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DEFORESTATION DETERMINANTS IN PARÁ STATE: AN ANALYSIS WITH QUANTILE REGRESSIONS FOR PANEL DATA

DETERMINANTES DO DESMATAMENTO NO ESTADO DO PARÁ: UMA ANÁLISE COM REGRESSÕES QUANTÍLICAS PARA DADOS EM PAINEL

Vanessa da Paixão Alves[1]

Abstract

This paper aims to analyze the deforestation determinants in Pará's municipalities from 2006 to 2016. For this purpose, the quantile regression method was used for panel data which allows the evaluation of possible differences between groups of municipalities regarding their deforestation patterns, as well as responsible factors for such heterogeneity. The results indicate that deforestation different levels are influenced both by the populational and per capita GDP growth and by the cattle herd expansion as well as temporary and permanent land crops. Other factors such as socioeconomic development (employment, income, health, education), environmental indicators (remaining forest areas) and implementation of command-and-control policies for compliancy with the environmental laws (priority municipalities' actions to combat deforestation), which indirectly reflect public authorities' effective performance in these areas also correlated with deforestation and being considered relevant for the environmental problem mitigation.

Keywords: deforestation determinants. Quantile Regressions. Priority Municipalities. Socioeconomic Development.

Resumo

Este trabalho tem por objetivo analisar os determinantes do desmatamento nos municípios do estado do Pará no período de 2006 a 2016. Para esse fim, foi utilizado o método de regressões quantílicas para dados em painel que permitem avaliar as possíveis diferenças entre grupos de municípios quanto a seus padrões de desmatamento, assim como os fatores responsáveis por tal heterogeneidade. Os resultados indicam que os diferentes níveis de desmatamento são influenciados tanto pelo crescimento do PIB per capita e populacional quando pela expansão do rebanho bovino e de áreas das lavouras temporária e permanente. Outros fatores como melhorias dos indicadores de desenvolvimento socioeconômico (emprego, renda, saúde, educação) e ambientais (área de floresta remanescente) e implementação de políticas de comando e controle para o cumprimento da lei ambiental (municípios prioritários para ações de combate ao desmatamento), que refletem indiretamente a atuação efetiva do poder público nessas áreas, também estão correlacionados com o desmatamento, portanto sendo relevantes para a mitigação deste problema ambiental.

[1] PhD in economics from the Federal University of Pará (UFPA), Belém – PA, Brazil. Email: vass321@hotmail.com

Palavras-chave: Determinantes do desmatamento. Regressões Quantílicas. Municípios Prioritários. Desenvolvimento Socioeconômico.

Introduction

Since the 1970s, the policies directed towards the Brazilian Amazon integration into the national economy have been an incentive to colonization and territory's occupation. Conducting to a based deforestation economy and land speculation (TOUNEAU; BURSZTYN, 2010; REYDON et al., 2012). The recent dynamics of agricultural activity expansion have shown to be the region's main source of deforestation. However, the conversion of the forest into pastures and croplands are not reflecting in the indicators of development in the Amazon (DINIZ, 2017).

Several important changes were observed in Brazilian's environmental policy, including the creation of institutions such as the National System of Conservation Units, the Brazilian Forest Service and the national climate change policy (HECHT, 2012). As a result of these and other policies implementation, Brazil has achieved a significant drop in its deforestation and emission levels, particularly in Amazon between 2004 and 2012.

Considering the high deforestation rates return to recent years, the advance in a series of constitutional amendment law projects that imply in an effective threat to the environmental protection system created in recent decades which have reinforced this behavior. These initiatives aim to reduce restrictions on environmental licenses for new infrastructure projects, mining, and other economic activities alongside to the indigenous reduction protection and protected areas in order to prioritize private land exploitation (CARVALHO et al., 2019; FERRANTE; FEARNSIDE, 2019; REYDON; FERNANDES; TELLES, 2020).

Considering the points, it is concluded that the study of issues that affects deforestation problem and it is important to provide subsidies to environmental policy strategies improvement. Based on this, this article aims to develop an econometric study, using the method of quantile regressions for panel data to analyze the deforestation determinants in Pará state where most deforestation in the Brazilian Amazon in seen. In contrast with studies that consider the aggregated influence of deforestation factors, the methodology used in this study allows us to evaluate possible differences between municipalities groups in terms of deforestation patterns, as well as the factors responsible for such heterogeneity.

The article itself is organized in sections that consist of an introduction, a literature review about the deforestation in Pará which is used as support to this research, the database, the variables used, and the methodological fundaments are also presented, followed by the results, discussions and finally the conclusions.

Deforestation in Pará state

Data released by the National Institute for Space Research (INPE) indicates annual deforestation average rates in Amazon between 2000 and 2012 of 14,970 km². The lowest deforestation rate registered was 4,700 km² in 2012. However, deforestation started to grow again in 2013, reaching a rate of 5,800 km². So, there was an interruption of the downward trend observed since 2008 (INPE, 2020).

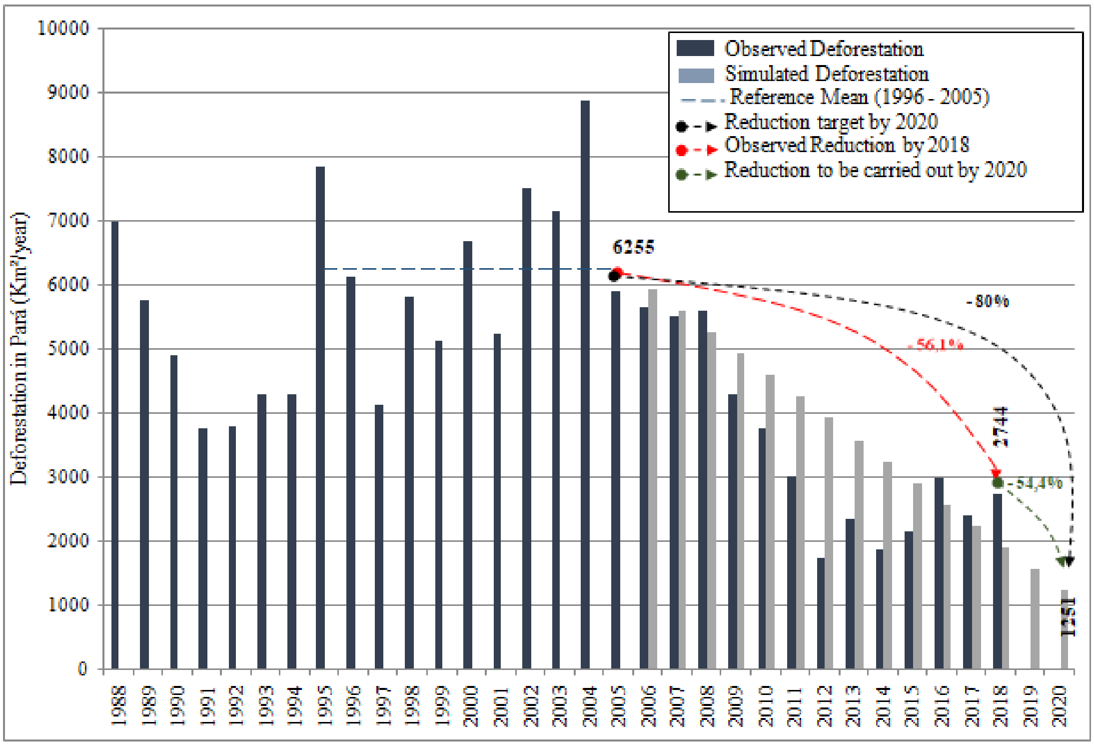
Pará State showed a reduction in deforestation of 2,540 km² between 2009 and 2012, contributing to decrease 88% in the entire Amazon. The states' contribution to the region's total deforestation fell from 57.4% in 2009 to 38.1% in 2012. Nonetheless, there is a forest clearing increase in the region between 2013 and 2016 of which Pará had contributed with 32% of the total (646 km²).

Due to high deforestation rates, the state of Pará led the ranking of CO_2 emissions in Brazil, releasing 280.2 million tons in 2016. The Land Use Sector Change responds for approximately 81% of total state's emissions (SEEG, 2020).

To contribute to Brazil's environmental governance strengthening, Pará presented PMV experience during Rio+20 where it was announced a commitment to reduce deforestation to 80% in the state by 2020, compared to the annual average of 6,255 Km² registered in the period of 1996-2005 and to obtain from that date, zero net deforestation (GOVERNO DO ESTADO, 2013).

Considering the annual rate of 2018 (2,744 Km²), a reduction of56.1% (3,511 Km²) has been achieved so far (Figure 1). With the reduction in deforestation observed so far this year, it is estimated that the state stopped releasing 236.3 million tons of CO_2[2].

Figure 1: Reduction targets for deforestation in Pará by 2020



Source: Elaborated by the author (2020) based on data from INPE, 2020.

The state reached 264,691 Km² of degraded areas or approximately 21% of its territory in 2017 (INPE, 2020). Due to these areas' extensions, Pará state would already have enough land to house its agricultural and mining production.

So, the limit for the total deforested area in the state is a maximum of 265,000 km² by 2020. From this total amount, each new destroyed area must be compensated with the restoration of damaged native forests. In reality, for each hectare authorized by environmental license, it will be necessary to restore at least 2 hectares. In that context, considering the assumed targets for reducing deforestation by 2020, Pará will still be able to deforest 309 km² (265 thousand – 264,691 km²) by that year.

The increase in deforestation at the end of 2007 led the government to adopt measures such as between the Central Bank of Brazil initiative (BACEN) and the Ministry of Environment to launch the Critical Municipalities Program (Decree Nº. 6,321/2007) that suspended farmers access to credit in 36 municipalities with the highest deforestation rates (ASSUNÇÃO et al., 2012).

According to the Ministry of Environment (MMA) and its ordinance Nº. 361 of September 8, 2017, Pará has 14 cities that are part of an embargoed list which are the priority for actions to prevent, monitor and control deforestation. These cities are approximately 80% of the Rural Environmental Registration areas (CAR) of the total ones able to registration in Pará. Deforestation has substantially increased among the priority municipalities from 2004 to 2016, despite the impositions placed by the Program (CASTELO; ADAMI; SANTOS, 2020). As shown above, the inflection of environmental policies and the effective municipal environmental management is fundamental to control deforestation in Pará (AZEVEDO-RAMOS et al., 2017)

Empirical studies on deforestation determinants

2This estimate results from multiplying the deforestation reduction of 351,100 hectares by the average carbon stock values between 1996 and 2017 equal to 183.36 tons of carbon per hectare of forest (or 672.9 tons of CO_2) based on data from the CCAL Brazil (2018).

The empirical literature about deforestation determinants has been growing since the 1990s. Socioeconomic aspects have been associated to deforestation which indirectly influences economic agents through various ways. Factors connected to economic, demographic, macroeconomic, and institutional development are usually mentioned in surveys around the world (DAMETTE; DELACOTE, 2012).

The relationship between economic development and deforestation has been widely discussed under the Environmental Kuznets Curve hypothesis (EKC) which defends the idea of an inverted U-shaped curve relating per capita income and environmental degradation. According to this thesis, in the early stages of development, economic growth is positively related to environmental degradation. However, when per capita income reaches a certain level, degradation begins to decrease with the growth (CULAS, 2007; INDARTO and MUTAQIN, 2016).

The Environmental Kuznets Curve concept (CKA) emerged in the 1990s and became one of the main instruments which analyze the impacts of economic growth on environmental degradation, showing that economic development would not necessarily result in higher levels of environmental degradation. In short, it was observed that initial growth degrades the environment, nevertheless the continuous growth tends to ease environmental problems (BIAGE and ALMEIDA, 2015; DINIZ, 2017).

In addition, some authors consider that the CKA hypothesis assumes that the initial increase in environmental degradation is temporary. The subsequent decreasing is not permanent, therefore the "U-inverted" CKA would not be sustained for a long term, resulting in an "N"-shaped curve and indicating that degradation increases again in stages with higher income levels (DINDA, 2004; AVELINO, 2018; CARVALHO, CARVALHO, CARVALHO and GUIMARÃES, 2020).

More recently, Faria and Almeida (2016) exposed that economic growth, measured by of GDP per capita evolution, indicates a growth tendency of a set of economic activities, including those that promote deforestation such as the production of soy and cattle. consequently, the growth cycle with greater availability of income creates an inducing effect, allowing new investments which lead to an increasing deforestation level. Soares (2019), who identifies the deforestation determinants in Pará through the analysis of municipal data from 2011 to 2016, also concludes that the expansion of cattle ranching and positive changes in the GDP per capita has influenced the deforestation increase in the state.

Additionally, it is observed that regions with high populational density (especially rural density) and high population growth tend to experience high rates of deforestation (CROPPER; GRIFFITHS, 1994; DINIZ, 2017). Demographic pressure, identified as important in the evolution of land occupation and its use processes, is correlated with some attractive factors such as settlement projects, mining, infrastructure projects, and the agricultural borders' expansion (HAGRAVE; KIS-KATOS, 2013; FEARNSIDE, 2017; SEYMOUR; HARRIS, 2019; REYDON; FERNANDES; TELLES, 2020).

Other factors related to the country's macroeconomic situation as the agricultural and timber prices, real exchange rates, and exports can lead to land-use changes, resulting in deforestation (DAMETTE; DELACOTE, 2012; NEPSTAD et al., 2014; FARIA; ALMEIDA, 2016; CARVALHO et al., 2019).

Another argument given is environmental governance quality, shown by environmental policies such as the establishment of protected areas contribute positively to deforestation decline (SOARES-FILHO et al., 2010; AZEVEDO-RAMOS; MOUTINHO, 2018; WEHKAMP et al., 2018; AZEVEDO-RAMOS et al., 2020; JAFFÉ et al., 2021).

Furthermore, the forest initial endowment has a positive relationship with deforestation. The larger the forest area is, less expensive the wood extraction is the due to activities related to transport and scarcity. Moreover, as there is no land available the agriculture is less likely to happen, reducing the pressure on forests (NEPSTAD et al., 2008; FERREIRA; COELHO, 2015). Regarding the forest transition hypothesis, as the forest becomes scarce and deforestation grows, the marginal utility of the forest increases, hence the decreasing of agriculture marginal utility (DAMETTE; DELACOTE, 2012).

According to Diniz and Oliveira Jr. (2009) who develop a study using different analytical instruments and estimation techniques to evaluate deforestation in Legal Amazon from 1997 to 1998. The results of the research showed that in damaged cities not only farm for cattle but also permanent and temporary land crops act to deforestation increase. Furthermore, the variables representing human capital proved to be relevant to explain deforestation. Particularly, adult education favors the creation of alternatives for the survival of families, determining less pressure on the use of natural resources, as showed in Loening and Markussen (2003), Arraes, Mariano and Simonassi (2012). consequently, it is observed that better educational levels allow individuals to choose for economic activities such as services, for example, rather than degrading activities such as illegal logging and cattle-raising.

In this regard, the underlying causes of deforestation also reflect the quality of individuals lives in response to public policies for sustainable development in the Amazon region (DIAS; DIAS; MAGNUSSON, 2015; CASTELO; ADAMI; SANTOS, 2020; JAFFÉ et al., 2021)

Database, variables description and methodological foundations

The data used in this study are related to the 143 cities in Pará between 2005 and 2016. The data of accumulated deforestation and remaining forests come from the National Institute Space Research (INPE). The GDP and population data come from the Brazilian Institute of Geography and Statistics (IBGE). In addition to these, the number of cattle heads from the Municipal Livestock Research (PPM/IBGE), planted areas of permanent and temporary land crops of the Municipal Agricultural Production (PAM/IBGE). The GDP variable was deflated by the General Price Index of Getúlio Vargas Foundation (FGV) based on December 2016.

Furthermore, a dummy variable is adopted for the structural change before (0) and after (1) the implementation of the policy proposed by the MMA focused on priority municipalities for actions against deforestation.

Therefore, the Employment and Income, Education, and Health components were used, which are part of the Firjan Municipal Development Index (IFDM) that monitors the development of Brazilian cities in these three areas. The human development indicator elaborated by the Federation of Industries of Rio de Janeiro State (Firjan) is exclusively based in official public statistics (Ministry of Labour, Education, and Health), it is an index that varies from 0 to 1, so that the closer to 1, greater the development of the locality is. To establish reference values to facilitate the analysis, four concepts were stablished to the IFDM: low development stage (0.0 to 0.4); regular development (0.4 to 0.6); moderate development (0.6 to 0.8) and high stage development (0.8 to 1.0).

The Firjan System provides data from the IFDM from 2005 to 2016 reflecting the annual monitoring of the socio-economic development of Brazilian cities, justifying the choice of the temporal delimitation of the period between 2005 and 2016 under analysis in this present study. consequently, it is possible to make a historical series of data to the set of variables that are part of the econometric model proposed in this study.

Due to the peculiarities of this study which involves characteristics that limit the exclusive of Multiple Regression application such as the presence of extreme cases (outliers), as well as the presence of variables considered to be explanatory so they do not influence in the same extent all values assumed by the variable dependent, it was decided for the Quantile Regression application technique (QR)which was initially presented in the studies of Koenker and Basset (1978). The idea behind quantile regressions is to estimate what the effect is under any separator on the distribution of y as a function of x when x changes. Hence the quantile regressions allow analyzing the explanatory variables impact from different points in the conditional distribution of dependent variable.

It's a semi-parametric model defined by Cameron and Trivedi (2010) which avoids hypotheses about the parametric distribution of regression errors. It allows us to observe the effect of independent variables from different points in the distribution of the dependent variable and they are appropriate when this is asymmetric and heteroskedastic considering the other variables in the model (BUCHINSKY, 1998).

Therefore, the results found for the different quantiles of the conditional distribution can be separately interpreted as variations in the dependent variable caused by changes in the regressors from different points in the conditional distribution of the dependent variable (BUCHINSKY, 1998; COSTA et al, 2015). So, when the quantiles change systematically with the explanatory variables, the angular coefficient will be different for each quantile, this estimation does not consist of a simple estimative analysis, but of a process.

In this specific case of this study, it is the process by which different groups of cities classified according to their angular coefficients are differently affected by the selected explanatory variables. Considering an increasing deforestation order, in the first quantiles are the cities with the lowest level of deforestation and in the last quantiles are the most deforested cities of Pará state. The research covers from 2005 to 2016, the Quantile Regression was estimated to panel data.

This method was studied by Koenker and Xiao (2001) and Lamarche (2010), as well as extensions made by Harding and Lamarche (2009) and Galvão and Montes-Rojas (2010), among others. Regression models with panel data provide a greater amount of information, greater data variability, reduction of the collinearity problem between the explanatory variables, greater number of freedom degrees, and greater estimated parameters efficiency (MARQUES, 2000).

Thus, since the explanatory variables do not affect in the same level the municipal deforestation, quantile regressions were estimated around 10%, 25%, 50% (median), 75%, and 99%. The p-th quantile conditional of $\ln DEF_{it}$ is given by:

$$Q_\theta(\ln DEF_{it} \setminus X_{it}) = \alpha_i + \beta_\theta X'_{it} + \varepsilon \qquad (1)$$

$$\theta \in [0,1]$$

Where $\ln DEF_{it}$ = natural log of municipal accumulated deforestation and X'_{it} dependent variable model = explanatory variables vector used in the model; β_θ = estimated parameters for each conditional quantile of the dependent variable variation; α_i = intercept parameter; ε = represents the error term. The specific form of the estimated regression model is written as:

$$\begin{aligned} \ln DEF_{it} = {} & \alpha_0 + \beta_1 \ln GDP\_PC_{it} + \beta_2 \ln GDP\_PC^2_{it} + \beta_3 \ln GDP\_PC^3_{it} + \beta_4 \ln POP_{it} + \beta_5 \ln CH_{it} \\ & + \beta_6 \ln P\_CROPS_{it} + \beta_7 \ln T\_CROPS_{it} + \beta_8 IFDM\_EI_{it} + \beta_9 IFDM\_E_{it} + \beta_{10} IFDM\_H_{it} \\ & + \beta_{11} \ln FOR_{it} + \beta_{12} \ln FOR^2_{it} + \beta_{13} P\_MUNIC_{it} + \varepsilon \end{aligned} \qquad (2)$$

Where deforestation (lnDEF) is the variable of interest; lnGDP_PC is the natural logarithm of municipal per capita GDP (in linear, quadratic, and cubic forms), lnPOP is the municipal population natural logarithm, lnCH is the cattle herd natural logarithm, lnP_CROPS and lnT_CROPS are the municipal planted area natural logarithms of permanent and temporary land crops, respectively, IFDM_EI, IFDM_E, and IFDM_H are the Employment and Income, education and health indicators (socioeconomic development proxies), lnFOR is the remaining municipal forest area natural logarithm (in linear and quadratic forms); P_MUNIC is a dummy variable, with 0 being assigned to the period till 2009 and 1 in 2009 onwards. This variable refers to the period before and after the release of municipalities list where priority actions to the prevention, monitoring, and control of illegal deforestation take place; ε is the random error term and βi (with i = 1,2, 3...,13) is the of the empirical model parameter.

Initially, an Exploratory Data Analysis (AED) is used to previously examine the data of econometric technique application. Thus, it is sought a data basic understanding and the relationships between the variables analyzed through descriptive analysis that allows them to be organized and synthesized to obtain information from the data set. Therefore, to analyze the quantitative variables it is calculated the average and standard deviation of the values, the first is a position measurement, a value around which the data are distributed and the second is a dispersion measurement which summarizes the data variability. In addition, it is distributed the dependent variable accumulated deforestation per quintile which can be visualized on a map, allowing the forest spatialization and tree felling in Pará's territory to be observed.

To validate the chosen model, the following tests were used: Wooldridge, for serial autocorrelation; Breusch-Pagan, for heteroscedasticity and Wald, to verify the existence of significant differences between different quantiles in the relationship between the dependent variable and the explanatory variables included in the model to confirm the relevance of the method. The bootstrap resampling method was also applied, enabling greater reliability in the inferences made. In addition, this method allows heteroscedasticity and autocorrelation correction, as explained by Cameron and Trivedi (2010).

Results and discussion

Descriptive data analysis

To analyze municipal deforestation implications considering the determinants selected, five quantile regressions were estimated, in addition to the OLS regression, considering quantiles 10, 25, 50, 75, and 99 of the variables explained that tare presented according to the limits in Table 1:

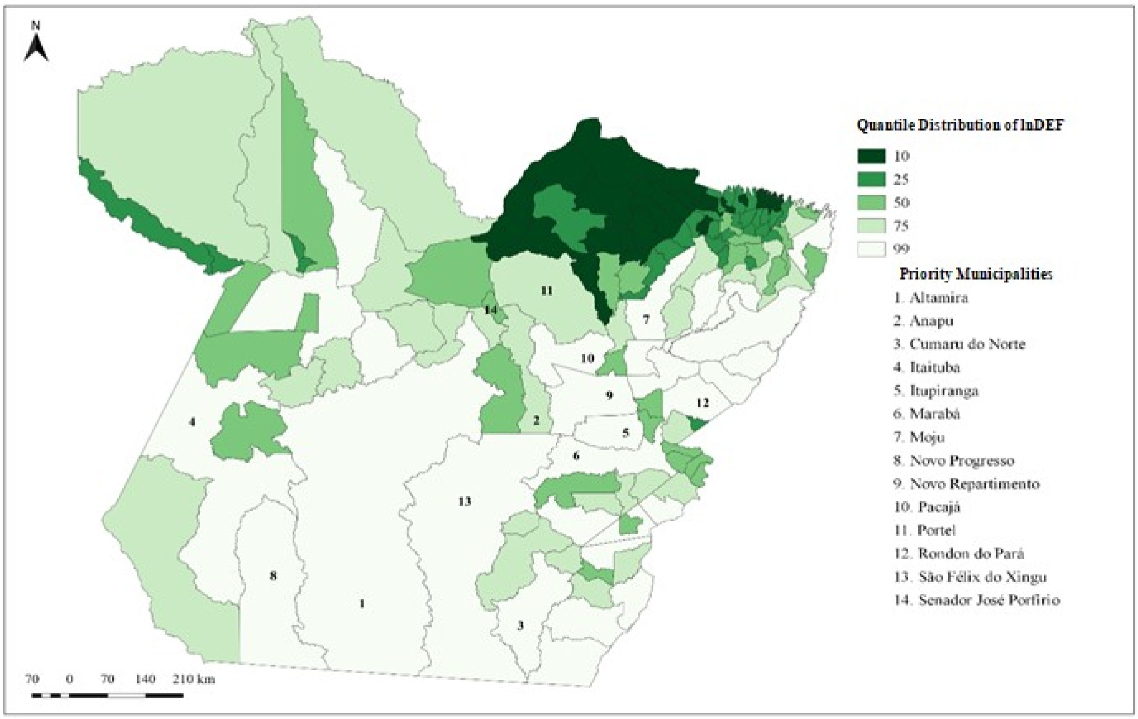
Table 1: Limits of the distribution of the dependent variable lnDEF (2005 – 2016)

Quantiles	Inferior Limit	Upper Limit
10	3,13	5,42
25	5,42	6,53
50	6,53	7,27
75	7,28	7,90
99	7,91	9,81

Source: Research Results.

Therefore, five different levels of accumulated deforestation in these cities results are obtained. Quantile 10 provides results for 10% of deforested municipalities, while quantile 99 provides results for 99% to the most deforested. The 50 quantile represents the median and its interpretation and those of 25 and 75 quantiles are made in a similar way comparing to the others. The spatial distribution of municipalities in relation to the dependent variable lnDEF distribution, as well as the priority municipalities list to deforestation combat actions which can be better visualized in Figure 2:

Figure 2: Spatial distribution of municipalities considering the dependent variable lnDEF and priority municipalities distribution for combat deforestation actions



Fonte: Elaborated by the author.

There's a greater concentration of the most deforested municipalities in the quantiles above the median, representing approximately 82% of deforested areas in Pará state and smaller deforested areas (6% of the total) are captured by the quantiles below the median. are mostly located in the northeast state's region. In this sense, deforestation is a phenomenon that has been established in most of Pará's municipalities which reveals the lack of environmental governance capacity actions to deal with serious environmental problem.

An Exploratory Data Analysis (AED) is used in order to comprehend the municipalities characteristics and their distribution throughout Pará. The analysis results are shown in Table 2:

Table 2: Descriptive statistics of variables

Variable	Measures	Quantiles 10	25	50	75	99
lnDEF	Mean	4,641	6,028	6,957	7,567	8,442
	Standard Deviation	0.577	0.299	0.224	0.188	0.415
lnGDP_PC	Mean	8,500	8,819	9,036	9,306	10,021
	Standard Deviation	0.157	0.062	0.069	0.099	0.492
lnGDP_PC²	Mean	72,282	77,781	81,656	86,612	100,668
	Standard Deviation	2.627	1.108	1.241	1.849	10.344
lnGDP_PC³	Mean	614,844	686,036	737,944	806,192	1,013,894
	Standard Deviation	33.055	14.649	16.828	25.880	163.684
lnPOP	Mean	9,148	9,874	10,249	10,703	11,596
	Standard Deviation	0.381	0.139	0.080	0.151	0.714
lnCH	Mean	6,655	9,240	10,733	11,747	12,847
	Standard Deviation	1.339	0.576	0.342	0.262	0.499
lnP_CROPS	Mean	3,697	5,273	6,224	7,186	8,778
	Standard Deviation	0.946	0.317	0.189	0.352	0.728
LnT_CROPS	Mean	5,646	7,130	7,943	8,765	9,823
	Standard Deviation	0.876	0.263	0.252	0.240	0.566
IFDM_EI	Mean	0.333	0.421	0.462	0.525	0.679
	Standard Deviation	0.050	0.014	0.012	0.024	0.090
IFDM_E	Mean	0.337	0.451	0.519	0.569	0.644
	Standard Deviation	0.053	0.023	0.015	0.016	0.036
IFDM_H	Mean	0.257	0.374	0.461	0.542	0.665
	Standard Deviation	0.051	0.025	0.024	0.025	0.064
lnFOR	Mean	3,763	5,288	6,508	7,934	9,621
	Standard Deviation	0.922	0.285	0.440	0.386	0.900
lnFOR²	Mean	15,013	28,065	42,551	63,109	93,370
	Standard Deviation	5.444	3.036	5.714	6.144	18.112

Source: Research Results.

Besides having higher accumulated deforestation averages, the results presented allow us to verify that bigger quantiles municipalities are the ones with higher averages considering per capita GDP, population, agriculture and livestock areas, as well as forest areas. To 10% of municipalities, the remaining forest presented a higher standard deviation (0.922) considering the median that as an absolute variable, indicates a greater variability related to the size of the municipalities. It can be affirmed that smaller forest areas cities are more heterogeneous considering the environmental characteristic of their territories.

In addition, the deforested municipalities with the highest averages (quantiles 75 and 99) have socioeconomic development levels classified as regular development (between 0.4 and 0.6) in terms of Employment and Income, education, and health indicators averages. 10%, 25%, and 50% of analyzed municipalities seem to have lower development stages (between 0.0 and 0.4).

Empirical evidence: determinants of deforestation

Initially, the model relevance is based on Wald's test result [F (65.1470) = 19.43; Prob > F = 0.000] which shows the possibility of rejection of null hypothesis that the effects are homogeneous in the conditional distribution. It can be stated that, with a 1% level of significance, the slope coefficients of each quantile are different to all explanatory variables. As for the Breusch-Pagan tests [chi2(1) = 113.51; Prob > chi2 = 0.0000] and Wooldridge's [F(1,135) = 446,405; Prob > F = 0.0000], the results indicated the presence of heteroscedasticity and serial autocorrelation respectively and being corrected by estimation with robust standard errors and by bootstrap.

The presented results in table 3 demonstrate that all the explanatory variables used in the model were statistically significant at some point, even if the dependent variable behavior explanation is only in a part of its distribution.

The estimation results of the regression models that relate per capita GDP with deforestation from the perspective of CKA theoretical model by the cubic polynomial function demonstrate statistical significance of 10% of the least deforested municipalities and expected positive signs to $\beta1$ and negative to $\beta2$. Therefore, it is assumed that the development for this group of cities, there is an environmental Kuznets relationship with deforestation, showing that when income increases, deforestation reaches higher levels. . So deforestation reaches a maximum and then decreases.

Table 3: quantile regression and OLS Results

		Quantiles				
Variables	MQO	10	25	50	75	99
lnGDP_PC	-7.655	29,661*	-7.846	-15,526**	-14,721*	-52,604***
lnGDP_PC²	0,972	-2,897*	0,969	1,745**	1,632*	5,628***
lnGDP_PC³	-0,039	0,093	-0,039	-0,065**	-0,060**	-0,198***
lnPOP	0,128***	0,01	0,186***	0,161***	0,209***	0,283***
lnCH	0,325***	0,400***	0,391***	0,364***	0,342***	0,294***
lnP_CROPS	0,072***	0,070***	0,064***	0,065***	0,048***	0,058
LnT_CROPS	0,230***	0,385***	0,173***	0,150***	0,146***	0,146***
IFDM_EI	0,447***	0,922***	0,460***	0,276**	0,207*	0,654
IFDM_E	-1,104***	-0,871**	-0,665***	-0,713**	-1,026***	-1,659***
IFDM_H	0,246**	0,749***	0,195**	0,084	-0,033	0,344
lnFOR	0,186***	0,1	0,312***	0,321***	0,266***	0,141
lnFOR²	-0,008***	-0,004	-0,020***	-0,017***	-0,012***	-0,008
P_MUNIC	0,171***	0,279***	0,168***	0,143***	0,178***	0,008
contant	18.045	-102,288**	18.084	44,139*	42.838	161,918**
R²/pseudo R²	0,8345	0,6085	0,6315	0,6375	0,6374	0,6152
Wald Test Prob > F	19,43***					
Breusch-Pagan Test Prob > X²	113,51***					
Wooldridge Test Prob > F	446,405***					

Note: *10% of significance; ** 5% of significance; *** 1% of significance.
Source: Research Results.

On the other hand, the quantile regressions coefficients (quantiles 50, 75, and 99) statistically significant, show that the format found for the relationship between economic growth and deforestation is the "inverted N". Consequently to 50%, 75% and 99 % of the most deforested municipalities, the loss of forest cover is decreasing to lower levels of per capita GDP, increasing as per capita GDP increases and decreasing again for higher levels of GDP per capita.

The result suggests that in heavily deforested municipalities with successive income increases would lead to a reduction in deforestation levels. Thus, the CKA hypothesis with an “N” format is rejected. These results diverge from those found by Carvalho, Carvalho, Carvalho and Guimarães (2020) who find through the multiple linear regression model to Brazilian Amazon a possible CKA in the form of an “N” of which the “inverted U” is just an early stage of this relationship. Other similar works such as Faria and Almeida (2016) and Soares (2019) prove a positive and significant relationship between per capita GDP and forest deforestation in the region.

The of populational growth impact (lnPOP) on deforestation is positive and significant (except for quantile 10), corroborating studies by Cropper and Griffiths (1994), Ferreira and Coelho (2015), Diniz (2017), Reydon, Fernandes, and Telles, (2020). Stated a variation of 1% in population, there would be a positive variation of 0.186%, 0.161%, 0.209% and 0.283% on quantile deforestation of 25, 50, 75 and 99 respectively which indicate that the lnPOP effect results are greater in great part of deforested municipalities due to greater quantiles elasticities of 75 and 99.

The results demonstrate that the proxy variables of productive activities, livestock (lnCH) and temporary land crops (lnT_CROPS) are statistically significant at any deforestation level, while the proxy variable of permanent farming (lnP_CROPS) did not show statistical significance only for 99% of most deforested municipalities. The variables are positively correlated to deforestation. In addition, these results are similar to those found in other works in the literature, such as Diniz and Oliveira Jr. (2009), Faria and Almeida (2016) and Diniz (2017), although the authors do not work with quantile regressions for panel data.

The impact of livestock on deforestation was much higher than agricultural activities considering that the deforestation variation would be respectively in the order of 0.400%, 0.391%, 0.364%, 0.342%, 0.294% in the quantile 10, 25, 50, 75 and 99, given the bovine herd variation of 1%.

Regarding the IFDM indicators effect, it is observed that Employment and Income component (IFDM_EI) showed statistical relevance and positive correlation with deforestation, except in quantile 99. The magnitude of Employment and Income effect decreases in highest quantiles of the distribution, considering that in Pará municipalities this is an important factor in forest clearing stimulus. However, the incremental effect on deforestation is smaller in heavily deforested municipalities which suggests that in these municipalities individuals may be inclined to invest in less degrading economic activities.

On the other hand, Education component (IFDM_E) has a negative and significant relationship for all deforestation levels. From Health perspective, expressed by the IFDM_H variable, a positive and significant correlation was inferred with deforestation by OLS and quantiles 10 and 25, indicating that the positive effect is bigger in less deforested municipalities or those in an initial deforestation stage. The other quantiles proved to be statistically irrelevant to explain some influence of health indicator on deforestation.

In this sense, the presented results in this paper follow somehow in concordance with some studies such as those developed by Loening and Markussen (2003), Diniz and Oliveira Jr. (2009), Arraes, Mariano and Simonassi (2012), and Diniz (2017). According to them, a growing economy is desirable due to its positive social and economic effects such as well-being which often converted into environmental indicators improvements such as the drop in deforestation.

In turn, the remaining forest area (lnFOR) showed statistical significance and a positive sign to most of deforestation distribution quantiles. Knowing this, it is possible to infer that the bigger the forest area is, bigger the availability of susceptible areas to deforestation are. On the contrary, the $lnFOR^2$ variable in its quadratic form, has presented the negative sign expected that is corroborated by the forest transition hypothesis (NEPSTAD et al., 2008; FERREIRA; COELHO, 2015).

From this perspective, a maximum level is reached from which there is a decline in devastation. Therefore, there would be less incentive to convert the forest for other uses, implying a reduction in subsequent deforestation. In addition, the result reinforces the thesis which after the initial deforestation intensification process in native forest regions with large areas due to the environmental impact promoted by human action.

In conclusion, aiming to investigate the hypothesis of effectiveness of actions to combat deforestation in Pará, it is inferred that the dummy variable priority municipalities for preventive actions, monitoring and combating illegal deforestation (P_MUNIC) showed statistical significance and positive correlation with deforestation, except for quantile 99. The positive sign indicates that the agents promoting forest conversion for illegal land uses are not being effectively restricted by actions to combat these practices, as demonstrated by the positive contemporary effect variable. It is stated that the policy is not contributing to deforestation reduction as asserted in studies developed by Azevedo et al. (2017) and Castelo, Adami and Santos (2020).

Final considerations

This paper asserts that the variables related to economic development, mainly per capita GDP, populational growth, cattle herd, and temporary crops are determinants of municipal deforestation dynamics in the state of Pará. The populational growth impact on deforestation is positive, mainly in most deforested municipalities. In addition, there is evidence of a CKA relationship in the shape of an "inverted N" between economic growth and deforestation measured by per capita GDP, suggesting that successive increases in income would lead to a reduction in the deforestation levels in heavily deforested municipalities.

Furthermore, the remaining forest area variable case, this relationship was positively significant considering the statistical point of view and a positive sign to great part of the deforestation distribution. The result suggests that the initial deforestation's worsening in big native forest regions reaches a maximum level from which there is a decline in deforestation, with lower economic incentive to use the forest itself for other purposes, implying a subsequent deforestation reduction.

The results also demonstrate that activities as livestock and temporary crops have influenced the devastation expansion at any municipal deforestation level. The permanent farming activity was statistically significant for only 99% of most deforested cities.

Regarding socioeconomic aspects associated to deforestation, the IFDM indicators results indicate a positive correlation of Employment and Income with deforestation. In Pará municipalities these factors can be potential sources which encourage the forest clearing. However, in order to ease environmental impact, economic agents are invited to invest in activities which can lead to the improvement employment and income levels in heavily deforested municipalities.

On the other hand, the Education component have shown a negative correlation with deforestation, indicating that better educational levels can induce more sustainable activities considering an environmental point of view and consequently, contributing to deforestation reduction. Furthermore, from health indicator perspective, it proved to be statistically significant and positive to new deforestation areas considering only less deforested municipalities.

In addition, policy against deforestation did not have a great influence on deforestation decrease in municipalities with the highest forest loss as demonstrated by the variable 's contemporary effect.

In conclusion, deforestation in Pará state is influenced both by per capita GDP and populational growth and the expansion of cattle herd as well as areas of temporary and permanent crops. Moreover, improvements in socioeconomic indicators such as employment, income, health, and education, command and control policies in compliance with environmental law and actions to combat deforestation, which are relevant to mitigate deforestation and indirectly reflect the effective performance of public authorities in these areas.

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