidence level. Occasional temporal trends in AD in the states of Legal Amazon were also investigated using the Mann-Kendall test (Mann, 1945; Kendall & Stuart, 1967) available in USEPA's ProUCL software. The magnitude of the trends was estimated by means of Sen's slope coefficients (SEN, 1968). Additional graphs and spatial representations were generated with MS Excel and ArcGIS 10.5, respectively.

### 2.44. Regression Model: Panel Data Analysis

Panel data are a combination of time series and cross-sectional data and are used in regression models to describe the effects of variables in spatiotemporal dimensions (Gujarati & Porter, 2011). In this study, the panel data regression model aimed to investigate the primary activities cited in literature that significantly contributed to increasing the deforested areas during 1988 to 2018. The explanatory variables were chosen according to previous studies, which pointed such activities as important precursors of Amazon deforestation (Nepstad et al., 2014; Laurance et al., 2004; Barona et al., 2010; Rivero et al., 2009; Domingues & Bermann, 2012; Diniz et al., 2009; Benami et al., 2018; Carvalho et al., 2015; Butler & Laurance, 2009; Fearnside, 2006). Thus, the following variables were selected:

- (i) SOY: Area intended for soybean cultivation (km<sup>2</sup>);
- (ii) POC: Area intended for palm oil cultivation (km<sup>2</sup>);
- (iii) FWE: Firewood and wood extraction (m<sup>3</sup>); and
- (iv) CAT: Cattle ranching (number of heads).

In view of this, the proposed model can be described by Equation 1.

$$AD = \beta_0 + \beta_1 SOY + \beta_2 POC + \beta_3 FWE + \beta_4 CAT \quad (1)$$

There are different types of panel data regression models, such as pooled, fixed effects, and random effects models. In pooled models, the spatiotemporal variance of each individual may be neglected. In fixed effects models, it is admitted a distinct and time-invariant intercept for each individual. In random effects regression models, the intercept of each individual is treated as a random variable. Furthermore, adopting a model of fixed or random effects, the errors resulted from omitted or irrelevant variables can be diminished (Gujarati & Porter, 2011; Duarte et al., 2007; Hill et al., 2011; Greene, 2002).

There are some assumptions that must be considered to ensure the appropriateness of linear regression models, such as homoscedasticity and the absence of autocorrelation and multicollinearity (Gujarati & Porter, 2011; Hill et al., 2011; Greene, 2002). In this regard, in the presence of heteroscedasticity, the residual variance must be estimated. Similarly, autocorrelation of the regression residuals implies the need to estimate it. The autocorrelation may arise from an omitted variable—i.e., when the dependent variable is not sufficiently explained by the independent variables—and whenever the variables are correlated to an omitted one. The estimation of robust standard errors and the feasible generalized least squares method (FGLS) are techniques commonly applied to fix such problems, and may be chosen according to the number of variables and the size of the time series (Hill et al., 2011). The FGLS estimation consists of an auxiliary regression which is specially applied when the nature of the autocorrelation and/or heteroscedasticity is unknown. In this way, the auxiliary

regression works as a balance on the main model (Candea et al., 2016).

In order to determine the most appropriate type of model, initially, the presence of multicollinearity and omitted variables was verified. Multicollinearity was assessed through the variance inflation factor (VIF). The presence of omitted variables was analyzed by the Ramsey RESET test. The work proceeded with the application of the Chow test for comparing the appropriateness of pooled and fixed effects models. In the Chow test, the non-rejection of null hypothesis ( $H_0$ ) reflects a better suitability of pooled models, while acceptance of the alternative hypothesis ( $H_1$ ) represents a higher adequacy of fixed effects models. Then, the Breusch-Pagan LM test was performed. The  $H_0$  of the Breusch-Pagan LM test indicates a better fit of pooled models, whereas  $H_1$  suggests the random effects model as the most appropriate of the two options. Finally, the Hausman test was used for counteracting the use of random effects ( $H_0$ ) and fixed effects ( $H_1$ ) models. After defining the model with the best fit, the Wooldridge test was used to verify the presence of autocorrelation. The Wald test was performed to check heteroscedasticity. Then, the FGLS methodology was applied to fix autocorrelation and heteroscedasticity. Figure 1 illustrates the methodological steps for determining the appropriate regression model.

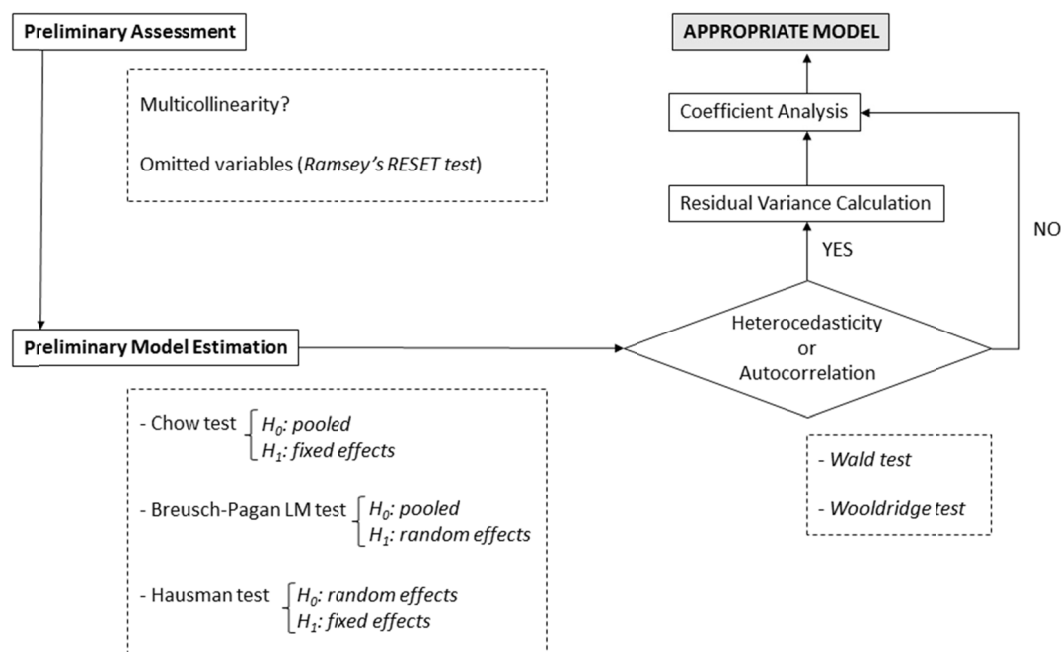


Figure 1. Panel data modeling methodology flowchart

Note. <sup>a</sup> $H_0$ : null hypothesis; <sup>b</sup> $H_1$ : alternative hypothesis.

### 3. Results and Discussion

In this topic, the results obtained in the context of descriptive, statistic, and graphical assessments were presented and discussed. Figure 2 shows the evolution of the deforestation rates in Legal Amazon from 1988 to 2018. The years 1995, 2003, and 2004 presented the largest deforested areas: 29,059 km<sup>2</sup>, 25,396 km<sup>2</sup>, and 27,772 km<sup>2</sup>, respectively. The smallest areas were ravaged in 2012 (4,571 km<sup>2</sup>) and 2014 (5,012 km<sup>2</sup>).

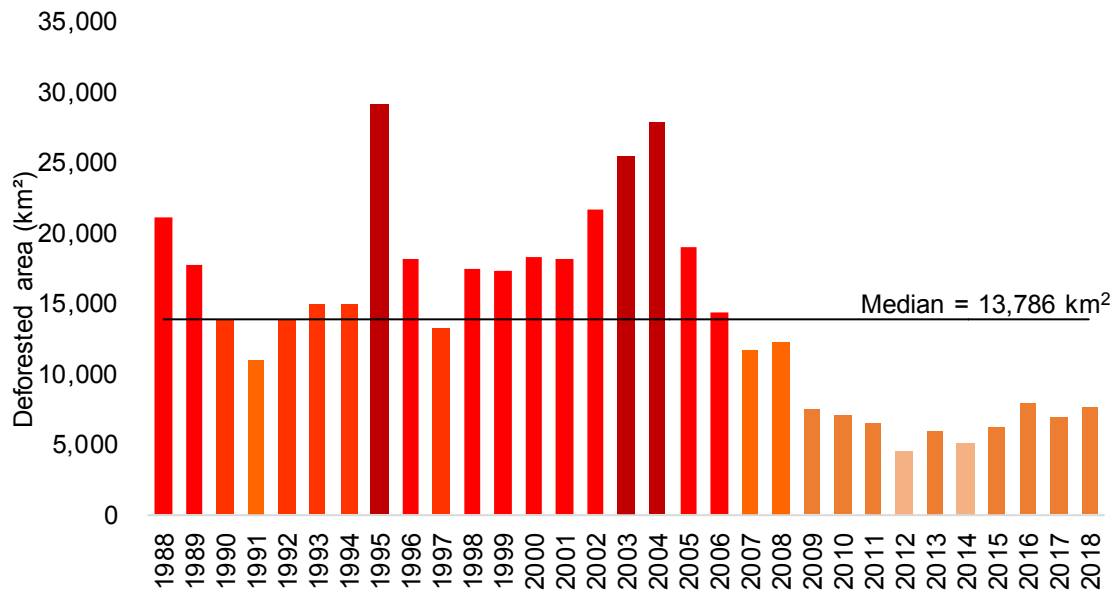


Figure 2. Evolution of yearly deforestation rates in Legal Amazon

During the period from 1988 to 2018, 435,617 km<sup>2</sup> of green area were deforested in Legal Amazon, being PA (147,763 km<sup>2</sup>), MT (144,457 km<sup>2</sup>), and RO (60,420 km<sup>2</sup>) the states that showed the highest accumulated values. The smallest areas occurred in the states of AP, RR, and TO, being 1,583 km<sup>2</sup>, 7,707 km<sup>2</sup>, and 8,678 km<sup>2</sup>, respectively (Figure 3). In percentage terms, the federative units that presented the largest deforested areas in the assessed period were RO (26.9% of its size), MT (16.0% of its size), PA (11.8% of its size), and AC (9.4% of its size).

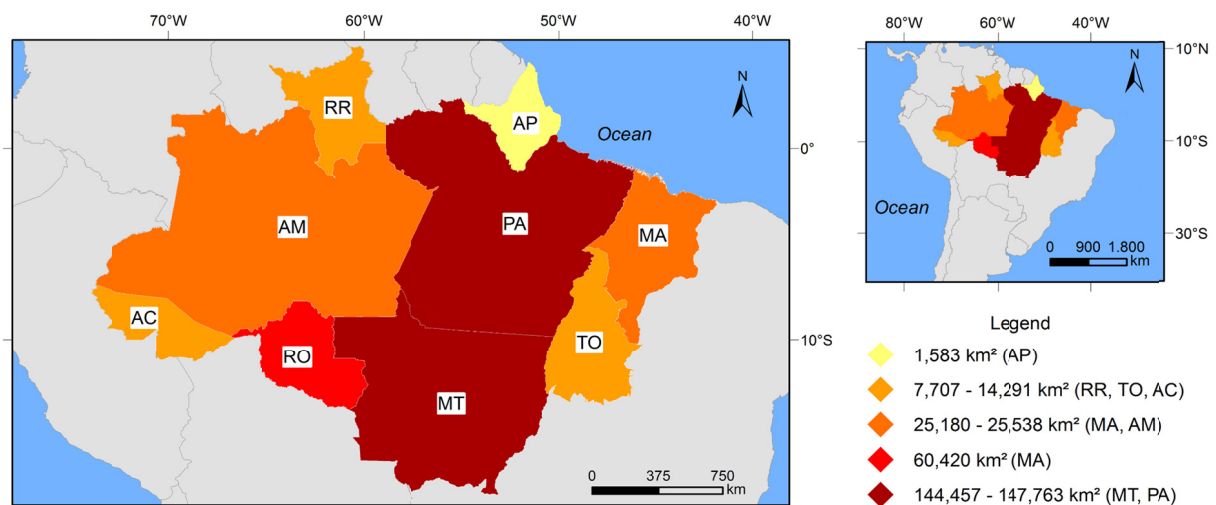


Figure 3. Map of total accumulated deforested area in the states of Legal Amazon between 1988 and 2018

The descriptive statistics of deforestation data recorded on the states and the whole Legal Amazon are shown in Table 2. The median for the whole territory from 1988 to 2018 was 13,786 km<sup>2</sup>. The states that presented the highest medians were PA and MT, with 4,890 km<sup>2</sup> and 4,674 km<sup>2</sup>, respectively. MA and TO had the largest deforested areas in 1988 (2,450 km<sup>2</sup> and 1,650 km<sup>2</sup>, respectively). In RR, the largest deforested area was registered in 1989 (630 km<sup>2</sup>). In the case of AP, 1991 was the year when the highest loss by clear-cutting (410 km<sup>2</sup>) occurred. In 1995, the deforestation peaks in AC (1,208 km<sup>2</sup>), AM (2,114 km<sup>2</sup>), and RO (4,730 km<sup>2</sup>). Finally, the apex of deforestation in MT and PA took place in 2004 (11,804 km<sup>2</sup> and 8,870 km<sup>2</sup>, Table 2).

Table 2. Descriptive statistics of yearly deforestation in the states of Legal Amazon from 1988 to 2018

Region	N <sup>a</sup>	Minimum (km <sup>2</sup> )	Maximum (km <sup>2</sup> )	Mean (km <sup>2</sup> )	SD <sup>b</sup> (km <sup>2</sup> )	Median (km <sup>2</sup> )
-	-	-	-	-	-	-
AC	31	154	1.208	461	246	419
AM	31	370	2.114	824	391	712
AP	25	7	410	63	88	31
MA	31	209	2.450	812	505	755
MT	31	757	11.814	4.660	3.132	4.674
PA	31	1.741	8.870	4.767	1.871	4.890
RO	31	435	4.730	1.949	1.048	1.986
RR	31	84	630	249	126	220
TO	31	25	1.650	280	329	189
Legal Amazon	31	4.571	29.059	14.052	6.739	13.786

Note. <sup>a</sup>N: number of observations; <sup>b</sup>SD: standard deviation.

In 50% of the 31 assessed years, the annual deforested area exceeded 13,786 km<sup>2</sup> (Table 2). The extrapolation of this measure of central tendency occurred in the period from 1988 to 2006 (Figure 2). Except for AM, all states had annual deforested areas wider than the median in years between 1988 and 2011. In AM, annual deforested areas higher than the median were also observed in years from 2015 to 2018 (Table 2). According to Meirelles and Cenamo (2017), the weakening of state environmental agencies in 2015 allied to expressive budget cuts reflected directly on deforestation rates reported for AM state. Figure 4 shows the deforestation data in the states belonging to Legal Amazon in terms of statistically significant differences at 95% confidence level.

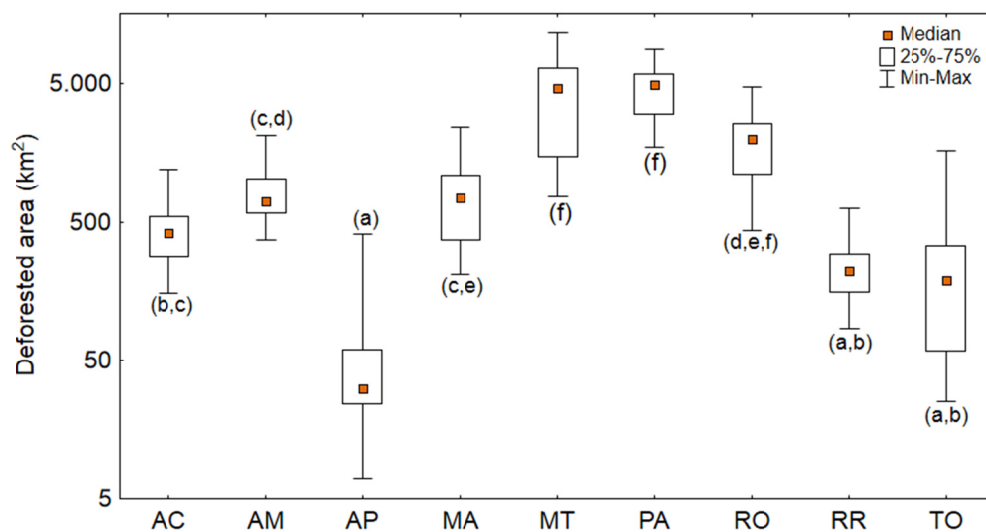


Figure 4. Yearly deforested areas in the states of Legal Amazon (1988-2018) and multiple comparisons test Y axis is in logarithmic scale; indexes (a, b, c, d, e, f) signal significant differences at 95% confidence level

Analyzing the results of multiple comparisons test (Figure 4) and cluster diagram (Figure 5), mainly four regions with similarities in deforestation dynamics may be observed: (i) MT and PA; (ii) AM and MA; (iii) RO; and (iv) AC, AP, RR, and TO. These groupings were also evident in Figure 2. In addition to presenting the most extensive deforested areas, PA and MT had the highest production of firewood and wood by vegetal extraction between 1988 and 2018 (658,373,018 m<sup>3</sup> in PA and 160,711,854 m<sup>3</sup> in MT) (IBGE, 2020c). This states also concentrated the highest cattle herd averages during that period (11,971,480 heads per year in PA and 19,503,627 heads per year in MT (IBGE, 2020a). With the third highest deforested area between 1988 and 2018, RO had the fourth largest annual average herd, with about 8,175,422 cattle heads per year during that period (IBGE, 2020a).

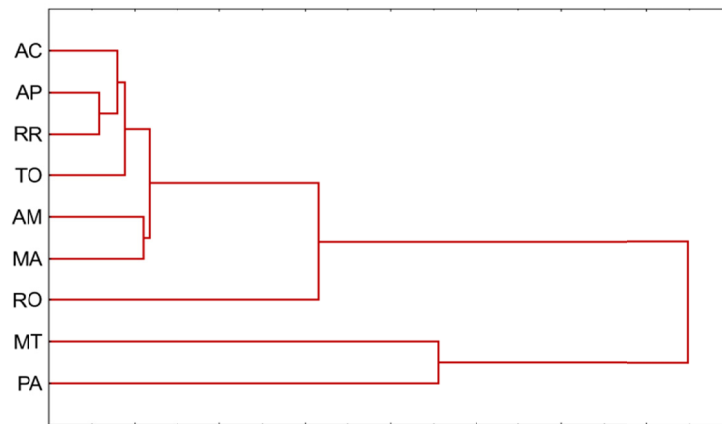


Figure 5. Cluster dendrogram of the deforested areas (AD) in the states of Legal Amazon from 1988 to 2018

Based on the Mann-Kendall test (Mann, 1945; Kendall & Stuart, 1967), except for AM, all states showed statistically significant downward trends in deforestation rates between 1988 and 2018 (Table 3). Similarly, the data from the whole Legal Amazon also presented a statistically significant decreasing trend for that period (p-value: 0.0009).

Table 3. Trend analysis for deforestation in the Legal Amazon between 1988 and 2018

State	AC	AM	AP	MA	MT	PA	RO	RR	TO
p-value	0.0031*	0.1750	0.0378*	0.0000*	0.0109*	0.0015*	0.0168*	0.0124*	0.00000*

Note. \* statistically significant evidence at 95% confidence level.

According to Godar et al. (2014), 48% of deforestation in Amazon between 2004 and 2011 was attributed to properties with areas bigger than 5 km<sup>2</sup>. In the largest landholders' portion (over 25 km<sup>2</sup>), deforestation decreased 63% between 2005 and 2011, while in properties with areas smaller than 1 km<sup>2</sup>, there was an increase of 69%. Deforestation in smallholdings (less than 0.1 km<sup>2</sup>) is also considered as an influential factor in some regions of PA, RO, MT, and RR, mainly along the Transamazonian Highway (Imazon, 2018). Moreover, the strengthening of monitoring, environmental policies, and interventions in beef, soy, and palm oil supply chains were also determinant for diminishing deforestation between 2004 and 2012 (Arraes et al., 2012; Nepstad et al., 2014; Gibbs et al., 2015; Benami et al., 2018; Tollefson, 2016). These facts may contribute to explain the results shown in Table 3. However, those require critical judgment. The PRODES data shows higher deforestation rates during the first years of the time series (Figure 2), mainly before 2006. Furthermore, since 2012, when the minimal deforestation rate in Legal Amazon between 1988 and 2018 occurred, the deforestation rates have been crescent (Figure 2).

In this context, applying the Mann-Kendall test (Mann, 1945; Kendall & Stuart, 1967) for the period from 2012 to 2018, several statistically significant increasing trends can be noticed (Table 4). A statistically significant upward trend (p-value: 0.0177, Sen's slope: +494.2 km<sup>2</sup>. year<sup>-1</sup>) was also evident considering all the extension of Legal Amazon. From this point of view, it is relevant to consider the current Brazilian political and economic aspects, with the consolidation of the influence of agribusiness in government and tendencies to softening of environmentally protective policies (Tollefson, 2016; Fearnside, 2015).

Table 4. Trend analysis for deforestation in Legal Amazon between 2012 and 2018

State	AC	AM	AP	MA	MT	PA	RO	RR	TO
p-value	0.1840	0.0358*	0.2240	0.1840	0.0667**	0.0358*	0.0358*	0.3820	0.1150
Sen's slope (km <sup>2</sup> . year <sup>-1</sup> )	+21.5	+95.6	-0.5	-2.7	+116.7	+167.2	+94.0	+5.0	-6.0

Note. \* statistically significant evidence at 95% confidence level; \*\* statistically significant evidence at 90% confidence level.

Figure 6 shows the spatial distribution of the annual deforested areas from 2012 to 2018. A clear spatial homogeneity can be observed during that period. Deforestation occurred mainly across the known 'arc of



deforestation' and Transamazonian Highway, as well as in part of RR and in a great portion of AC. This homogeneity reaffirms the ineffectivity of the command and control systems in Amazon (Oliveira et al., 2020) and the need to strengthen oversight in the region.

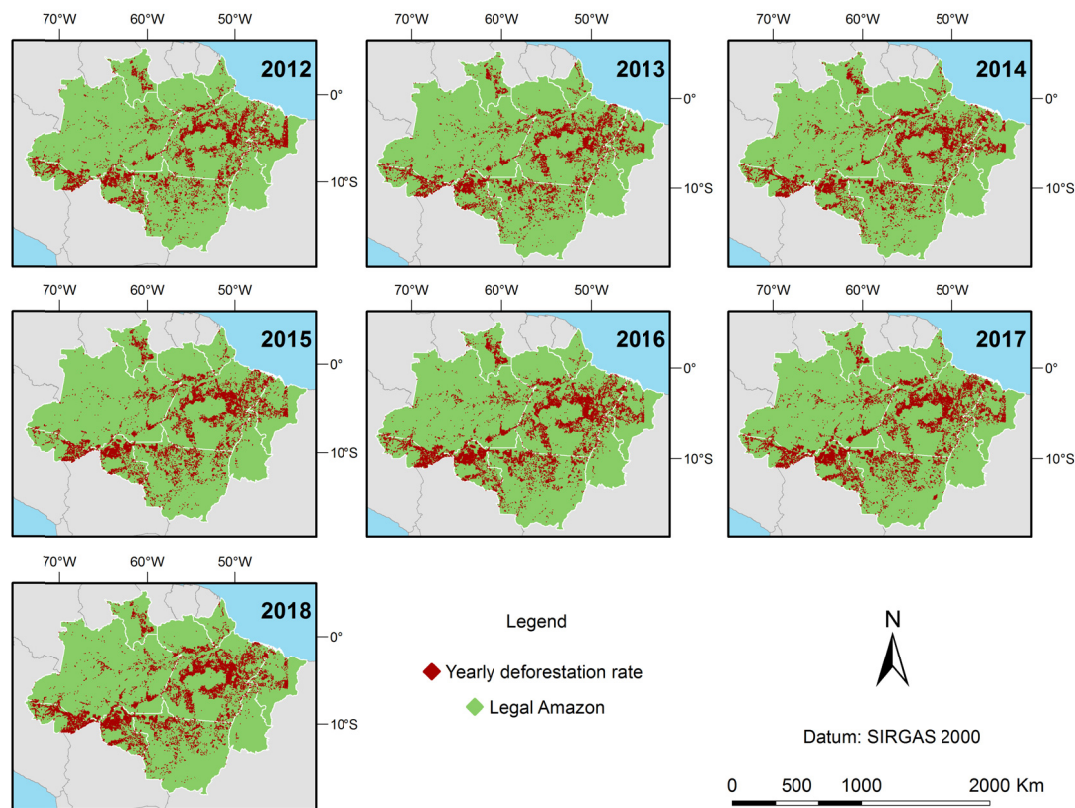


Figure 6. Spatial distribution of yearly deforestation rates Legal Amazon (2012–2018)

### 3.1 Panel Data Regression Analysis

For proposing the regression model, the presence of multicollinearity between the variables was initially tested. An acceptable level of multicollinearity was revealed, with a maximum VIF of 5.06. According to Gujarati and Porter (2011), with a maximum VIF higher than 10, the existence of linear relations between the independent variables could affect the least squares estimates. The Ramsey RESET test showed the existence of omitted variables, preliminarily indicating the inadequacy of pooled models.

The Hausman test has the suitability of fixed effects front to random effects models as its null hypothesis ( $H_0$ ) based on the difference between their variances (Wooldridge, 2011). In this work, a value of  $\chi^2 < 0.0001$  was computed, indicating the appropriateness of the fixed-effects model. This suitability may also be explained by the nature of the independent variables which were used in the proposed model. Green and Tukey (1960) defined fixed and random variables as a representation of different extremes of sampling. According to the authors, the random, as the name suggests, describes random samples of a population, while the fixed approximates to their actual values. This definition of fixed variables easily fits with the purposes of the datasets from which the variables applied in the model were collected. That is, all variables collected (CAT, SOY, POC, FWE) seeks to describe their total magnitude on a territorial unit (states of Legal Amazon) over time (1988–2018).

The Wooldridge and Wald tests exposed autocorrelation and heteroscedasticity in residuals. As previously mentioned, both problems may result from omitted variables, a fact confirmed by the Ramsey RESET test. Due to this, the FGLS method was applied for adjusting the proposed model, aiming for its adequate performance.

The coefficients ( $\beta_0$ ,  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ , and  $\beta_4$ ) are shown in Table 5. The p-values revealed statistically significant evidences of the influence of livestock (CAT) and palm oil cultivation (POC) under deforested areas (AD) in Legal Amazon. The model suggests that the increase of cattle herds and areas intended for palm oil cultivation positively contributed to the expansion of deforested areas ( $\beta_4 = 0.00005$  and  $\beta_2 = 1.83029$ ) at 95% and 90%

confidence levels, respectively (Table 5). Previous studies also pointed to cattle ranching as the main threat to Amazon forest (Barona et al., 2010; Rivero et al., 2009; Domingues & Bermann, 2012). Is also relevant to mention that the cultivation of palm oil is historically correlated to deforestation, especially in PA (Benami et al., 2018), which is the major producing state of palm oil in Brazil (IBGE, 2020d) and also has the highest deforested areas during 1988–2018, in average (Table 2).

The proposed model also suggests that the soybean cultivation and legal wood and firewood extraction not led to Legal Amazon deforestation with the same weight as the other primary activities (cattle and palm oil cultivation) from 1988 to 2018. According to Domingues and Bermann (2012), the establishment of soybean crops occurs especially in degraded soils previously destined for cattle breeding. In fact, states situated in the ‘arc of deforestation’, PA, MT, and RO, have the most developed cattle herds and soybean cultivation.

Table 5. Panel data regression model adjusted by FGLS proposed for Legal Amazon deforestation

Variable	<i>SOY</i> ( $\beta_1$ )	<i>POC</i> ( $\beta_2$ )	<i>FWE</i> ( $\beta_3$ )	<i>CAT</i> ( $\beta_4$ )	$\beta_0$
Coefficient	-0.01658	1.83029	0.00001	0.00005	123.42130
p-value	0.403	0.062**	0.337	0.004*	0.006*

Note. \* statistically significant evidence at 95% confidence level; \*\* statistically significant evidence at 90% confidence level.

Furthermore, the Ramsey RESET test previously exposed the insufficiency of explanatory variables in the proposed model. This fact is endorsed by the p-value of  $\beta_0$ , which evidenced the effective interaction of omitted variables leading Amazon deforestation. It is acknowledged that deforestation permeates several other factors besides primary activities, such as public governance, development of municipalities, and population growth, including elements deriving from illegal practices and which are infrequently quantified or expressed in databases (Arraes et al., 2012).

As reported by Greenpeace et al. (2017), 24% of Legal Amazon deforestation in 2016 emerged from land grabbing. According to Amazônia Protege (MPF, 2020), a survey of Brazilian Federal Prosecution Service (MPF), in 2017, 36% of the deforested area equal or above 0.6 km<sup>2</sup> identified via PRODES was a proven effect of illegal activities. The survey disclosed that the largest areas illegally deforested in that year were identified in MT and PA, with 530 km<sup>2</sup> and 470 km<sup>2</sup>, respectively, representing approximately 34% and 19% of total deforestation occurred in these states. However, according to a research conducted by ICV (2018), in MT, for about 89% of deforested areas identified by PRODES in 2017, were not issued authorizations by state or federal environmental agencies.

In 2007, Greenpeace denounced the creation of phantom rural settlements by INCRA (Brazil’s National Institute for Colonization and Agrarian Reform) to promote the illegal wood extraction in PA. According to the investigation, the autarchy allowed the activity of logging companies in areas of virgin forest and Conservation Units (UC) under the cover-up of alleged social projects and improvements in the scope of the agrarian reform. Already in 2012, Greenpeace returned to document allegations of illegal logging in rural settlements of INCRA (Greenpeace, 2020). All these facts evidence the preponderance of illegality on practices inherent to deforestation.

Additionally, other aspects also demonstrate notable participation in the suppression of native vegetation in Amazon. Sonter et al. (2017) exposed the parcel of mining in deforestation in several aspects, both during the implementation of infrastructures and the circumjacent urban expansion. Ramos et al. (2018) ratified the impact of road expansion on Amazon's vegetation cover. On the other hand, deforestation is not only a consequence of secondary activities, but it may also act as a conducting agent of various environmental problems. The literature reports deforestation for land use and occupation as a potential contributing factor to the occurrence of Amazon forest fires (Barni et al., 2015; Salame et al., 2016; Silva et al., 2018; Silva et al., 2018b), leading to expressive CO<sub>2</sub> emissions and biodiversity loss.

Finally, it is important to highlight that robust data analysis contributes to the environmental management, monitoring and studies of cause and effects. The methodology applied in the conception of the model presented in this work can provide valuable information on significant factors that lead to environmental effects and impacts, thus being able to guide decision-making processes and sustainable management strategies.

#### 4. Conclusions

This work aimed to investigate the role of the primary activities in Legal Amazon deforestation during 1988 to 2018. The regression model obtained in this study evidenced cattle ranching and palm oil cultivation as relevant

interveners for deforestation in Legal Amazon during that period. The model also showed a significant contribution of other factors for the degradation of the biome. The complexity of measuring each contribution, particularly in the context of illegal practices, was also pointed out. However, for local environmental managing purposes, the local land use dynamics must be considered. Key issues for reducing the progress deforestation include improvements in cattle productivity, reducing the m<sup>2</sup>/head ratio, advancing agriculture on degraded areas, incentives for sustainable crops cultivation and the combat of illegal activities. Mann-Kendall test also detected upward trends in deforested areas of AM, MT, PA, and RO between 2012 and 2018, possibly as a consequence of the attenuation of environmentally protective policies and the imminent weakening of environmental management agencies. Considering such increasing trends, further models may also be constructed considering different periods of the time-series to support predictive analyses of future scenarios of Legal Amazon deforestation. Additionally, the assessment of the spatial distribution of deforested areas during 2012 to 2018 reiterates the inefficiency of current oversight actions. Finally, this paper showed the applicability of panel data regression analysis for identifying factors that lead to significant changes in environmental quality. Furthermore, in this work, the selection of variables was supported by the literature. Although, identifying critical environmental, political, cultural or socioeconomic issues also is fundamental for determining potential eligible variables. In this concern, analyses such as SWOT or PESTLE may be useful. Considering that the panel data regression analysis is able to account the spatio-temporal heterogeneity of environmental phenomena, we highlight that the use of panel data regression models in environmental studies may improve management and impact minimization, guiding priority efforts, actions, and decision-making processes.

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