UNIVERSIDADE FEDERAL DO PARANÁ

PEDRO GABRIEL EDUARD VALERA MILWARD MEINERS

TWO ESSAYS ON AGRICULTURAL LAND AND ENVIRONMENT

CURITIBA PR

2022

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TWO ESSAYS ON AGRICULTURAL LAND AND ENVIRONMENT

Dissertação apresentada como requisito parcial à obtenção do grau de Mestre em Desenvolvimento Econômico no Programa de Pós-Graduação em Desenvolvimento Econômico, no Setor das Ciências Sociais Aplicadas, da Universidade Federal do Paraná.

Área de concentração: *Ciências Econômicas*.

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Coorientador: Dr. Marcelo de Oliveira Torres.

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Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação DESENVOLVIMENTO ECONÔMICO da Universidade Federal do Paraná foram convocados para realizar a arguição da Dissertação de Mestrado de **PEDRO GABRIEL EDUARD VALERA MIWARD MEINERS** intitulada: **TWO ESSAYS ON AGRICULTURAL LAND AND ENVIRONMENT**, sob orientação do Prof. Dr. ALEXANDRE ALVES PORSSE, que após terem inquirido o aluno e realizada a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.
A outorga do título de mestre está sujeita à homologação pelo colegiado, ao atendimento de todas as indicações e correções solicitadas pela banca e ao pleno atendimento das demandas regimentais do Programa de Pós-Graduação.

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Toda mata tem caipora para a mata vigiar
Veio caipora de fora para a mata definhar
E trouxe dragão de ferro, pra comer muita madeira
E trouxe em estilo gigante, pra acabar com a capoeira

Fizeram logo o projeto sem ninguém testemunhar
Pra o dragão cortar madeira e toda mata derrubar
Se a floresta meu amigo, tivesse pé pra andar
Eu garanto, meu amigo, que o perigo não tinha ficado lá

O que se corta em segundos gasta tempo pra vingar
E o fruto que dá no cacho pra gente se alimentar?
Depois tem o passarinho, tem o ninho, tem o ar
Igarapé, rio abaixo, tem riacho e esse rio que é um mar

Mas o dragão continua na floresta a devorar
E quem habita essa mata, pra onde vai se mudar?
Corre índio, seringueiro, preguiça, tamanduá
Tartaruga, pé ligeiro, corre, corre tribo dos Kamaiurá

No lugar que havia mata, hoje há perseguição
Grileiro mata posseiro só pra lhe roubar seu chão
Castanheiro, seringueiro já viraram até peão
Afora os que já morreram como ave de arribação
Zé de Nana tá de prova, naquele lugar tem cova
Gente enterrada no chão

Pois mataram o índio que matou grileiro que matou posseiro
Disse um castanheiro para um seringueiro que um estrangeiro
Roubou seu lugar

(Vital Farias, 1984)

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RESUMO

Esta dissertação de mestrado está dividida em dois ensaios sobre as relações econômicas da agricultura e do meio ambiente. Ambos os ensaios tratam de terras agrícolas no Brasil, porém cada um com foco em regiões. O bioma do Cerrado onde as terras agrícolas podem ser expandidas, e o estado do Paraná onde os assentamentos agrícolas praticamente esgotaram as terras virgens, com exceção das reservas ambientais e áreas de alta latitude. O primeiro ensaio avalia, a partir de um conjunto de dados em painel bienal para o período de 2002-2018, a relação entre o desmatamento municipal no *Cerrado* e as políticas de dissuasão realizadas pelo IBAMA. Os mecanismos de dissuasão utilizados foram concebidos com base na teoria da escolha criminal, e visavam abarcar três dimensões distintas: severidade, certeza e celeridade da punição. Devido a endogeneidade inerente ao modelo, variáveis instrumentais (IV) e técnicas de regressão em dois estágios são implementadas no contexto de uma análise de dados em painel com e sem consideração explícita do espaço, uma vez que o desmatamento geralmente apresenta dependência espacial. Em particular para os modelos de painéis espaciais, o método generalizado de momentos (GMM) é empregado. As especificações do modelo incluem relações não lineares, termos de *lag* espacial (SAR) e erro espacial (SEM). Entre nossos principais resultados, encontramos evidências de que a severidade da punição (intensidade da multa), a celeridade (espera do julgamento) e a certeza (julgamento da multa) desempenham um papel essencial na contenção do processo de desmatamento. No segundo ensaio os impactos das mudanças climáticas sobre os preços das terras agrícolas no *Paraná* são investigados usando especificações econométricas hedônicas baseadas em um modelo Ricardiano. Para tanto, utiliza-se um banco de dados bastante detalhado com medidas diárias de temperatura para a construção de um preciso indicador agronômico que mede absorção térmica de uma cultura, também conhecido como graus-dias de crescimento (GDD). O modelo estimado, juntamente com as projeções climáticas do IPCC, foi posteriormente empregado para projetar os impactos futuros das mudanças climáticas na agricultura do *Paraná*. Os resultados indicaram que o *Paraná* se beneficiará das mudanças climáticas com valorização de seus preços de terras agrícolas em todos os cenários projetados.

Palavras-chave: Desmatamento. Preços Fundiários. Modelos econométricos espaciais.

ABSTRACT

This MS thesis is divided into two essays on the economic relationships of agriculture and environment. Both essays concern agricultural land in Brazil, but focus on different regions. The *Cerrado* biome where farmland can still be expanded, and *Paraná* state where virgin lands are piratically exhausted by farm settlement, with exception of reservations and high latitude areas. The first essay assesses, through the use of a biennial panel data set for the period of 2002-2018, the relationship between municipal deforestation in the *Cerrado* and deterrence policies carried out by IBAMA. The deterrence mechanisms are designed based on the theory of criminal choice, and encompass three different dimensions: severity, certainty and celerity of punishment.Due to their inherent endogeneity, instrumental variables (IV) and two-stage regression techniques are implemented in the context of a panel data analysis with and without explicit consideration of space as deforestation usually has spatial dependence. The model specifications included non-linear relationships, spatial lag (SAR) and spatial error (SEM) terms. Among our main results, we found evidence that punishment severity (fine intensity), celerity (trial wait), and certainty (judged fines) play an essential role in curbing the deforestation process. In the second essay we investigated the impacts of climate change on farmland prices in *Paraná* using an hedonic econometric specification based on a Ricardian model. For such, a very detailed database with daily measures of temperature is used to the construction of an precise agronomic indicator of thermal intake of a crop, also known as growing-degree days (GDD). The estimated model, along with climate projections of IPCC, was subsequently employed to project the future impacts of climate change on *Paraná*'s agriculture. Results indicated that *Paraná* will benefit from climate change with appreciation of its farmland prices in all projected scenarios.

Keywords: Deforestation. Rural Land Prices. Spatial econometric models.

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ANA	National Water Agency
AR6	IPCC's Sixth Assessment Report
AWC	Available Water Capacity
BRL	Brazilian Real
CONAB	National Supply Company
CORDEX	Coordinated Regional Downscaling Experiment
DERAL	Paraná's Department of Rural Economics
EDD	Extreme-growing degree days
EMBRAPA	Brazilian Agricultural Research Corporation
FE	Fixed Effects
GDD	Growing Degree Days
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
GMM	Generalized Methods of Moment
HAC	heteroscedasticity- and autocorrelation-consistent
IAT	Paraná's Water and Land Institute
IBAMA	Brazilian Institute of Environment and Renewable Natural Resources
IBGE	Brazilian Institute of Geography and Statistics
INPE	National Institute of of Space Research
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental Variables
KNN	k-nearest neighbours
OLS	Ordinary Least Squares
PAM	Municipal Agriculture Production database
PPGDE	Programa de Pós-Graduação em Desenvolvimento Econômico
PPM	Municipal Livestock Production database
RE	Random Effects
SAR	Spatial Auto Regressive Model
SEM	Spatial Error Model
SIMEPAR	Paraná Technology and Environmental Monitoring System
TSLS	Two Stage Least Squares
TT	Termal Time
UFPR	Federal University of Paraná

LIST OF SYMBOLS

α	alfa;
β	beta;
γ	gamma;
δ	delta;
ε	epsilon;
λ	lambda
ρ	rho;
χ	chi;
σ	sigma;
ϕ	phi;

CONTENTS

1 PRIMEIRO ENSAIO: ASSESSING THE EFFECTS OF DETERRENCE MECHANISMS ON DEFORESTATION IN BRAZILIAN SAVANNA

ABSTRACT

The aim of this essay is to assess the effect of deterrence mechanisms on environmental crimes in the Brazilian Savanna (*Cerrado*). We used spatial and non-spatial panel econometric models with a sample of 948 municipalities in the period 2002-2018. Deterrence is composed by three variables (severity, celerity and certainty of punishment) which represents a major contribution to the literature as they were never jointly used in an econometric context. When endogeneity is properly taken into account, deforestation becomes responsive to both rises on fine intensity (severity) and to improvements in the bureaucratic process (certainty and celerity), being the latter a strong contributor to slowing deforestation rates. Such findings reinforce the importance of applying an efficient legal process concerning prevention and punishment deforestation.

Keywords: Deforestation, Deterrence, Cerrado, Spatial Econometrics, Brazil

RESUMO

O objetivo deste ensaio é avaliar o efeito de mecanismos de dissuasão sobre crimes ambientais no Cerrado brasileiro (Cerrado). Utilizam-se modelos econométricos de painel espacial e não espacial com uma amostra de 948 municípios no período 2002-2018. A dissuasão é composta por três variáveis (severidade, celeridade e certeza da punição) o que representa uma grande contribuição para a literatura, pois nunca foram utilizadas conjuntamente em um contexto econométrico. Quando a endogeneidade é devidamente considerada, o desmatamento torna-se responsivo tanto a aumentos na intensidade de multa (severidade) quanto a melhorias no processo burocrático (certeza e celeridade), sendo este último um forte contribuinte para a desaceleração das taxas de desmatamento. Estes achados reforçam a importância da aplicação de um processo legal eficiente na prevenção e punição do desmatamento.

Palavras-chave: Desmatamento, Dissuasão, Cerrado, Econometria Espacial, Brasil

1.1 INTRODUCTION

Forest clearance for agricultural expansion is considered to be the main culprit of deforestation in Brazil (Diniz et al., 2009; Rivero et al., 2009; Hargrave and Kis-Katos, 2013; Assunção et al., 2015). This type of deforestation can be modeled through Becker (1968)'s theory, in which all rational agents pursue their own best interests (*e.g.*, farmers expanding their property) and their behavior can be shaped by law, surveillance and punishment institutions (environmental code, agencies, and police). As explained by Polinsky and Shavell (2007), within law economics, rules are established in accordance with deterrence mechanisms, which are composed of punishment *per se* (fines or detention), the probability of punishment – derived from the public effort of surveillance – and the celerity of punishment, which results from the speed of the legal process and bureaucracy. When it comes to Brazil's scenario more specifically, environmental law is usually enforced by a single public entity, namely the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA).

The literature suggests that the driving forces of deforestation are associated with a great number of factors: from macroeconomic effects – *e.g.*, population pressure, economic growth, infrastructure network – (Andersen, 1996; Pfaff, 1999) to market-factors – as it is the case of commodity quantity/prices and currency devaluation (Diniz et al., 2009; Rivero et al., 2009) –, public policies – with their environmental reservations, rural credit and amnesties (Fearnside, 2005; Prates, 2008); and socioeconomic variables – education levels, income disparity and labor market are some examples (Pichón, 1997; Godoy et al., 1998; Angelsen, 1999; Godoy and Contreras, 2001; Pendleton and Howe, 2002; Zwane, 2007).

Recently, a handful of studies has shifted their focus from drivers of deforestation to measuring and understanding the efforts to curb deforestation. A pioneering article concerning IBAMA's activity is Hargrave and Kis-Katos (2013), which measures the relationship between environmental fine intensity and deforestation in the Amazon rainforest. Over the same period, De Souza et al. (2013) analyzes the impacts of rural technology, land concentration and IBAMA embargoes on deforestation, and achieves mixed results regarding IBAMA deterrence capacity. Also, the author emphasizes how fines and embargoes are crime-sensitive and therefore are concentrated on high deforestation areas. Börner et al. (2014) develop a spatial enforcement model by using a combination of the principal-agent relationship and the theory of criminal behavior in order to simulate the cost-effectiveness of command and control policies within the Brazilian Amazon's limits.

Another work worth mentioning is Assunção et al. (2015) which find out that the policy changes taken place in IBAMA in 2004 and 2008 contributed to slowdown deforestation rates in the Amazon. In Schmitt (2015)'s doctoral thesis, the author designs a model to assess the general deterrence value of IBAMA fines by making use of data on enforcement probability. In a technical report, Assunção et al. (2017) propose a novel instrumental variable –clouds in the satellite images used by IBAMA in surveillance (DETER)– to estimate the existing causality between fines and deforestation. A tragedy of commons situation, modeled through game-theory principles, is presented by de Araújo et al. (2021). Moreover, they discuss not only the importance of modeling deforestation based on the dissuasion theory in Brazil but also the main difficulties faced by environmental policing authorities on stopping deforestation. The slow process regarding the application of IBAMA's embargoes receives special attention by the authors once it represents an obstacle to the celerity of punishment.

The everlasting challenge to researchers that try to infer causality between deterrence factors and crime – regardless of which sort of criminal activity is under analysis (Cameron, 1988; Levitt, 2002; Draca et al., 2011) – concerns the endogeneity between crime and policing, and how one affects the other: the kind of relation from which it is hard to imply causality from. This issue is pervasive to all type of crime including deforestation. Hargrave and Kis-Katos (2013) and Assunção et al. (2017), for instance, advocate for the use of crime-oriented instruments to estimate the relationship shared by IBAMA's fines and deforestation. Both studies, however, are limited to only one dimension of deterrence, severity, and neglect other aspects of law enforcement, such as certainty and celerity. de Araújo et al. (2021) argues that focusing on severity and embargo quantity only is not enough to comprehend the full spectrum of IBAMA's activity, and point out that the slow nature of the processing phase – as defendants wait for trial – along with the inability of IBAMA to properly enforce fine payment are the main limits of environmental surveillance in Brazil and must be accounted for in a model interested in describing IBAMA's work. Similar environmental-policing hurdles have also been claimed to take place in other countries, as Lynch et al. (2016)'s study the US.

This essay adds two other dimensions to represent deterrence, certainty and celerity of punishment, in accordance with Schmitt (2015)'s proposals, as well as its instrument counterparts based on Hargrave and Kis-Katos (2013) instrument for fines. It also approaches the underexplored data on deforestation of the Brazilian Savanna, locally known as the *Cerrado*. The *Cerrado* is the second largest biome in Brazil, covering up nearly 24% of the national territory. Likewise in the Amazon region, settlement was sparse until the mid-twentieth century. A scenario which begins to change in the 1960s and 70s with the implementation of new farming techniques and plant selection advancements for soybean production – promoted by the Brazilian Agricultural Research Corporation (EMBRAPA). Such improvements allowed for soybean cultivation in the tropical climate of *Cerrado*. From the 1980s onwards an extensive land-use/land-cover-change process occurs in the area, which culminates with Brazil becoming the world largest soybean producer (Conab, 2020). Due to this expansion some studies even predict the extinction of this biome by 2030, *e.g.*, (Machado et al., 2004).

Given the extent of the deforestation in the *Cerrado* and the potentially large impacts on the ecosystem, there is a surprisingly low number of studies focusing on this area, a fact that contrasts to the striking number of investigations regarding the Amazonian biome. Part of this may be a result of the lack of international scrutiny towards the Cerrado, in opposition to the attention drawn to the Amazon rainforest. The low national and international media coverage for the biome and the common understanding of *Cerrados* as being a dry and lifeless biome seem to contribute to this poor visibility.

Our results present evidence that punishment severity (fine intensity), celerity (trial wait), and certainty (judged fines) play an essential role in curbing the deforestation process. Furthermore, parameter values for deterrence variables agree with de Araújo et al. (2021) in claiming that the slow bureaucracy of the legal process is the main culprit for IBAMA's enforcement inefficiency, as estimated elasticities suggest that improvements on the celerity of deterrence and certainty of trial present higher effect in hindering deforestation than the severity of fines.

In the following section we explore more deeply this investigation's area of study by presenting the *Cerrado*, discussing the theoretical foundation of our model, and describing the main variables of interest. In section 3 we explain our empirical approach, we show the selected control variables and describe our sample selection process. Also, endogeneity problems and instruments to solve them are specified. In section 4 we discuss results and tests. Finally, we conclude in section 5.

1.2 THE STUDY AREA

The *Cerrado* is a tropical savanna almost entirely located within Brazil's borders, being the second largest biome of the country. It is considered to be one of the most diverse ecosystems of the planet, with high levels of endemism – that is, the number of species unique to a biome – in both fauna and flora (Machado et al., 2008). This biological richness is followed by a rich economy: 24% of Brazilian GDP comes from municipalities from this region, which encompasses 38% of Brazilian agricultural production in 2018 (IBGE, 2021). The resulting agricultural expansion has exerted a heavy toll to the savanna's forests though, as the *Cerrado* has lost 50% of its original coverage by 2019 (INPE, 2020). This urges for a better understanding of deforestation in the area as well as the need of finding the best strategies to restrain its progress.

Information about *Cerrado*'s native vegetation suppression is provided by Brazil's National Institute of Space Research (INPE) as *shapefiles*. This dataset used to be published biennially from 2002 to 2012, but it turned to be released yearly from 2013 onward. Given this fact, we have chosen to aggregate the yearly portion of the data into biennial values by municipality, as it is usually the most disaggregated level of Brazilian datasets. Adding to it, the data is not organized in accordance with the Gregorian year: instead its measures are made on August 1st every two years (once a year since 2013). Those two timespan problems call for adjustments to our explanatory variables, i.e., any yearly data must be converted to what we call the INPE's year[1]. As it is possible to see in figure 1.3(a)[2], INPE's data show a downward trend in deforestation of the biome since 2004, with a brief spike in 2014. Additionally, figures 1.1(a) and 1.1(b) present the level of municipal deforestation in the first and last biennial for the municipalities under approach in this work: they indicate a shift of deforestation to the northern region of *Cerrado*[3].

As to the information on environmental policing, IBAMA is the institution responsible for. Since a specific date for each embargo is informed, no adaptation of INPE's year is needed. The first explanatory variable is fine intensity, which is used as a proxy for severity of punishment. It is computed identically to Hargrave and Kis-Katos (2013) – where data of issued fines per municipality per period is divided by municipal deforestation over the same period, and then they are converted to logarithm. From figure 1.3(b), it is possible to observe an increase in fine intensity, beginning in 2004 and stabilizing in 2008. Such periods coincide with the changes in IBAMA's structure, more deeply studied in Assunção et al. (2015). Figures 1.2(a) and 1.2(d) indicate the local trend of fine intensity. Also, there is a slight shift to north accompanying the deforestation trend.

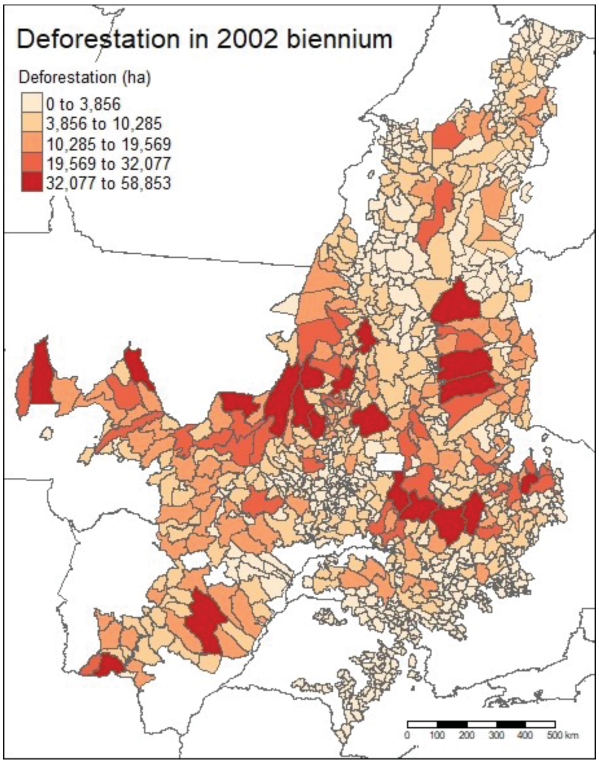
The celerity proxy is composed of the number of judged cases – up to a certain period – divided by the sum of days from the moment the fine is issued to the trial day of all judged cases – until the same period —, then converted into logarithms[4]. To better visualize why this imply celerity, observe that the fraction's inverse will be the mean number of days from IBAMA's embargo to trial, *i.e.*, the expected delay for conviction. Therefore, our proxy measures the celerity of the legal process from embargo to trial. Low levels of celerity – despite high certainty

[1]INPE's year is achieved by aggregating variables proportionally after values are deflated. In order to construct the 2004 data point for rural credit, for instance, we use 5/12 of the deflated value and quantity for the year 2002, the complete value and quantity of 2003, and 7/12 of the year 2004 – only then values are calculated. For those variables were averages are used, *e.g.* cattle heads, the proportions used are 5/24, 1/2 and 7/24 respectively.

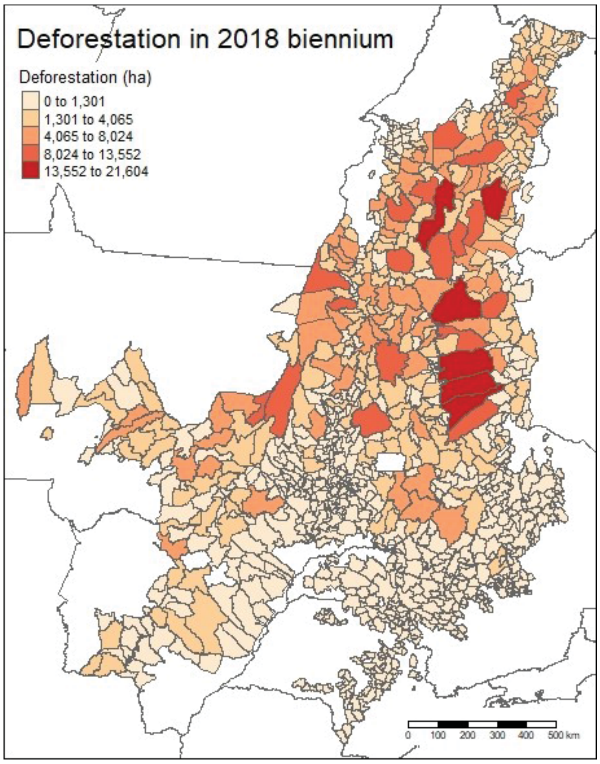
[2]All figures, graph, tables, and maps are obtained after a sample selection process depicted in section 1.3.1.

[3]This particular region is known as *Matopiba*, its name derives from the initials of the four states that composes it: *Maranhão, Tocantins, Piauí, Bahia*.

[4]Note that some municipalities in early periods had not had any fines judged – for those, the minimum value in the biennium is set.



(a)



(b)

Figure 1.1: Maps of *Cerrado* deforestation by municipality in hectares (first and last biennia)
Source: Own Calculations based on data from INPE

of conviction and severity of punishment – will signal to the agents late punishment application, what may lead to the prescription of the case and encourage further criminal behavior. In figure 1.3(c) there is a clear reduction of celerity along the studied period, with the 2018 average wait period being over twice as long as the 2002 average – 536 day *versus* 233 days. Maps 1.2(b) and 1.2(e) display the local values. From them, it is clear to notice the legal celerity presents a general downward trend, what indicates a loss of bureaucratic efficiency of IBAMA in all municipalities.

At last, the certainty of conviction proxy is achieved by taking the number of judged IBAMA's embargoes – until a given period – and dividing it by the total number of issued IBAMA's embargoes – under the same period –, then multiply the result by 100. To sum up, it is the percentage of the judged fines against the total number of issued fines within a certain period for a municipality. Assuming a constant chance of being caught – in case the proportion of solved embargoes is high –, these agents may be dissuaded to commit future environmental crimes since the chances of effective punishment after the embargoes are higher. The time trend of this variable is depicted in figure 1.3(d), where a clear growth is shown, indicating that IBAMA is processing trials faster than imposing new embargoes. Figures 1.2(c) and 1.2(f) depict the municipal distribution of certainty in 2002 and 2018 biennia, which shows a general improvement in the indicator.

Both the certainty and celerity variables take form of stock variables – in contrast to severity which represents a flow. This understanding has its grounds on the delay of environmental-related trials in Brazil, which can last years. The use of judged fines influx, therefore, would remove most cases from our dataset. It is important to notice that celerity and certainty proxies do not indicate conviction, just in case a trial is ordered – independently of the final decision. This may not represent a serious problem given that 90% of embargoes result in conviction, as it is pointed out by Schmitt (2015).

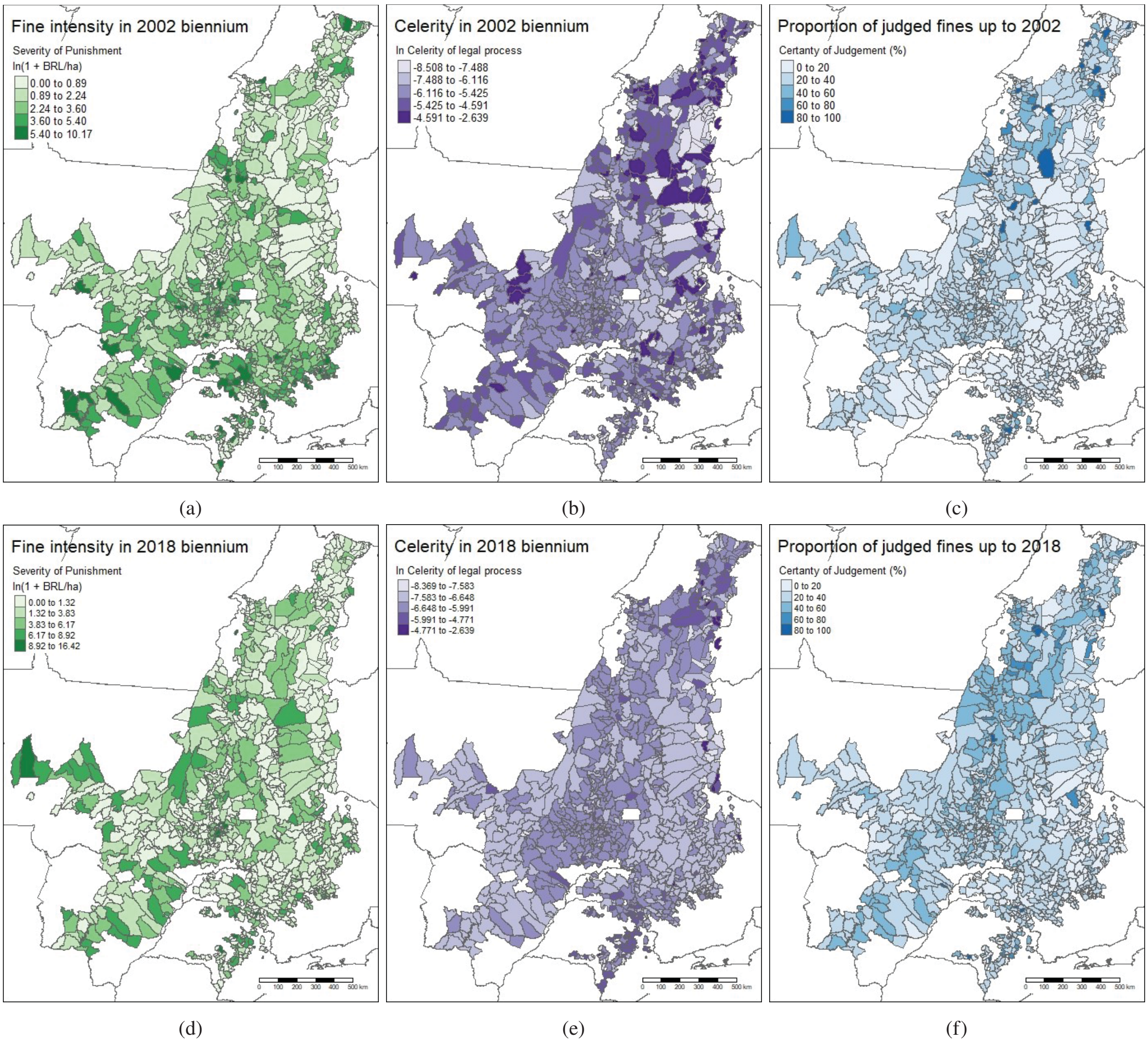


Figure 1.2: Maps of local distribution of deterrence variables (first and last biennium)
Source: Own Calculations based on data from IBAMA

Another key aspect of our data is that the embargoes and fines gathered here are not only composed of crimes against flora, but also against fauna. We apply this procedure to avoid missing data points given there are municipalities without registered flora crimes in some years. We presume this will not be problematic situation since IBAMA's surveillance capability and bureaucratic speed are shared across fauna and flora monitoring. As criminals observe actions against other environmental crimes to assess how likely they are of being punished, *i.e.*, there is a spillover of deterrence from IBAMA's actions against fauna offenders to flora offenders, and *vice versa*.

1.3 EMPIRICAL STRATEGY

For economic studies concerning deforestation, panel analyses have been the key method for econometric inference, both for country and municipal level. As to the latter, Pfaff et al. (2007) and Hargrave and Kis-Katos (2013) represent important works that identify spatial correlations – dealt with spatial econometrics. The odds of spatial spillovers regarding the 'migration' of criminals in different periods of time are also predicted in the rational choice theory (Cameron, 1988).

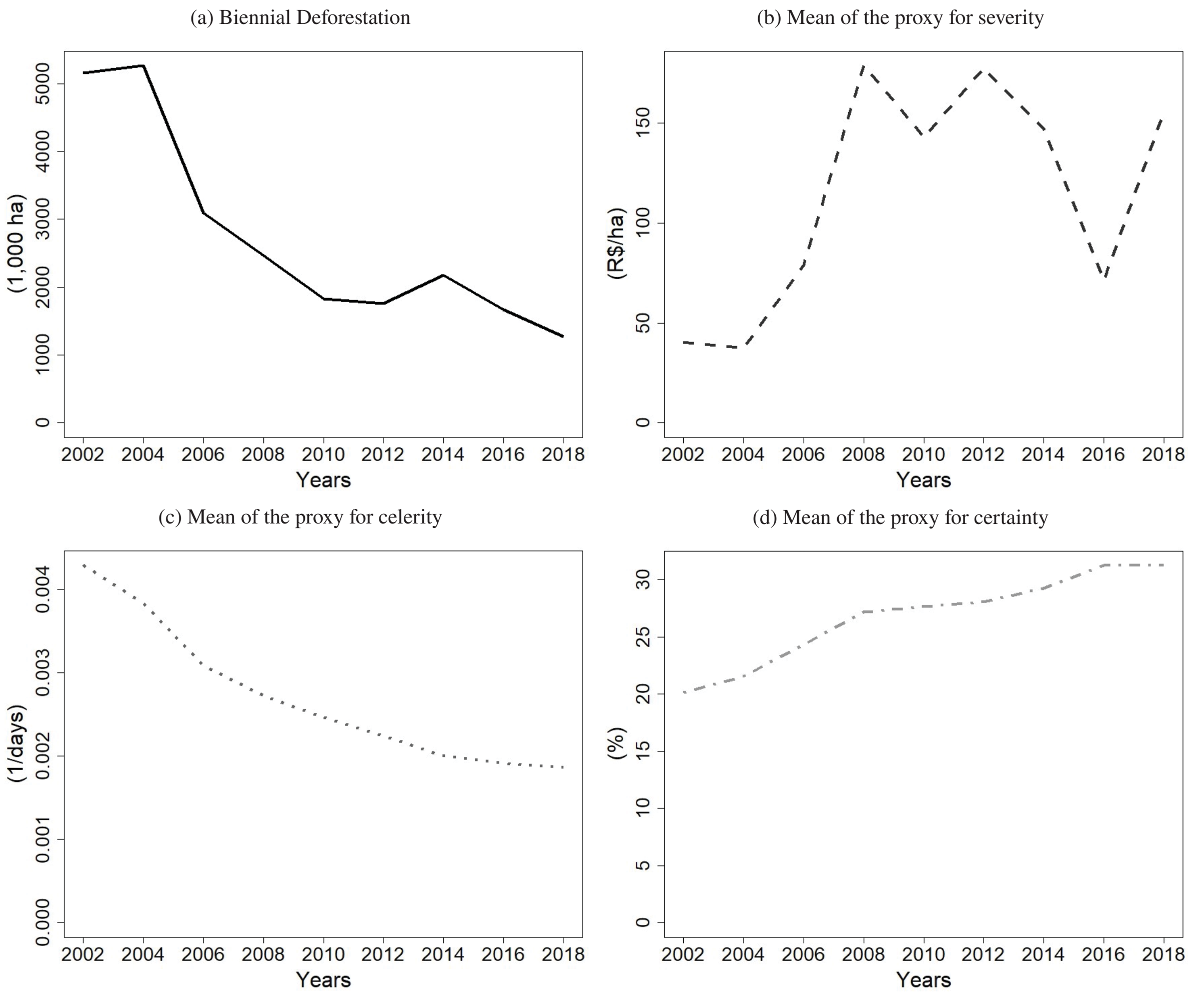


Figure 1.3: Deforestation in Brazilian Savanna & Severity, Celerity, and Certainty of Punishment by IBAMA. *Source*: Own calculations based on data from INPE and IBAMA

Rational choice theory also agrees with the use of the three dimensions of deterrence, as the probability of punishment is observed by criminals when deciding whether or not to commit the transgressions (Polinsky and Shavell, 2007). More specifically for deforestation, de Araújo et al. (2021) claim that deforestation models should incorporate all dimensions of deterrence in order to understand the full effects of the environmental police towards curbing deforestation, as well as their shortcomings. To comply with this critique, we devised an econometric model which encompasses the three dimensions of deterrence theory (severity, celerity and certainty) along with several other factors, represented by the set X, used as control variables in equation (1.1).

$$DEF = f(severity, \ celerity, \ certainty, \ X) \tag{1.1}$$

As a means to estimate (1.1), we conceived a model selection strategy that intends to, first, find the best functional form using traditional panel modeling, then use Wald tests for nested selection, and finally identify whether fixed or random effects are more appropriate in conformity to a Hausman test. Subsequently, we used the selected function, instruments and controls in the spatial panel estimation. In the process of choosing the functional form for (1.1), quadratic and cubic terms were included to address any nonlinear effects. We picked the functional form with the best fit to compose the final model[5]. For spatial models we presented the three main types:

[5]Estimates without the final set of nonlinear variables, or with specific combination, are available by request.

spatial error, spatial lag and mixed, given that spatial GMM models lack a direct form to test the best specification.

The model to be estimated here, defined in equation (1.1), followed the assumptions on crime rational choice, where the deforestation level is a function of deterrence and other control variables, such as agricultural production, rural credit availability, GDP, and climate. Our empirical model, presented on equation (1.2), is built around the three proxy variables for severity, certainty and celerity already discussed.

$$\ln DEF_{it} = \alpha_i + \alpha_t + \beta_S \ln Sev_{it} + \beta_{Cl} \ln Cel_{it} + \beta_{Cr} Cer_{it} + X_{it}\beta + \varepsilon_{it} \tag{1.2}$$

Where, Sev_{it} represents the intensity of environmental fines in each municipality for each period; Cel_{it} is the speed of the legal process, measured by the average number of IBAMA's trials per day in a municipality; Cer_{it} depicts the percentage of fines that were judged in a municipality for a biennium; X_{it} is a matrix of control variables; α_i and α_t are municipal and biennium fixed effects respectively; ε_{it} is assumed to be an i.i.d. error term; β is a vector of linear coefficients for each control variable.

1.3.1 Controls

Variables that compose X_{it} were selected according to the deforestation literature of Amazon. To what comes to the control for agricultural expansion and intensification, we followed Diniz et al. (2009) and Rivero et al. (2009) in using quantities. From the Municipal Agricultural Production database (PAM) – managed by Brazilian Institute of Geography and Statistics (IBGE) –, we extracted data on the total area employed into annual crop production for each municipality in a giver year, then transformed them into two-year means on each INPE's year and converted them into logarithm form. In order to hold control over livestock's demand for land, we used the logarithm of the total number of cattle heads on a given municipality in a given year, as such information is available in the IBGE's Municipal Livestock Production (PPM). The same treatment applied to annual crop land is employed.

Government policies, such as rural credit, can also influence forest retraction. If unchecked credit and subsides rise difficulties once they provide the means for funding property expansion on one hand, on the other, programs planned more thoroughly may offer the opportunity for restraining deforestation. Fearnside (2005) and Prates (2008) argue that monetary incentives such as price supports, credit concessions, and frequent debt amnesties are government supported policies that cover deforestation costs. Rural credit, concerning both agriculture and livestock, was obtained from the Central Bank of Brazil database, regarding each municipality by year. To assess credit density per municipality, the total value of rural credit is divided by the initial non-forested *Cerrado* area for each municipality, in accordance with Hargrave and Kis-Katos (2013). In addition, general growth and demand are controlled by municipal GDP per capita – obtained from IBGE and transformed into the INPE's year framework. All monetary values – prior to calculating prices if possible – were deflated to 2000 BRL levels using IPCA indexer; monthly data were reduced according to January 2000 levels.

Geoclimatic variables may also play a crucial role in deforestation. With regard to Amazon, it is believed that high levels of precipitation increase the risk of crop loss, what decreases the profitability of plantations (Hargrave and Kis-Katos, 2013). For *Cerrado* the mechanisms works differently, as discussed by Pivello (2011), the *Cerrado* is a fire prone biome that can withstand natural fires that arise during the dry season. Most wildfires in this area are a result of slash-and-burn practices to clear native vegetation and establish new pastures or crops. Since drier months favor fire-related conditions, human-induced initiatives become more frequent. (Pivello, 2011) corroborates this point by showing that drier-years have more wildfire occurrences in both the Amazon and the *Cerrado*. Therefore, we expect higher levels of deforestation in dryer years.

Precipitation levels were borrowed from Camarillo-Naranjo et al. (2019), which were available in a monthly basis from 1900 to 2019. We first create a variable that counts dry- (or wet-) months based on historical data. Those months considered wet were at least two standard deviations to the right and the dry ones were at least two standard deviations to the left of the historical mean for that month. Thus, two variables come to light: the number of relative dry months over a certain period on one hand; and one under the same restrictions for the relative wet months on the other. For clarification, equation (1.3) bellow describes how these variables were built, where P_{imt} is the precipitation level of municipality i in month m in the year t, Z is a standardized variable, D and W are dummies for extreme dry or wet months.

$$
\begin{aligned}
Z_{P_{imt}} &= \frac{P_{imt} - \overline{P_{im}}}{s_{P_{im}}} \\
D_{imt} &= \begin{cases} 1, \text{if } Z_p < -2. \\ 0, \text{otherwise.} \end{cases} \quad \text{similarly,} \quad W_{imt} = \begin{cases} 1, \text{if } Z_p > 2. \\ 0, \text{otherwise.} \end{cases} \\
DryMonths_{it} &= \sum_m D_{imt}, \qquad WetMonths_{it} = \sum_m W_{imt}
\end{aligned} \tag{1.3}
$$

1.3.2 Sample Selection

Due to some characteristics of the database, few adjustments in the sample needed to be made. Firstly, the sample contains only municipalities with at least 75% of its area within *Cerrado*'s borders. This is done to remove municipalities that are not representative of the *Cerrado*, but contains small parts of *Cerrado* in it. Also, the sample is reduced to municipalities which in July 2000 had at least 10% of its area covered with primary *Cerrado* forest. This approach removes outliers that, despite being highly deforested, do not present deforestation since their forests are already exhausted. Those selection processes reduce our sample from 1388 to 953 municipalities. Finally, 4 municipalities that were created after the year 2000, as well as *Brasília*, needed to be neglected to balance the panel. Descriptive statistics of this sample are presented on table 1.1.

Some of these cutoff points are arbitrary and a sensitivity analysis with alternative cutoff points were performed in section 1.4.3, particularly, by changing the threshold of *Cerrado*'s area from 75% to 50%, and removing the threshold of initial forest coverage.

1.3.3 Endogeneity and Instruments

The effect we are interested in – how law enforcement affects crime (specifically illegal deforestation) – suffers from known endogeneity (Cameron, 1988; Levitt, 2002; Draca et al., 2011; Hargrave and Kis-Katos, 2013; Assunção et al., 2017). The presence of IBAMA agents affects the decision about whether people commit environmental crimes or not, in the same way IBAMA focuses its activity on areas where environmental crimes are occurring more frequently, or in larger scale. The first of our variables of interest – severity – measures an equilibrium situation where fines and infractions are simultaneous. A different relationship occurred with celerity and certainty variables because a high number of fines is emitted due to high deforestation. As a result, the high number of fines will 'clog' the bureaucratic and legal departments of IBAMA, culminating in longer periods for setting a trial (lower celerity). Similarly, if IBAMA emits

Table 1.1: Descriptive Statistics of Restricted Sample (>75% *Cerrado* and >10% Forest)

Variable	Scale	Mean	SD.	Min.	Max.
ln Deforestation	ln (ha + 1)	6.488	2.170	0.000	11.757
ln Fine Intencity (Sev)	$\ln 1 + \frac{(\text{Fines in BRL})}{(\text{Defor. in ha} + 1)}$	2.193	2.371	0.000	16.419
ln Celerity	$\ln \frac{\text{Num. of Judged Fines}^*}{(\text{Total Days to Trial}^*)}$	−6.384	0.928	−8.508	−2.639
Perc. Judged (Cer)	$\frac{100 \times \text{Num. of Judged Fines}^*}{\text{Num. Fines}^*}$	26.719	16.763	0.000	100.000
ln Cattle Heads	ln heads	10.383	1.246	4.965	14.103
ln Annual Crop Area	ln (ha + 1)	8.358	1.839	0.000	13.957
ln Credit Density	$\ln 1 + \frac{(\text{Cred. in BRL})}{(\text{Ini. Land in ha})}$	5.919	1.426	0.000	10.359
Dry Months in Period	Num.of Months**	0.144	0.488	0	8
Wet Months in Period	Num.of Months**	1.037	1.092	0	6
ln GDP per capita	ln GDP/pc	8.520	0.751	6.485	11.637
ln State Severity	$\ln \frac{(\text{Fines in BRL})}{(\text{Defor. in ha})}$	4.734	1.396	0.810	9.427
ln State Celerity	$\ln \frac{(\text{Num. of Judged Fines}^*)}{(\text{Total Days to Trial}^*)}$	−6.207	0.392	−7.001	−5.011
State Certanty	$\frac{100 \times \text{Num. of Judged Fines}^*}{\text{Num. Fines}^*}$	25.241	6.224	10.644	42.407

Statistics refer to N = 8,532 observations for 948 municipalities spamming 18 years in a two by two basis. All prices and economic values are expressed in constant 2000 Brazil Reais (BRL). *These variables represent accumulated values up to a certain year. **The specific way in which these variables are calculated is depicted in equation (1.3). *Source*: Own calculations.

embargoes faster than processes them, the proportion of convicted judged cases decreases (lower certainty). A forward-looking criminal will internalize that their present profit may be higher than the present value of future fines. Therefore, severity, celerity and certainty are all endogenous and call for special treatment to avoid inconsistency in our econometric estimators.

We addressed the resulting endogeneity by using an instrumental variables procedure (IV) together with two stage least square (TSLS). This method consisted in estimating the problematic variables – severity, celerity, and certainty – by making use of instruments correlated with these predictors but not with the original dependent variable. For such, we selected the intensity of IBAMA's fines in any given biennium within the state of the municipality – excluding the municipality itself – as an instrument for the intensity of environmental fines in a municipality (severity), in accordance with Hargrave and Kis-Katos (2013). These authors defend that this instrument mirrors adequately the activities of IBAMA over time and captures IBAMA's units administrative boundaries, coordinated at the state level. Such conclusion goes along with

Schmitt (2015), which states that once environmental legislation is decentralized in Brazil, each state of the Union is free to create and amend environmental laws as long as they do not contradict national rules[6].

From this evidence, we assumed that the same type of instrument may be suitable for the other two endogenous variables: celerity and certainty. Meaning that, we instrument the celerity of the legal process for each municipality by the state-average celerity of the legal process (excluding the given municipality). Analogously, certainty of judgement is instrumented by the proportion of judged embargoes to the total number of embargoes of the state, excluding the given municipality[7]. Moreover, these instruments (and the severity one) were not affected by deforestation of a given municipality since embargoes coming from a given municipality will not add to the bureaucratic backlog of the whole state nor will exert an effect on the severity of fines in the rest of the state.

1.3.4 Spatial Panel Regression

The econometric model proposed in equation (1.2) can be estimated by usual panel data techniques, fixed effects or random effects, as it is demonstrated in other studies of crime deterrence (Levitt, 2002; Draca et al., 2011) and deforestation (Pfaff et al., 2007; Arima et al., 2007; Assunção et al., 2015, 2017). However, it is well understood within rational choice theory (Cameron, 1988; Anselin et al., 2000; Andresen, 2006a,b) and in econometric deforestation works (Robalino and Pfaff, 2012; Hargrave and Kis-Katos, 2013) that there are geographical spillovers of crime/deforestation, and spatially organized variables affecting it that may be omitted in our model.

To deal with such issues, the use of spatial models addressing the possible spatial correlation, such as a spatial autoregressive (SAR) and spatial error (SEM) models, is advisable. The SAR model assumes that there is spatial autocorrelation of the dependent variable, whereas the SEM model assumes that there is a spatial relationship in the residuals, probably because some omitted variables are of spatial nature. The panel versions of such models are specified in Elhorst (2003, 2008) and a generalization of the composite model (SARAR) is provided by Millo and Piras (2012). We then re-estimated the model of equation (1.2) and included both spatial error correction (SEM) and spatial lag element (SAR), which follows the form:

$$\ln DEF_{it} = \lambda W_N \ln DEF_{it} + X'_{it}\beta + \alpha_i + \alpha_t + u_{it} \tag{1.4}$$

where W_N is a $N \times N$ spatial weighting matrix[8], λ is the spatial spillover parameter from the SAR specification. The disturbance vector is the sum of two terms:

$$u_{it} = \rho(I_T \otimes W_N)u_{it} + \varepsilon_{it} \tag{1.5}$$

[6]Currently, the national legislation allows states to authorize the exploitation of forests, both in public and private domains. When it comes to environmental crimes, the complementary law nº 140 of 2011 states that, apart from some powers that are exclusive to the Federal Government, the competence for emitting environmental infraction notices and instituting administrative actions for the investigation of environmental infractions belongs to the body that holds the competence of licensing or the authorization of the enterprise or activity, object of the infringement (Brasil, 2011). It means that, in this case, IBAMA follows state rules and answers to each state's environmental agency.

[7]The severity instrument is composed of other municipalities of the same state that are in the *Cerrado* biome. This limitation emerges from the lack of organized data on deforestation beyond the Amazon or the Cerrado areas during the period. In the case of certainty and celerity, the terms used in composing the instruments were statewide, that is, not just limited to those municipalities in the *Cerrado*.

[8]A symmetric k-nearest neighbors (KNN) matrix of degree 5 in our case.

with ρ as the spatial error parameter from the SEM specification and ε being i.i.d errors. In order to control for endogeneity, we employed the Generalized Method of Moments (GMM) estimator for spatial models – as proposed by (Kapoor et al., 2007; Baltagi and Liu, 2011) –, where ρ and σ_ε^2 were calculated by GM[9] and the model coefficients were computed by applying a Feasible Generalized Least Squares (FGLS) estimator. The latter allows for a two stage estimation through the use of the instrumental variables of SAR, SEM, and SARAR models. Estimating spatial panels thought GM came at some costs. First, there are no tests to identify which of the spatial models are best suited for estimation (SEM, SAR or SARAR); second, spatial GM models are unable to estimate Durbin specification, *i.e.*, with spatially lagged exogenous variables, which would capture spatial effects of exogenous variable directly.

Fortunately, the estimation of spatial impacts becomes possible with spatial GM, as we can decompose exogenous variables effects through it. The usual interpretation of the parameter estimates under the 'marginal effects' label is only possible for spatial error models; as for the other two specifications, the calculation of direct, indirect, and total impact is essential. This differentiation emerges because any increase in a variable x_{jt} of a municipality j will create a β impact on DEF_j. Given the spillover effect, however, neighbor municipalities will suffer an impact equal to $\beta \cdot \lambda$. This spillover will also affect neighbors-of-neighbors by $\beta \cdot \lambda^2$ and so on, even returning to the original source. To obtain the complete impact of each variable we performed an estimation according to the routine proposed in Piras (2014), using the statistical program R (R Core Team, 2020) – an explanation of this process is available in Appendix A. To our understanding, studies based on spatial panel data before 2014 rarely present such impacts, and even recent works may lack these results for the reason that a simple function is not present in the main package of spatial panel statistics in R, "splm" (Millo and Piras, 2012).

1.4 RESULTS AND DISCUSSION

1.4.1 Non-spatial Panel Model

In view of selecting a more efficient model specification, we ran some tests assessing which regression technique is better suits our data set. This can be seen in table 1.2. We began the analysis by comparing a pooled model with a fixed effect model through a F-test, which confirms the use of a fixed effects specification (FE). The next test employed was a Hausman test, responsible for verifying if a FE model and a random effects model (RE) are both consistent in the null hypothesis, or if FE is consistent by itself. If both models are similar, RE must be chosen since it provides better efficiency. Here, the results conferred FE as the best model.

Breusch-Pagan and Breusch-Godfrey tests verify heteroscedastic and serially correlated errors respectively. Our results indicated that both problems were observed. Therefore, heteroscedasticity-and autocorrelation-consistent (HAC) standard errors needed to be estimated. For this purpose, we decided to incorporate Arellano et al. (1987)'s sandwich estimators in the covariance matrix. The last test concerned the usefulness of the TSLS estimator over the OLS. The analysis of the results attested to the validity of using TSLS estimator for panel along – with the selected instruments – once it is consistent compared to the usual OLS estimation. Weak instruments were tested with an F-test, which suggests that all three instruments were strong predictors[10].

In table 1.3 the results for the four models were shown. Model (1) was polled least squares; model (2) was individual fixed effects; time dummies were added in model (3); and

[9]This is valid for fixed effects models; for random effects, another variance component is calculated.
[10]An J-test is not available since our model was exactly identified.

Table 1.2: Tests for Panel Models

Test	Comparison	Statistic	Verdict
F test	Pooled vs. Fixed Effects	F = 112.03 p-value < 0.001	Fixed Effects
Hausman Test	Fixed Effects vs. Random Effects	χ^2 = 390.99 p-value < 0.001	Fixed Effects
Breusch-Pagan	Homocedastic vs. Heteroscedastic	BP = p-value < 0.001	Heteroskedastic Errors
Breusch-Godfrey	Serial Correlation in idiosyncratic errors	χ^2 = 3868.1 p-value < 0.001	Serial Correlation
Wu-Hausman Test	TSLS vs. Least Squares	χ^2 = 75.576 p-value < 0.001	TSLS

Source: Own calculations

(4) represented the second stage of a two staged regression with instrumentalized deterrence variables.

Fine intensity showed a significant hindering impact on deforestation, which agreed with what was reported in both Hargrave and Kis-Katos (2013)'s and Assunção et al. (2017)'s works. The TSLS model demonstrated to have a better performance than the least squares, and presented a greater effect of fines on the struggle against deforestation. The interpretation of this coefficient was of an elasticity, a 1% increase in fine intensity implied a 0.23% reduction in deforestation.

In respect to celerity, we observed non-significant effects in models (1) and (3), and a positive relationship in model (2) – contrary to what was expected. When however, we corrected for endogeneity with IV, we found ,instead, a very expressive negative relationship between celerity and deforestation, what reinforcing our hypothesis on endogeneity. The final relationship, in model (4), between celerity and deforestation was an elasticity as well, and therefore the model implied that a 1% rise in the celerity of the legal process would reduce deforestation by 1.85% – the biggest impact of any deterrence variable.

The coefficients for certainty showed significant and negative effects in all models but (3). This variable cannot be interpreted as an elasticity, instead, it must be understood as log-linear variable, meaning that, for model (4), a one percentage point growth in the percentage of the judged cases translated to a 5.5% reduction in deforestation. If we used the mean value of Perc. Judged from table 1.1 (26.7%), a one percent point rise is equal to a 3.74% change, which in terms of elasticity on the mean implies a 1% rise in the judged cases lessen deforestation by 1.47%.

All of the three results previously explored – when combined – provided robust evidence to infer that bureaucratic process, after fine issuing, is the key aspect to be improved by IBAMA. This goes along with de Araújo et al. (2021)'s critique, which lies on the inability of IBAMA to process all their cases in a short time, hindering its potential in preventing illegal deforestation.

Our agricultural goods controls (cattle heads and farmland) provided evidence for the agricultural expansion vs the deforestation of the *Cerrado* correlation. This follows the

Table 1.3: Panel Regression Results for *Cerrado* Deforestation

	ln *Deforestation*			
	(1) Polled	(2) FE	(3) FE/TE	(4) IV FE/TE
ln Fine Intensity	-0.033^{***}	-0.077^{***}	-0.067^{***}	-0.230^{***}
	(0.008)	(0.008)	(0.007)	(0.078)
ln Celerity	-0.008	0.126^{***}	-0.038	-1.846^{***}
	(0.021)	(0.029)	(0.024)	(0.426)
Perc. Judged	-0.003^{**}	-0.014^{***}	-0.001	-0.055^{**}
	(0.001)	(0.002)	(0.001)	(0.028)
ln Cattle Heads	0.939^{***}	0.688^{***}	0.372^{***}	0.121
	(0.016)	(0.095)	(0.083)	(0.196)
ln Farmland	0.273^{***}	0.164^{***}	0.108^{***}	0.188^{***}
	(0.012)	(0.029)	(0.024)	(0.052)
ln Credit Density	-0.142^{***}	-0.387^{***}	0.151^{***}	0.211^{***}
	(0.015)	(0.025)	(0.035)	(0.067)
Dry Months	-0.172^{***}	0.018	0.146^{***}	0.131^{***}
	(0.038)	(0.024)	(0.023)	(0.042)
Wet Months	-0.066^{***}	-0.023^{**}	-0.015	0.013
	(0.016)	(0.011)	(0.011)	(0.019)
ln GDPpc	36.406^{***}	38.135^{***}	33.308^{***}	67.198^{***}
	(4.431)	(5.841)	(4.414)	(15.113)
ln GDPpc^2	-4.764^{***}	-4.286^{***}	-3.468^{***}	-7.141^{***}
	(0.504)	(0.677)	(0.507)	(1.684)
ln GDPpc^3	0.198^{***}	0.157^{***}	0.120^{***}	0.251^{***}
	(0.019)	(0.026)	(0.019)	(0.062)
Constant	-91.474^{***}	—	—	—
	(12.917)			
Individual FE	No	Yes	Yes	Yes
Time Dummies	No	No	Yes	Yes
Instruments	No	No	No	Yes
Observations	8,532	8,532	8,532	8,532
R^2	0.427	0.290	0.465	—
Adjusted R^2	0.427	0.201	0.397	
F Statistic	577.882^{***}	282.411^{***}	346.768^{***}	χ^2: 2154.99^{***}

Notes: Significance levels * p<0.1; **p<0.05; ***p<0.01. R^2 and Adjusted R^2 reported are for fixed effect models with demeaned values of individual and dummies for time. Models have Arellano et al. (1987) robust standard errors. *Source*: Own calculations.

empirical (Diniz et al., 2009; Rivero et al., 2009) and theoretical Allen and Barnes (1985); Ehrhardt-Martinez (1998); Angelsen (1999); Barbier (2004) literature consensus.

As for credit density, we could see that the models with only time fixed effects – (1) and (2) – indicated a negatively inclined curve, which, in ordinary/general contexts, would imply that rural credit curbed deforestation. This intuition must be rejected, however, once an analysis without taking the time dummies into consideration would lead to misconceptions due to the trend nature of both rural credit (increasing along time) and deforestation (decreasing along the same period). According to models (3) and (4) – where time dummies were introduced –, there was a positive inclined curve revealing a boost effect, which corroborates with Fearnside (2005) and Prates (2008). As claimed by these authors, unsupervised rural credit is an incentive for deforestation.

Climatic control variables suggested that drier than expected months have a significant impact on deforestation, endorsing the hypothesis of landowners taking advantage from the dry months to clean the land proposed by Pivello (2011). Finally, as GDP per capita was usually endogenous during the deforestation process, we cannot provide comments on its causal effects on deforestation.

1.4.2 Spatial Panel Model

Table 1.4 presented the preliminary regression results for the three spatial panel models. While (5) model is of SAR specification, (6) is SEM, and (7) is a mixed model (SARAR). All models considered fixed effects, time dummies and instrumented IBAMA variables.

The spatial error component, ρ, allowed for more efficient results in our models since it removed from the error component spatially correlated residuals, which emerged from omitted relevant variables with a spatial distribution. In the GMM specification, though, there were no standard errors for ρ, preventing us from testing for the significance of it – particularly, to check if the SARAR model's ρ was statistically greater than -1, which is an important premise in models with a spatial error component. The spatial lag coefficient of deforestation, λ, presented values around 0.85 in both models estimated with the spatial lag term which agrees with other studies, that point out deforestation has a spillover effect among municipalities (Robalino and Pfaff, 2012; Hargrave and Kis-Katos, 2013). In our analysis, the effect was that a one percent rise in deforestation concerning a given municipality would result in a 0.85% rise in deforestation on neighboring municipalities.

As discussed in the section 1.3.4, the calculation of direct, indirect and total impacts was essential to visualize the marginal effects of both SAR and SARAR models, and to promote a better understanding of the importance of λ. The effects just mentioned above are available in table 1.5. In order to have a clearer view, only significant variables – of p-value < 0.10 – have their impacts shown[11]. The direct effects columns showed the marginal impact – in a given municipality – of a one unit rise of a variable in that same place after the feedback loop was calculated. Indirect effect portrayed the marginal change of deforestation in a given municipality when all other municipalities had a unit rise in the variable under discussion here. Finally, total effect was a junction of both and represented the marginal effect on the deforestation of all municipalities when a variable increased by one. It was interesting to note that the total effects displayed in table 1.5 are similar to the results of the non-spatial models, in table 1.4. It is then useful to perceive table 1.5 as a decomposition of local vs. global effects of the results presented by the panel models.

[11]Other impacts are available upon request.

Table 1.4: Spatial GMM Regression Results for *Cerrado* Deforestation

	ln *Deforestation*		
	(5) SAR	(6) SEM	(7) SARAR
Spatial lag (λ)	0.8471***	___	0.8587***
	(0.0383)		(0.0243)
ln Fine Intensity	−0.0074	−0.2384***	−0.0096
	(0.0307)	(0.0824)	(0.0148)
ln Celerity	−0.1539**	−2.0293***	−0.1076***
	(0.0840)	(0.2592)	(0.0060)
Perc. Judged	−0.0033	−0.0603***	−0.0009
	(0.0051)	(0.0156)	(0.0027)
ln Cattle Heads	0.1224**	0.1443	0.0761*
	(0.0542)	(0.1049)	(0.0430)
ln Farmland	0.0732***	0.1714***	0.0693***
	(0.0177)	(0.0353)	(0.0145)
ln Credit Density	0.0822***	0.2103***	0.0719
	(0.0176)	(0.0348)	(0.0139)
Dry Months	0.0410*	0.0884**	0.0574***
	(0.0229)	(0.0442)	(0.0168)
Wet Months	0.0148	0.0186	0.0037
	(0.0092)	(0.0183)	(0.0059)
ln GDPpc	7.8002**	67.054***	7.0904***
	(3.8662)	(8.3516)	(2.7469)
ln GDPpc^2	−0.7751*	−7.1864***	-0.6943**
	(0.4380)	(0.9435)	(0.3118)
ln GDPpc^3	0.0255	0.2543***	0.0223*
	(0.0164)	(0.0352)	(0.0117)
Spatial error (ρ)	—	0.1899	−0.9990
Time Dummies	Yes	Yes	Yes
Instruments	Yes	Yes	Yes
Observations	8,541	8,541	8,541

Notes: Significance levels * p<0.1; **p<0.05; ***p<0.01. *Source*: Own calculations.

The SEM specification provided significant results for all the three variables of interest here, showing greater effects of punishment variables on deforestation than the non-spatial models, with elasticities of: -0.23% for severity; -2.03% for celerity; and (on average) -1.68% for certainty.

In SAR and SARAR models, only celerity had significant impacts. Table 1.5 describes, for SARAR, that an increase of 1% in the celerity of the legal process in one municipality would slow deforestation by 0.14% (local effect), while rises in all other municipalities (global effect) would decrease deforestation by 0.61%. The sum of both effects was the total effect of a general rise in celerity. While for the SAR model these effects are -0.20% and -0.80%. Such results further endorses the importance of a swift bureaucracy in controlling deforestation.

Table 1.5: Marginal Impacts of Variables for SAR and SARAR Models

	ln *Deforestation*					
	SAR			*SARAR*		
	Direct	Indirect	Total	Direct	Indirect	Total
ln Celerity	−0.2028*	−0.7973*	−1.0001*	−0.1442***	−0.6098***	−0.7541***
	(0.1088)	(0.4916)	(0.5894)	(0.0547)	(0.2520)	(0.3024)
ln Cattle Heads	0.1612**	0.6340*	0.7953**	0.1020*	0.4314*	0.5335*
	(0.0714)	(0.3633)	(0.4256)	(0.0571)	(0.2528)	(0.3075)
ln Farmland	0.0964***	0.3791**	0.4755***	0.0929***	0.3930***	0.4859***
	(0.0237)	(0.1605)	(0.17864)	(0.0192)	(0.1070)	(0.1225)
ln Credit Density	0.1083***	0.4260***	0.5343***	0.0964***	0.4077***	0.5041***
	(0.0231)	(0.1626)	(0.1789)	(0.0178)	(0.0988)	(0.1123)
Dry Months	0.0540*	0.2124	0.2664*	0.0770***	0.3255***	0.4025***
	(0.0300)	(0.1376)	(0.1649)	(0.0216)	(0.0964)	(0.1151)
ln GDPpc	10.276**	40.3969*	50.6732**	9.4998***	40.162***	49.662***
	(4.9535)	(21.100)	(25.4629)	(3.5325)	(14.095)	(17.345)
ln $GDPpc^2$	−1.0211*	−4.0142*	−5.0354*	−0.9302**	−3.9330**	−4.8633**
	(0.5651)	(2.3941)	(2.9048)	(0.4045)	(1.64311)	(2.0232)
ln $GDPpc^3$	___	___	___	0.0299*	0.1264*	0.1563**
				(0.0153)	(0.0635)	(0.0782)

Notes: Significance levels * p<0.1; **p<0.05; ***p<0.01. *Source*: Own calculations

1.4.3 Sensitivity Analysis

As noted in section 1.3.2, the threshold values for the sample selection process, yet sensible, are somewhat arbitrary. In order to check for possible sample selection bias, the requirements were relaxed, that is, instead of including only municipalities characterized by having (i) their territory composed of 75% of the *Cerrado* (originally) and (ii) at least 10% of their forests untouched, we included in our model any municipality holding more than 50% of the *Cerrado*'s biome, despite of initial deforestation levels.

Table 1.6 presents all four relaxed models – one TSLS and three spatial GMM, akin to models (4), (5), (6) and (7) showed before, respectively. The parameters estimates did not deviate significantly from what was shown in the restricted sample, and indicated that there was no sample selection bias created by our selection process. Estimates from the unrestricted models seemed to be of a lower magnitude than in our main sample, what suggests that our sample selection process was indeed appropriate since its intent was to remove municipalities that neither were part of the biome or had already depleted their forests. As such data would lower the effects of exogenous variables due to the low report of the *Cerrado*'s deforestation, in spite of their reality being of high deforestation.

1.5 FINAL REMARKS

Based on the panel data of 948 municipalities organized biennially from 2002 to 2018, this study provided empirical evidence on the curb of deforestation in the Brazilian Savanna. It investigated how environmental policing affect outlaw agents' decisions to deforest this biome during the period. This work made some contributions to the empirical literature of deforestation

Table 1.6: Sensitivity Analysis for Deforestation Models

	ln *Deforestation*			
	(4') IV FE/TE	(5') SAR	(6') SEM	(7') SARAR
Spatial lag (λ)	___	0.767***	___	0.852***
		(0.039)		(0.027)
ln Fine Intensity	−0.187***	−0.022	−0.187***	−0.020
	(0.049)	(0.027)	(0.060)	(0.014)
ln Celerity	−1.514***	−0.187**	−1.620***	−0.131***
	(0.169)	(0.081)	(0.205)	(0.046)
Perc. Judged	−0.047***	−0.001	−0.048***	−0.003
	(0.010)	(0.005)	(0.012)	(0.003)
ln Cattle Heads	0.048	0.095*	0.084	0.007
	(0.083)	(0.050)	(0.084)	(0.040)
ln Farmland	0.146***	0.073***	0.125***	0.065***
	(0.029)	(0.017)	(0.028)	(0.015)
ln Credit Density	0.193***	0.082***	0.176***	0.060***
	(0.028)	(0.017)	(0.029)	(0.014)
Dry Months	0.149***	0.075***	0.108***	0.070***
	(0.034)	(0.021)	(0.035)	(0.018)
Wet Months	0.004	−0.001	−0.015	0.001
	(0.014)	(0.008)	(0.011)	(0.006)
ln GDPpc	60.283***	16.758***	57.092***	10.445***
	(5.852)	(3.744)	(6.224)	(2.983)
ln GDPpc^2	−6.422***	−1.769***	−6.101***	−1.075***
	(0.667)	(0.424)	(0.705)	(0.338)
ln GDPpc^3	0.225***	0.061***	0.215***	0.036***
	(0.025)	(0.015)	(0.026)	(0.012)
Spatial error (ρ)	—	—	0.2049	−0.879
Individual FE	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Instruments	Yes	Yes	Yes	Yes
Observations	9,891	9,891	9,891	9,891
χ^2	3226.19***	—	—	—

Notes: Significance levels * p<0.1; **p<0.05; ***p<0.01. *Source*: Own calculations.

in Brazil. First, it introduced two new variables to measure the activity of IBAMA, as well as their instruments, second, in terms of data, it used the underexplored database on deforestation of the *Cerrado* rather than the Amazonian rainforest, which has already been exhaustively discussed. Information concerning the latter was not neglected, though. By considering it, we were able to show robust evidence that some of the factors that have influenced the deforestation of the Amazon have also interfered in the investigation of other biomes, thus becoming of crucial importance its recognition. Such procedure reinforces the need to study of such variables for future studies and policies, irrespective of location. The control variables used here were municipal rural credit, local commodity quantities, GDP, and month of unusual precipitation. The last of which conceived in a unique way so that the effects of climate on deforestation could be captured more effectively.

This study focused in understanding the impacts of environmental surveillance on Brazilian deforestation and, for such intent, it employed three variables concerned with the punishment of illegal activity. Similarly to what was shown regarding the Amazon, it found evidence that fine intensity – as a proxy for severity of punishment – discourages deforestation in the *Cerrado*. The novel variables – celerity of the legal process and certainty of legal persecution – showed greater impacts on curbing the deforestation process than severity of fines. This result agrees with the understanding that the main problem about controlling environmental crimes does not lie on the ability to detect and fine agents, but on the slow bureaucracy imposed by the legal process and the easiness in which criminals can postpone their punishment. Results pointed out (i) that environmental policing can be effective against deforestation in this region, (ii) that IBAMA operations should be encouraged rather than dismantled in the country, and (iii) that policymakers should direct their efforts to improve the speed of the legal process instead of simply proposing harsher punishments.

Nevertheless, policy seems to be heading to the opposite direction. As the average time for final decision of embargoes – inverse of celerity – is increasing since 2002 in the region. This shows a shrinkage in IBAMA capacity in punishing deforestation in the last decade. Which can be explained by the lower budgets for environmental protection in past years, or by the political appropriation of these intuitions by the agricultural sector in latter governments. However, the political causes are not the main focus of this study, a more in depth discussion of the causes may be addressed in future research.

Additional results indicate that agricultural incentives – represented by rural credit availability – are positively correlated with deforestation, what goes along with previous works on the Amazon. These authors claim rural credit to be a funding source for deforestation. We also observed evidence that the dry climate of the *Cerrado* would be another transmission channel affecting the deforestation process. The spatial nature of deforestation is verified and confirms that a spillover effect is present in the region.

All these findings can guide several policy improvements. First, deforestation is responsive to rural credit and subsidies, and therefore policymakers should either restrict the supply of such benefits in areas with high deforestation or implement new incentives for the conservation of the biome. The fact that larger dry seasons may favor deforestation as well as the predictions of the Intergovernmental Panel on Climate Change (IPCC) for the next years claiming greater incidence of droughts in the region raises the need of intensifying environmental surveillance and punishments throughout those periods, and of enhancing environmental command and control policies.

Other improvements would, yet, be welcomed to our study. More variables concerning IBAMA's activity, such as, funding, surveillance capability and personnel size, could improve our findings and provide more evidence towards IBAMA's efficiency in combating environmental crimes. Making use of yearly time periods could allow for market level variables (*e.g.*, commodity prices and fuel cost) to be introduced in our model once such variables do not offer enough variance when aggregated into bienniums to show significant results. Some results obtained from our control variables are difficult to be interpreted confidently: introducing instruments for rural credit and new controls for climate may contribute to new and better conclusions. Finally, testing our model in the Amazonian data or even aggregating the Amazon's and the *Cerrado*'s data may provided further evidence to the arguments defended in this article.

2 SEGUNDO ENSAIO: CLIMATE VARIABILITY AND AGRICULTURAL LAND PRICES: AN ANALYSIS FOR THE PARANÁ STATE, BRAZIL

ABSTRACT

This essay aims to analyze the effect of climate change on farmland prices in *Paraná* with the use of a Ricardian model. A very detailed database with daily measures of temperature is used to the construction of an precise agronomic indicator of thermal intake of a crop, also known as growing-degree days (GDD). By using an hedonic empirical specification this work finds a positive impact of GDD on farmland value. The estimated model, along with climate projections of IPCC, was subsequently employed to project the future impacts of climate change on *Paraná*'s agriculture. Results indicated that *Paraná* will benefit from climate change with appreciation of its farmland prices in all projected scenarios.

Keywords: Climate Change, Agriculture, Spatial Econometrics, Brazil, Land Prices

RESUMO

Este ensaio procura analisar o efeito das mudanças climáticas sobre os preços das terras agrícolas no *Paraná* são investigados com o uso de um modelo Ricardiano. Para tanto, utiliza-se um banco de dados bastante detalhado com medidas diárias de temperatura para a construção de um preciso indicador agronômico que mede absorção térmica de uma cultura, também conhecido como graus-dias de crescimento (GDD). Usando uma especificação empírica hedônica, este trabalho encontra uma relação positiva entre GDD no valor das terras agrícolas. O modelo estimado, juntamente com as projeções climáticas do IPCC, foi posteriormente empregado para projetar os impactos futuros das mudanças climáticas na agricultura do *Paraná*. Os resultados indicaram que o *Paraná* se beneficiará das mudanças climáticas com valorização de seus preços de terras agrícolas em todos os cenários projetados.

Palavras-chave: Mudanças Climaticas, Agricultura, Econometria Espacial, Brasil, Preço da Terra

2.1 INTRODUCTION

In its most recent report, the Intergovernmental Panel on Climate Change (IPCC) provided alarming evidence on the advancing climatic crisis, as well as predictions concerning the future changes in climatic variables for fifty-eight sections of the planet –forty-six being land regions. Of those Brazil is part of four: Northeast S. America, North S. America, S. America Monsoon, and Southeast S. America, with the latter being of greatest interest for this essay. According to IPCC sixth assessment report (AR6), South-east S. America region will very likely experience rises in temperature at greater rates than the global average. Also, the frequency of extreme precipitation is predicted to increase in the region. These environmental changes can provide advantages or harm for some sectors of the economy, particularly in agriculture.

In order to understand such effects of climate on agriculture we follow the well established literature which uses Ricardian analysis (Mendelsohn et al., 1994; Schlenker et al., 2005, 2006; Mendelsohn and Reinsborough, 2007; Mendelsohn et al., 2010; Massetti and Mendelsohn, 2011; Massetti et al., 2013). This approach consists in measuring the impacts of climate in farmland[1] value using hedonic models, rather than production functions (Dell et al., 2012; Auffhammer et al., 2012; Castro et al., 2020) or profit functions (Deschênes and Greenstone, 2007). The hedonic model is chosen given its advantages over the aforementioned methods, since studies focusing agricultural output instead of on farmland prices have the risk of overestimating the impact of climate, as they do not allow farmers to change their production strategies, *e.g.*, crop switching (Kurukulasuriya et al., 2007; Seo and Mendelsohn, 2008). Although studies that focus on profits do not face the same problem, as profits already capture the changes in crop mixes, they face problems with data availability as profits are usually not available.

Being one of the largest agricultural producers in the world, Brazil is the object of many economic studies about farmland value (Rezende, 2003; Plata, 2006; Gasques et al., 2008; Ferro and Castro, 2013; Malassise et al., 2015; Caetano Bacha et al., 2016; Volsi et al., 2017; Flexor and Leite, 2017; Telles et al., 2018; Porsse et al., 2020) which link farmland prices to different factors such productivity, rural credit, tillage, deforestation, land distribution inequality, commodity prices, and other market conditions. The relationship of farmland value and climate, and what it means for the country when facing the effects of climate change, is also well studied (Sanghi et al., 1997; Evenson and Alves, 1998; Massetti et al., 2013; Da Cunha et al., 2015; Castro et al., 2020; DePaula, 2020). In order to expand this literature, this essay introduces a climatic variable that is underexplored by the economic literature –with exception of Schlenker et al. (2006)– which captures the effects of temperature on crop growth, known as growing degree days (GDD). This agronomic indicator measures the thermal intake of a plant given the temperature during its growing season using daily data.

As we are interested in estimating a Ricardian model measuring the impacts of climate on agriculture, some data concerns must be addressed. First, farmland value data must be available for the object of study. Second, daily climatic data must be obtained for the calculation of the GDD. For such reasons we have selected the Brazilian state of *Paraná*, for which there is one unique database available on mean farmland sale prices publicly published, also climate data on a daily resolution. *Paraná* is located at the south of Brazil, in the division between tropical and subtropical regions. Historically, the economic base of this state was developed with strong linkage with the agricultural activity. The first agricultural cycle of the state begins in the early XIX century with large scale mate herb production aimed for exports. By the late XIX century coffee became the main agricultural product of Brazil, including *Paraná* which eventually turned

[1]The term "farmland" is used as a synonym for the term "agricultural land", meaning "land including arable land, land under permanent crops, and land under permanent meadows and pastures"

into the main coffee producer in the country, reaching 58% of Brazil's production by the 1960's. Currently, *Paraná* is the country's second largest producer both of soybeans (15% of national production) and maize (15%), and the first of wheat (49%) (IBGE, 2020). This makes *Paraná* one of the most important states in Brazilian agriculture.

Farmland has interesting particularities when compared to other common economic goods. It is a heterogeneous and durable good that cannot be produced, but only transformed by agents, *e.g.* changing soil composition and/or inclination. Another specificity is that land is immobile, *i.e.*, land acquired in a specific location can only be used in that particular location which implies that it is a spatial good. Therefore, hedonic studies of farmland may need to employ spatial econometric models to deal with the spatial heterogeneity and spatial dependence in the data, as is considered by Patton and McErlean (2003), Schlenker et al. (2006), Huang et al. (2006), Dillard et al. (2013), Huttel and Wildermann (2014) and Lehn and Bahrs (2018).

In summary, this essay aims to estimate a Ricardian model for the state of *Paraná* using spatial econometrics and climatic variables supported by agronomic literature which better capture the relationship between climate and plant growth. After that, the estimated coefficients are combined with IPCC projections to simulate the effects of climate change on *Paraná*'s farmland value.

The following section presents the Ricardian model used in this study. Section 3 describes how the main variables and controls are computed, also the advantages in using the GDD variable are discussed. In section 4 the econometric models employed in the estimations are layout. Section 5 presents estimation results for the Ricardian models. In section 6 the impacts simulations are presented. And section 7 concludes.

2.2 RICARDIAN MODEL

Ricardian analysis emerges from the notion that a farm's value is the result of the discounted value of all future profits, or rents that can be acquired for it, assuming that the farmer is always maximizing profit with its usage of land. In this sense, the Ricardian approach can be viewed as a hedonic model of farmland prices with climate being one of the qualitative variables associated with a plot's value, despite what is the current use of the specific tract of land (Mendelsohn et al., 1994; Schlenker et al., 2006; Mendelsohn et al., 2010; Massetti et al., 2013).

Similar to what is proposed in Massetti et al. (2013) we can define farmland value as the net present value of all future farm profits, shown in equation (2.1):

$$V = \int_0^\infty [P \times Q(I, C, Z, X) - R \times I] e^{-\delta t} dt \tag{2.1}$$

where V denotes land value; P and R are output and input prices; Q is output; I are all necessary inputs; C are climatic variables; Z are time unvarying characteristics; X are time varying exogenous factors (*e.g.*, demographic, economic, geographic); and δ is the discount rate.

Assuming that a farmer always optimize I for any values of P,C,Z,X, and δ, equation (2.1) reduces to the general form of the Ricardian model (2.2):

$$V = f(X, C, Z) \tag{2.2}$$

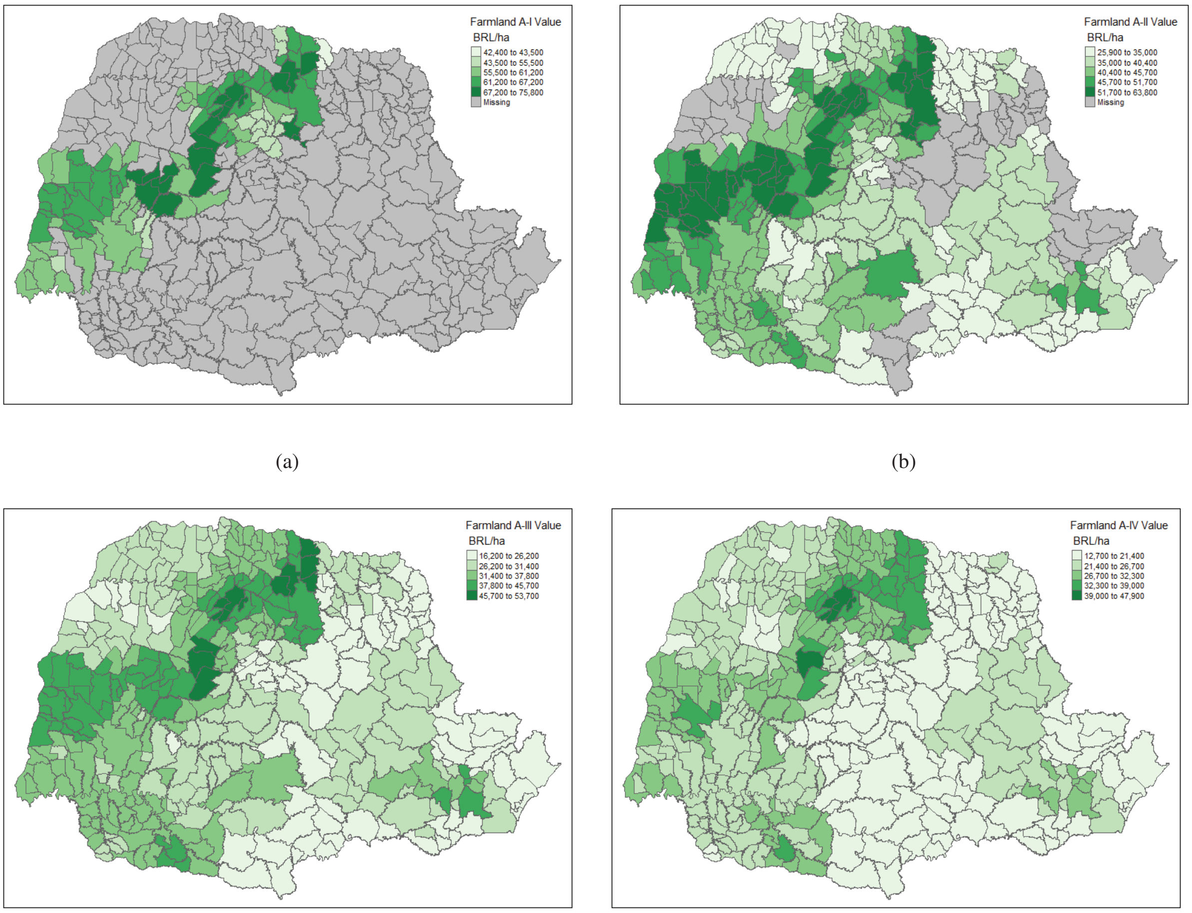
where P, R and δ are aggregated into the X variable set. Note that equation (2.2) denotes a similar relationship of product value and implicit qualities as the hedonic prices model proposed in Rosen (1974), where the value of a good is defined by a function of its characteristics.

2.3 DATA

In this section we present the dependent variables, municipal average farmland prices, separated into four different qualities of soil for the year 2017. The conceptual definition and calculation procedure related to climatic variables GDD and mean precipitation are also discussed. Remaining control variables are presented in the end of this section.

Farmland value data, provided by *Paraná*'s Department of Rural Economics (DERAL), is composed of mean sales prices per hectare of farmland in any given municipality. The data is further subdivided into seven classes according to land quality. Land classes range from I to VIII where the smaller roman algorithm indicate that the land can be used for more intensive production, therefore, class I is the best kind of available farmland and class VIII the worst.

In figure 2.1 we present the average value for the four first classes (class-I through class-IV), which are usually employed in crop planting, therefore, of greater interest for this essay. It is easy to see that there is a belt from north to west where prices are significantly higher, this coincides with the soybean productive region of the state. Another noticeable aspect on the map is the price concentration around Curitiba, where prices fall into the same level as those for farmland on the "soy belt". According to von Thünen model of agricultural land use, rural land prices approach urban land prices at the limit between both areas.



(a) (b)

(c) (d)

Figure 2.1: Mean farmland prices per hectare of for 2017 in the state of Paraná, land classes I to IV
Source: Own Calculations based on data from DERAL

Generally, Ricardian models of climate change like Sanghi et al. (1997); Evenson and Alves (1998); Massetti et al. (2013); DePaula (2020) use monthly mean estimates of temperature and precipitation for climatic variables. For this essay we employ high frequency climate data for the state by using daily measures of temperature. We produce an agronomic variable which describe the real, non-linear, relationship between plant growth and climate, GDD (Ritchie and Nesmith, 1991; McMaster and Wilhelm, 1997; Snyder et al., 1999).

This is a traditional agronomic measure of heat accumulation based on the notion that plant growth is associated with the accumulated temperature in its growing season (Ritchie and Nesmith, 1991; McMaster and Wilhelm, 1997). Moreover, a plant will start to grow after the air temperature reaches a certain base temperature, T_{base}, specific to each crop species. Then for every additional degree of heat the plant's growth will be faster until an optimum level, T_{opt}, where growth is maximum. Every degree after this level will diminish plant growth until it reaches zero at T_{up}, as shown in figure 2.2. This measures the daily thermal intake (TI) of a plant, *i.e.*, how much energy the plant received in that day. Aggregating this value in a season we find the GDD. This captures a non-linear effect of temperature in plant growth, which is more representative than using monthly mean temperatures. The GDD also accounts for plant growth stopping above certain extreme level of heat, as we remove from the GDD calculation any day where the maximum is above a threshold ($T_{max} > T_{up}$). The daily temperature, $T - d$, used for TI calculations is the average of the minimum, T_{min}, and maximum temperatures, T_{max}, as it understood that daily extremes are a better approximation of the range temperature which the plant has experienced along the day (Snyder et al., 1999). Therefore, we use equation (2.4) bellow to calculate GDD values for a specific season from day 1 to day D:

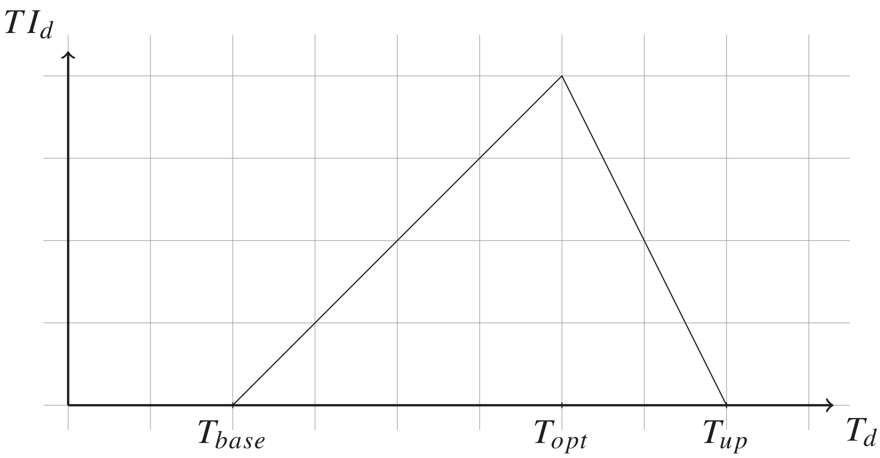


Figure 2.2: Thermal intake relationship with temperature
Source: Own drawing.

$$TI_d = \begin{cases} T_d - T_{base}, & T_{Base} \leq T_d \leq T_{opt} \\ \frac{T_{up}-T_d}{T_{up}-T_{opt}}(T_{opt} - T_{base}), & T_{opt} < T_d \wedge T_{max} \leq T_{up} \\ 0, & \text{otherwise.} \end{cases} \tag{2.3}$$

$$GDD_{1,D} = \sum_{d=1}^{D} TI_d \tag{2.4}$$

Notice that GDD will always be beneficiary to a plant, *i.e.*, a higher thermal intake will always increase the plant growth rate. However, GDD is not a linear function of temperature, capturing the negative effects of temperatures above certain levels.

The climatic data set, used in the calculation of GDD and mean precipitation, provided by SIMEPAR (*Paraná*'s Technology and Environmental Monitoring System) is composed of 18 years (from 2000 to 2017) of daily measures of precipitation, maximum, and minimum temperatures from 21 ground stations scattered across *Paraná*, which leaves 378 municipalities without climatic data. This problem is solved bellow.

To synthesize the data for the other municipalities –those without weather stations– we use the distances between stationed and non-stationed municipalities and the inverse distance weighting (IDW) method (Shepard, 1968). From SIMEPAR data set we have a matrix of each climatic variable C with 6,569 rows (for days) and 21 columns (for stations). We then create a matrix of inverted square distances of every non-stationed municipality to every stationed municipality called $D_{378;\,21}$ where every entry is equal to $1/(Dist_{i,j})^{\phi}$ of municipality centroid (row) i to the station (column) j. This matrix D is then treated by normalizing each row dividing every entry by the sum of all entries in the row $\sum_{j=1}^{21} 1/(Dist_{i,j})^{\phi}$ obtaining a normalized inverted square distance matrix matrix $ND_{378,21}$.

Following this process, the matrix multiplication according to equation (2.5) bellow will provide a synthetic base of daily temperatures and precipitation for every non-stationed municipality, $\hat{C}$, which is then combined with the original base C to obtain a block matrix $\hat{B}$ for each climatic variable. The term ϕ defines the sensibility of climate to distance, by changing the value of ϕ we can adjust the proportional impact of far away stations to a non-stationed municipality, *i.e.*, a higher power produces estimates closer to the nearest station, when the power approaches 1 the effect becomes linear. As the power becomes closer to 0 the weights of each station are the same, regardless the distance. For this model we use $\phi = 2$, as temperature and precipitation follows Tobler's first law of geography, that is, "Everything is related to everything else, but near things are more related than distant things".

$$
\begin{aligned}
ND &= \begin{pmatrix} \frac{1}{Dist^2_{(1,1)}} \div \sum_{j=1}^{21}\left(\frac{1}{Dist^2_{(1,j)}}\right) & \cdots & \frac{1}{Dist^2_{(1,21)}} \div \sum_{j=1}^{21}\left(\frac{1}{Dist^2_{(1,j)}}\right) \\ \vdots & \ddots & \vdots \\ \frac{1}{Dist^2_{(378,1)}} \div \sum_{j=1}^{21}\left(\frac{1}{Dist^2_{(378,j)}}\right) & \cdots & \frac{1}{Dist^2_{(378,21)}} \div \sum_{j=1}^{21}\left(\frac{1}{Dist^2_{(378,j)}}\right) \end{pmatrix} \\
\hat{C} &= C \times ND^{\top} \\
\hat{B} &= \begin{bmatrix} C & | & \hat{C} \end{bmatrix}
\end{aligned} \tag{2.5}
$$

For the sake of visualization, we present in figure 2.3 the *Paraná*'s GDD distribution using thresholds for soybeans, as defined by de Souza et al. (2013), where $T_{base} = 10°$, $T_{opt} = 30°$, $T_{up} = 40°$ for the months between September and December –in accordance to National Supply Company (CONAB) planting season for soybeans in Paraná, this is the final format of the GDD variable used in this study. It is easy to observe that the northwest region of *Paraná* has higher GDD per season than the rest of the state, with the "soy belt" shown in figure 2.1 existing in this higher temperature region. The average soy-season GDD for *Paraná* between 2000 and 2017 was of 1465 degree-days per season. In what concerns precipitation, we employ SIMEPAR database to calculate the eighteen years seasonal averages of precipitation for every municipality in mm of rain.

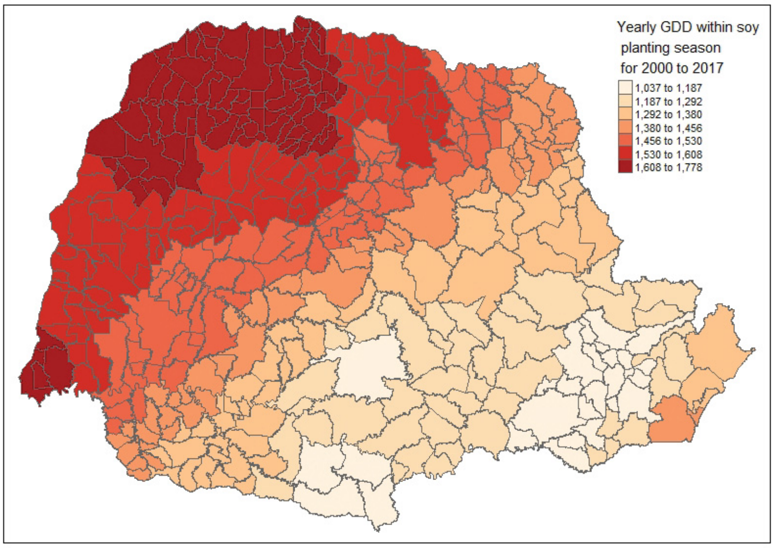


Figure 2.3: Average Paraná's GDD from September to December 2000-2017
Source: Own Calculation based on data from SIMEPAR

2.3.1 Controls

Other factors are connected with farmland value, as the literature in Ricardian models shows (Schlenker et al., 2006; Mendelsohn et al., 2010; Sklenicka et al., 2013; DePaula, 2020). To control for these factors we selected seventeen variables from three different dimensions that may affect land value: physical, economic, and geographic factors.

Physical factors refer to the qualitative aspects of the farmland of each municipality. These are somewhat treated by the different classes of land as defined by DERAL's database. Together with running different models for different land-type prices, we use data from Paraná's Water and Land Institute (IAT) to get the proportion of each class of land in a municipality (clayey, medium-clayey, clayey-medium, medium, silty, medium-sandy, and sandy). Based on those we construct two variables: percentage of the best soil type (clayey); and percentage of the worst soil type (sandy). From the National Water Agency (ANA) we collect data on soil's Available Water Capacity (AWC), from which we calculate the area-weighted average for each municipality. We also use municipal latitude, as lower latitudes have higher solar incidence.

Economic/demographic factors, such as a municipal GDP and population density is believed to exert significant effects on farmland value (Sklenicka et al., 2013; DePaula, 2020). Rural credit may also be as it allows for investments on more productive practices and cost reductions. These were obtained in IPARDES (Paraná Institute of Economic and Social Development). To address the competition for land of rural and urban regions, we calculate the proportion of urban coverage in every municipality using IBAMA's data on urban sprawl divided by municipal area.

Geographic factors encompass distances of big consumer markets, *e.g.*, large cities and trading ports, as these are the markets where rural commodities mostly go. It is also understood that good transport infrastructure is advantageous in time-shortening those distances (Sklenicka et al., 2013; Hüttel et al., 2016; DePaula, 2020). Therefore, both set of variables –distance and road infrastructure– must be incorporated into the model. For distances this is done via GIS calculations using linear distances from a municipality centroid to key municipalities (*Curitiba*, *São Paulo*, *Paranaguá* port, *Santos* port, *São Francisco* port). For road network size we use the public available GEOFABRIK's openstreetmaps data extracts for Brazilian roads for 01/01/2018 in order to calculate road density (km roads/ km^2 county area), railroad density, and highway density.

Additionally, irrigation showed to be important in a number of studies (Sklenicka et al., 2013; DePaula, 2020). Differently to past census, the 2017 version of the agricultural census has irrigation broken into several classes, some with more technologically advanced, *e.g.*, center pivot or drip irrigation, or only simple systems, *e.g.*, furrow, flood, or level-basin irrigation. However, due to IBGE policy for individual privacy, a large proportion of municipalities have area covered specific irrigation techniques censored. Therefore, we use total irrigated area of each municipality. In order to capture more advanced irrigation method we use EMBRAPA's 2019 cartographic data on pivot irrigation to calculate the total area covered by this technique[2].

2.4 EMPIRICAL STRATEGY

The relationship between climatic variables and farmland prices for each of the four farmland classes will be firstly estimated through OLS using the following model:

$$\ln FV_{ic} = \beta_0 + \beta_{gdd} GDD_i + \beta_p Prec_i + \beta_{p2} Prec_i^2 + \gamma_1 PC1_i + \cdots + \gamma_n PCj_i + \varepsilon_i. \tag{2.6}$$

where FV_{ic} is the municipal mean farmland value for each class for 2017 in BRL; GDD_i is is an index of accumulated thermal time in thousands of degree Celsius in the season; $Prec_i$ is the mean seasonal precipitation for each municipality; PCj_i represent principal component indexes used for dealing with the fact that there is a large number of highly correlated control variables; β and γ are parameters and represent the willingness to pay of farmers to the marginal increase of that characteristic in the farmland; ε_i is assumed to be i.i.d. errors. A squared term for precipitation is added as rain is beneficiary to plant growth until a certain level, after which it becomes detrimental. This quadratic relationship is already captured by the equation (2.4) for GDD in the range where the is no harm[3].

2.4.1 Principal Components

As it is pointed out in Hermann and Haddad (2005), hedonic models with a large number of control variables may be affected by multicollinearity. This will not produce biased results, but may enlarge the standard errors, leading to type II errors when observing the significance of our estimates. In order to avoid such problem we reduce the number of variables using principal components (PC). The seventeen selected controls where reduced into orthogonal components which best represent the variance of all controls. Then only the principal components with standard deviation higher than unit were introduced into our model. The vectors are computed separately for each of the four farmland classes prices, which can generate different number of significant components (five PCs for classes I, III, and IV; six PCs for class II). In appendix B, the composition of every significant principal component for all four classes is presented.

2.4.2 Spatial Regression and Impacts

Farmland prices can be subject to spatial dependence, as land prices of a farm are similar to their neighbours given unobserved spatial relationships (omitted variables) or due to

[2]Although irrigation information being considered important for Ricardian studies, it may be less so in this study as *Paraná* has high levels of precipitation during the year, with irrigation being only supplemental to precipitation.

[3]To be able to have more comparable results to Schlenker et al. (2006), all models are also estimated using the quadratic form of GDD.

neighborhood effects (Patton and McErlean, 2003; Schlenker et al., 2006; Huang et al., 2006; Dillard et al., 2013; Huttel and Wildermann, 2014; Lehn and Bahrs, 2018).

To address this issue we employ the spatial econometrics in the form of the spatial autoregressive (SAR) and spatial error (SEM) models. The SAR model assumes that there is spatial autocorrelation of the dependent variable, while the SEM model assumes that there is a spatial relationship in the residuals, which emerges from spatially distributed omitted variables. We then re-estimated the model of equation 2.6 and including separately the spatial error correction (SEM) and spatial lag element (SAR), which follows the generic form form:

$$\ln FV_{ic} = \beta_0 + \lambda W_c \ln FV_{ic} + \beta_{gdd} GDD_i + \beta_p Prec_i + \beta_{p2} Prec_i^2 + \sum \gamma PC + u_{it} \tag{2.7}$$

$$u_{it} = \rho W_c u_{it} + \varepsilon_{it} \tag{2.8}$$

where W_c is a queen style neighborhood matrix for each class c, λ is the spatial spillover parameter from the SAR specification ranging from 0 to 1. While ρ is the spatial error parameter from the SEM specification ranging from -1 to 1 and ε being i.i.d errors. In SEM model we assume that λ is zero, while in SAR model we assume ρ is zero. OLS is a particular case where both λ and ρ are null.

We apply Moran-I test on the OLS residuals of each land-class model to check for spatial autocorrelation. As seen in table 2.1, the test rejects the null hypothesis of spatial independence in all classes, meaning that there is spatial correlation. Also, we use Lagrange-multiplier tests to verify which type of spatial model is better suited for our data. Although both the error and lag models present significant results in their respective LM tests, the robust form of LM tests suggest that lag model proves to be adequate. Therefore, we only estimate SAR models.

Table 2.1: Spatial tests

Model	Moran-I	LMerr	LMlag	RLMerr	RLMlag
Class-I	0.379^{***}	13.95^{***}	22.50^{***}	2.64	11.19^{***}
Class-II	0.746^{***}	209.59^{***}	274.54^{***}	0.14	65.09^{***}
Class-III	0.709^{***}	167.34^{***}	248.18^{***}	0.76	81.60^{***}
Class-IV	0.704^{***}	190.75^{***}	257.54^{***}	0.11	66.91^{***}

Notes: Values in parenthesis are p-values. Significance levels * p<0.1; **p<0.05; ***p<0.01. *Source*: Own calculations.

In order to obtain marginal effects for SAR models, we need to calculate the spatial impacts. The usual interpretation of the parameter estimates as marginal effects is not possible for spatial autoregressive models, as any growth in GDD_i will impact FV_i locally first, and then spillovers to neighbouring municipalities through λ, with positive effects on $FV_{j \neq i}$ and on their neighbours, including the first municipality. Therefore, there are three different impacts of an independent variable on the dependent variable: the direct effect, akin to the marginal effect of usual OLS models; the indirect effect, portraying the marginal change in a municipality land price given changes in the GDD of all other municipalities (global effect); and the sum of both, which is the total effect. The mechanisms of how to calculate these impacts are shown in Kim et al. (2003).

2.5 EMPIRICAL ESTIMATION

Prior to presenting the results we run Breusch-Pagan tests on all OLS models to verify for heteroscedastic errors, with results indicating that all models suffer from it. Therefore, heteroscedasticity-consistent standard errors need to be estimated, for such we chose to use the HC3 estimator, as recommended by MacKinnon and White (1985) and Cribari-Neto (2004).

Results of the first four empirical models are presented in table 2.2. Models (1) through (4) have only linear GDD and are ordered from class I to class IV, while (5) through (8) have quadratic GDD added to it and are ordered in the same way. In the linear models, parameter estimates for GDD are significant in all but the first class of farmland, ranging from 0.440 to 0.561. Considering the log-linear specification and the fact that the GDD variable measures thousands of degree-days, this means that farmers are willing to pay 4.4% to 5.6% more for farmland with additional 100 GDD for these classes of land. In terms of elasticity, using the average seasonal GDD of 1465, we have that for each 1% increase in GDD a farmland experiences an 0.64% increase in its price.

Such result follows what is expected, since GDD is by definition good for farming, and the way which temperature affects our models is by increasing or diminishing GDD. The quadratic models present significant results only for the first and last farmland class. The other estimates for GDD, despite not being statistically significant, follow closely what is found in Schlenker et al. (2006) which estimated coefficients of around 1.6 for linear and −0.3 for squared GDD. This similarity indicates that the models may be well specified, but the sample is too small to find significant results. It is important to notice that the coefficients of model (5) are extremely large, this may be due to the fact that the sample for this class is much smaller compared to the samples off the other land classes.

Estimates for the precipitation parameters predict an U-shape relationship between rain and farmland value, unlike the results found by Schlenker et al. (2005). Nevertheless, they are in accordance to other findings such as those in Mendelsohn et al. (2010); Massetti et al. (2013); Zhang et al. (2017). In the particular case of this study, all municipalities in the sample face very high levels of precipitation during the four months in the season, which tend to distort models results.

The spatial models regression results are shown in table 2.3. These are ordered in the same manner as in the non-spatial models. The spatial lag component in all classes is significant, indicating a neighborhood effect where landowners observe their surroundings to price their farmland. Again, coefficients for precipitations take an counter intuitive sign, indicating slightly negative added value of additional rain within all the range of precipitation in our data.

In the linear models the GDD coefficients turned statistically insignificant in all but one model, Class-II, after controlling for spatial dependence of farmland value. It is likely that the spatial nature of the GDD variable has contributed to this result. That is, after controlling for unobserved spatial dependence the estimations did not reveal statistically significant correlation between GDD and farmland value. This, however, is not an evidence that GDD is irrelevant for land value; it only emphasizes the spatial nature of our variables. More so, the fact that GDD provided significant coefficients in one model confirms the importance of the variable even when spatial autocorrelation is removed. As in the OLS estimation, the coefficients associated with the GDD quadratic specification for the class I are significant, but values remain large.

Table 2.2: Non-Spatial Regression Results for Farmland Value

	ln FV cls-I (1)	ln FV cls-II (2)	ln FV cls-III (3)	ln FV cls-IV (4)	ln FV cls-I (5)	ln FV cls-II (6)	ln FV cls-III (7)	ln FV cls-IV (8)
GDD	−0.116	0.594***	0.466**	0.532**	27.120**	1.745	0.914	2.846
	(0.406)	(0.143)	(0.193)	(0.231)	(11.251)	(2.110)	(2.198)	(2.361)
GDD^2					−8.660**	−0.424	−0.165	−0.852
					(3.575)	(0.769)	(0.794)	(0.848)
Precipitation	−0.006	−0.012**	−0.022**	−0.027**	−0.008	−0.014**	−0.022**	−0.031**
(mm per season)	(0.010)	(0.005)	(0.009)	(0.011)	(0.009)	(0.007)	(0.010)	(0.014)
Precipitation^2	0.00000	0.00001**	0.00002**	0.00002**	0.00001	0.00001*	0.00002**	0.00002**
	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
PC1	0.010	−0.007	−0.022	−0.023	0.011	−0.011	−0.024	−0.031*
	(0.011)	(0.012)	(0.016)	(0.019)	(0.010)	(0.012)	(0.015)	(0.019)
PC2	0.024***	−0.029	−0.003	−0.001	0.030***	−0.026	−0.002	0.004
	(0.009)	(0.020)	(0.031)	(0.032)	(0.008)	(0.024)	(0.035)	(0.038)
PC3	−0.003	0.071***	−0.079***	−0.072***	−0.006	0.072***	−0.079***	−0.071***
	(0.007)	(0.018)	(0.015)	(0.016)	(0.007)	(0.019)	(0.015)	(0.017)
PC4	−0.013	−0.036***	0.047***	0.045***	−0.011	−0.035***	0.046***	0.042***
	(0.010)	(0.008)	(0.008)	(0.009)	(0.010)	(0.007)	(0.008)	(0.009)
PC5	0.023	−0.002	0.005	0.010	0.024*	−0.003	0.005	0.007
	(0.014)	(0.008)	(0.009)	(0.010)	(0.013)	(0.009)	(0.010)	(0.011)
PC6		0.015				0.015		
		(0.010)				(0.009)		
Constant	13.196***	13.824***	17.158***	18.537***	−7.369	13.768***	17.141***	18.449***
	(3.812)	(1.780)	(2.779)	(3.408)	(8.698)	(1.965)	(2.918)	(3.819)
Observations	107	329	387	387	107	329	387	387
R^2	0.257	0.463	0.501	0.469	0.303	0.465	0.501	0.473
Adjusted R^2	0.196	0.448	0.491	0.458	0.239	0.448	0.490	0.460
Residual Std. Error	0.092	0.138	0.149	0.163	0.090	0.138	0.149	0.163
F Statistic	4.228***	30.599***	47.489***	41.752***	4.693***	27.597***	42.129***	37.601***

Notes: Significance levels * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Models have HC3 robust standard errors, as in MacKinnon and White (1985). GDD and Precipitation variables are the season of September to December average of all 17-years from 200 to 2017. *Source*: Own calculations.

Table 2.3: Spatial Regression Results for Farmland Value

	ln FV cls-I (9)	ln FV cls-II (10)	ln FV cls-III (11)	ln FV cls-IV (12)	ln FV cls-I (13)	ln FV cls-II (14)	ln FV cls-III (15)	ln FV cls-IV (16)
Spatial lag (λ)	0.570***	0.770***	0.743***	0.745***	0.553***	0.770***	0.743***	0.743***
	(0.082)	(0.033)	(0.036)	(0.036)	(0.085)	(0.033)	(0.036)	(0.036)
GDD	0.022	0.197***	0.095	0.123	21.414**	0.480	−0.191	0.526
	(0.353)	(0.073)	(0.084)	(0.092)	(8.749)	(0.804)	(0.869)	(0.953)
GDD^2					−6.803**	−0.104	0.105	−0.148
					(2.779)	(0.295)	(0.319)	(0.349)
Precipitation	0.001	−0.005**	−0.007***	−0.010***	−0.002	−0.005*	−0.007**	−0.011***
(mm per season)	(0.007)	(0.002)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)
Precipitation^2	−0.00000	0.00000*	0.00001***	0.00001***	0.00000	0.00000*	0.00000**	0.00001***
	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)
PC1	0.005	−0.001	−0.009	−0.009	0.007	−0.002	−0.008	−0.011
	(0.009)	(0.005)	(0.006)	(0.006)	(0.009)	(0.006)	(0.007)	(0.007)
PC2	0.017***	−0.012***	0.002	0.002	0.022***	−0.011**	0.001	0.002
	(0.006)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	(0.005)
PC3	−0.008	0.028***	−0.028***	−0.026***	−0.011*	0.028***	−0.028***	−0.026***
	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)
PC4	−0.011*	−0.020***	0.029***	0.027***	−0.010*	−0.020***	0.029***	0.026***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)
PC5	0.020***	−0.005	−0.003	−0.0001	0.021***	−0.005	−0.003	−0.001
	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)	(0.006)
PC6		0.012**				0.012**		
		(0.005)				(0.005)		
Constant	4.622	3.803***	5.064***	5.815***	−11.279	3.796***	5.067***	5.825***
	(3.015)	(0.929)	(1.060)	(1.156)	(7.153)	(0.929)	(1.061)	(1.156)
Observations	107	329	387	387	107	329	387	387
Log Likelihood	120.346	319.439	308.341	272.535	123.268	319.501	308.395	272.624
σ^2	0.006	0.007	0.010	0.012	0.005	0.007	0.010	0.012
Akaike Inf. Crit.	−218.692	−614.878	−594.682	−523.070	−222.536	−613.003	−592.790	−521.248
Wald Test	47.786***	519.497***	422.444***	413.425***	41.724***	517.016***	424.244***	409.218***
LR Test (df = 1)	25.277***	257.821***	231.257***	230.608***	24.171***	257.145***	231.237***	227.919***

Notes: Significance levels * p<0.1; **p<0.05; ***p<0.01. GDD and Precipitation variables are the season of September to December average of all 17-years from 200 to 2017. *Source*: Own calculations.

2.6 CLIMATE CHANGE IMPACTS

In the following calculations we use our estimates, along with predictions from regional climate models, to evaluate the impacts of climate change on farmland price in the *Paraná*'s state. The climate projections are obtained from the median value of 18 models that compose the Coordinated Regional Downscaling Experiment for South America (CORDEX South America), which were used for regional prediction and analysis in the sixth IPCC Assessment Report, as well as, made available in IPCC WGI Interactive Atlas. Specifically, predicted changes in mean minimum and maximum daily temperatures in the interval of September to December are available for three standard greenhouse gas (GHG) concentration scenarios identified in the IPCC AR6: RCP 2.6, RCP 4.5, and RCP 8.5, each denoting a climate projection with higher concentration of GHG, respectively.

CORDEX data comes in the form of grid cells with a 0.44 degree size (mapped squares of around 50 km side). GIS tools are then used to calculate the weighted mean value of each variable for each municipality with weather stations. The temperature values are added to our original climate data (2000-2017) and used together with equations (2.5) and (2.4) to calculate the predicted seasonal degree days for two times spans, mid century –2040-2060– and end of the century –2081–2100. In this essay we only provide analysis for RCP 8.5, as it is the most extreme case, nevertheless, results from other RCP's will not diverge.

Figure 2.4(a) shows the modeled seasonal GDD for *Paraná* by the end of the century, while figure 2.4(b) shows the projected net effect on farmland value due to the new temperature levels for the class-II spatial model. This projection is done by only observing the marginal effect of GDD assuming all other factors are constant. The first figure, 2.4(a), shows that even in the worst case scenario of IPCC predictions the state's GDD will not diminish in any municipality. Figure 2.4(b) presents the projected effect of the GDD increase across the state in the farmland value, depicting a scenario were farmland gains value across the whole state, with greater effect in the central region. This indicates a favorable position of *Paraná* given current global warming predictions. However, *Paraná* –together with the south region of Brazil– may be the exception rather than the rule when it comes to global warming impacts on Brazilian agriculture, as their are located in a higher (south) latitude than the rest of the country and experience a colder climate.

(a) Projected GDD

(b) Projected Farmland Value Change in Spatial Class-II model

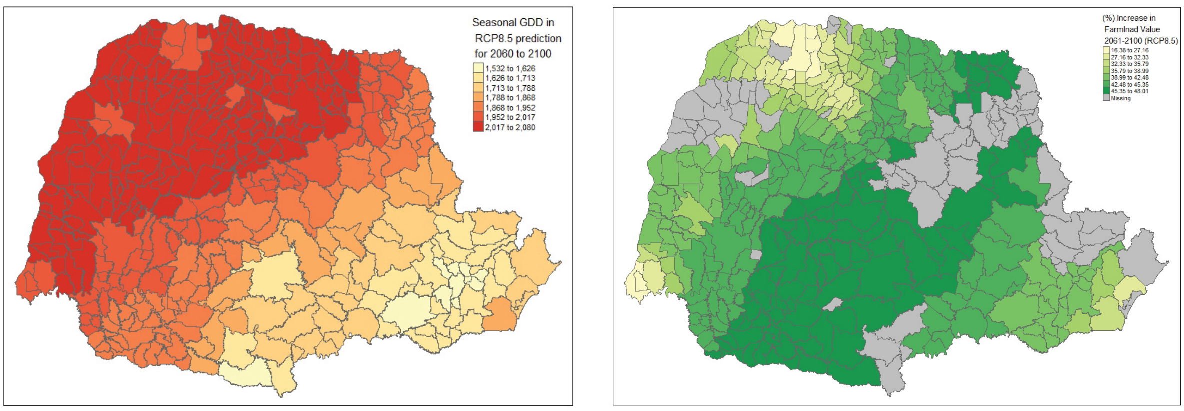


Figure 2.4: Projected *Paraná*'s GDD and farmland Value 2081-2100 in *Paraná*'s (RCP 8.5)
Source: Own Calculations.

In table 2.4 the projected increase in farmland value is presented for all models, OLS and spatial, with significant GDD for two time spans, medium and long term.

Table 2.4: Decomposition of relative changes in Farmland value due to change in GDD (RCP8.5)

	2041-2060 (%) Average				2081-2100 (%) Average			
Model	Mean	Min.	Max.	σ	Mean	Min.	Max.	σ
Class-I*	659.27	411.15	761.86	51.16	1111.98	486.29	1262.96	124.35
Class-II	15.78	9.48	18.53	1.33	28.93	11.34	33.80	3.79
Class-III	12.38	7.44	14.53	1.04	22.69	8.89	26.52	2.97
Class-IV	14.12	8.49	16.58	1.19	25.91	10.15	30.27	3.39
Spatial Class-I*								
Direct	571.65	356.43	660.66	44.38	964.65	421.60	1095.82	107.99
Indirect	595.63	371.39	688.38	46.25	1005.12	439.29	1141.79	112.52
Total	1167.27	727.82	1349.03	90.64	1969.75	860.88	2237.58	220.50
Spatial Class-II								
Direct	6.43	3.86	7.54	0.54	11.78	4.62	13.77	1.54
Indirect	16.36	9.83	19.20	1.38	29.98	11.75	35.03	3.93
Total	22.79	13.69	26.75	1.92	41.76	16.38	48.01	5.47

Notes: *Projection of model with squared GDD. *Source* Own calculations.

Our results agree with Massetti et al. (2013) which suggests that *Paraná* agriculture will be a winner in the studied scenarios. But are not in line with Schlenker et al. (2006)'s findings for regions that have analogous Köppen climate classifications to *Paraná* –southern USA. This discrepancy can be attributed to some differences in the construction of the GDD variable and data availability. They use a strictly linear GDD with lower threshold of 8° and upper of 32° Celsius, and an extreme-growing-degree days[4] (EDD) variable for days with maximum above 34°. These thresholds are not representative of *Paraná* and are more suitable to portray wheat's thermal needs than soybeans', the predominant crop in *Paraná*. Therefore, or our GDD variable we followed de Souza et al. (2013) thresholds for Brazilian variants of soybeans.

2.7 FINAL REMARKS

This study estimated a hedonic land price model using high frequency data on temperature and precipitation to assess the impacts of climate on farmland value in the state of *Paraná*. Based on the econometric results and recent climatic predictions provided by the Coordinated Regional Downscaling Experiment (CORDEX) and the Intergovernmental Panel on Climate Change (IPCC), evidence of farmland appreciation was found for the state, indicating that agriculture in the region will experience benefits from climate change. Our findings agree with Massetti et al. (2013), which observed Brazilian data at the micro-regional level and found that increase in temperature in *Paraná* –and the other southern states– will result in farmland prices rising.

This essay also provided insight on the methods and problems in understanding the effects of climate change on the agricultural economy in Brazil –particularly in *Paraná*. It as

[4]EDD measures a crop heat accumulation for temperatures above a high threshold that may damage the plant's growth. It was not incorporated into our models since *Paraná*'s climate is too mild, with days above 40° Celsius (EDD threshold for soybeans according to de Souza et al. (2013)) being very rare in the studied season. As they become more common, a likely IPCC scenario, EDD should be incorporated into our analysis.

shown that using a measure of thermal intake, GDD, that better[5] represents climate's impacts on agriculture is possible and provides good results.

Future research efforts should concentrate on the expansion of the sample to accommodate a more diverse set of regions where high temperature days are common. Extreme weather events could then be better controlled through, for example, an EDD variable, which can improve our estimates. Also, a more climate diverse sample, possible with a grater region of study, will likely provide better estimates for GDD and precipitation in particular, as the current sample does not have enough variance.

[5]Compared to monthly mean temperature.

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APPENDIX A – CALCULATING SPATIAL GMM IMPACTS IN R

This appendix shows a non-reviewed algorithm on how to calculate spatial impacts, and error estimates for them, using already established functions from two packages in R, **spatialreg** version 1.1-8 and **splm** version 1.5-2. The algorithm shown here is an improvisation as the usual function for impact calculatio of spatial models is not available for GM models, with or without endogenous variables, therefore results should be taken carefully.

A.1 IMPACTS FOR SPATIAL GM MODELS

Impact calculation of Maximal Likelihood (ML) of static panels are obtained from the following R function, `impacts.splm`

```
function (obj, listw = NULL, time = NULL, ..., tr = NULL, R = 200,
          type = "mult", empirical = FALSE, Q = NULL)
{
  if (is.null(listw) && is.null(tr))
    stop("either listw or tr should be provided")
  if (!is.null(listw)) {
    if (listw$style != "W")
      stop("Only row-standardised weights supported")
    if (is.null(time) && is.null(tr))
      stop("time periods should be provided")
  }
  if (is.null(tr)) {
    sparse.W <- listw2dgCMatrix(listw)
    s.lws <- kronecker(Diagonal(time), sparse.W)
    tr <- trW(s.lws, type = type)
  }
  if (is.na(match(obj$type, c("fixed effects lag",
                              "fixed effects sarar",
                              "random effects ML",
                              "fixed effects GM",
                              "lag GM", "fixed effects GM"))))
    stop("object type not recognized")
  if (obj$type == "fixed effects lag") {
    class(obj) <- "Gmsar"
    obj$type <- "SARAR"
    obj$data <- as.vector(obj$model)
    obj$s2 <- obj$sigma2
    obj$secstep_var <- obj$vcov
    imp <- impacts(obj, tr = tr, R = R, ...)
  }
  if (obj$type == "fixed effects sarar") {
    class(obj) <- "Gmsar"
    obj$type <- "SARAR"
    rho <- obj$coefficients[2]
```

```
    obj$coefficients <- obj$coefficients[-2]
    obj$data <- as.vector(obj$model)
    obj$s2 <- obj$sigma2
    obj$secstep_var <- obj$vcov[-2, -2]
    imp <- impacts(obj, tr = tr, R = R, ...)
  }
  if (obj$type == "fixed effects error")
    stop("Impacts Estimates are not available for Error Model")
  if (obj$type == "random effects ML") {
    if (!is.null(obj$arcoef)) {
      class(obj) <- "Gmsar"
      obj$type <- "SARAR"
      obj$coefficients <- c(obj$arcoef, obj$coefficients)
      obj$data <- as.vector(obj$model)
      obj$s2 <- obj$sigma2
      obj$secstep_var <- matrix(0, nrow(obj$vcov) + 1,
                           nrow(obj$vcov) + 1)
      obj$secstep_var[1, 1] <- obj$vcov.arcoef
      obj$secstep_var[(2:(nrow(obj$vcov) + 1)),
        (2:(nrow(obj$vcov) + 1))] <- obj$vcov
      imp <- impacts(obj, tr = tr, R = R, ...)
    }
    else stop("Impacts Estimates are not available for Error Model")
  }
  if (obj$type == "fixed effects GM") {
    if (is.null(obj$endog)) {
      obj$secstep_var <- vcov(obj)
      class(obj) <- "Gmsar"
      obj$type <- "SARAR"
      obj$data <- as.vector(obj$model)
      obj$s2 <- obj$sigma2
      imp <- impacts(obj, tr = tr, R = R, ...)
    }
    else stop("No impacts estimates when endogenous
            variables are present in the system")
  }
  if (obj$type == "lag GM") {
    if (is.null(obj$endog)) {
      class(obj) <- "Gmsar"
      obj$type <- "SARAR"
      obj$secstep_var <- obj$var
      obj$data <- as.vector(obj$model)
      obj$s2 <- obj$sigma2
      imp <- impacts(obj, tr = tr, R = R, ...)
    }
    else stop("No impacts estimates when endogenous
            variables are present in the system")
  }
```

```
  if (obj$type == "random effects GM") {
    if (is.null(obj$endog)) {
      class(obj) <- "Gmsar"
      obj$type <- "SARAR"
      obj$secstep_var <- obj$vcov
      obj$data <- as.vector(obj$model)
      obj$s2 <- obj$sigma2
      imp <- impacts(obj, tr = tr, R = R, ...)
    }
    else stop("No impacts estimates when endogenous
                variables are present in the system")
  }
  return(imp)
}
```

As it is pointed by the beginning section of the formula, there are sections of this function dedicated to deal with GM models, however the `obj$type` of a GMM object –as outputted by a `spdm` function is never one of the options listed:

```
if (is.na(match(obj$type, c("fixed effects lag",
                             "fixed effects sarar",
                             "random effects ML",
                             "fixed effects GM",
                             "lag GM", "fixed effects GM"))))
```

instead the object types are as follows: `Spatial w2sls model` for GMM lag-within models; `Spatial fixed effects SARAR model (GM estimation)` for GM SARAR-within models; `Spatial ec2sls model` for lag-random models; `Spatial random effects SARAR model (GM estimation)` for GM SARAR-random models; `Spatial ec2sls model` for lag-random models. Assuming that this is just a mistake on how the objects are typified across two different packages we can force `impacts.splm` to accept `spgm` objects by changing their types accordingly, in a similar manner to:

```
spatialGM_within <- spgm(y ~ x1 + x2, data = df,
                    listw = listw.wts, spatial.error= F,
                    lag = T, model = "within")
spatialGM_within$type <- "fixed effects GM"
```

This will allow the function to complete; however, if we look inside "fixed effects GM"fork in the function we have argument allocations occurring, `$sigma2` and `$model`. These are not present within `spgm` models, unlike `splm`.

```
if (obj$type == "fixed effects GM") {
if (is.null(obj$endog)) {
  obj$secstep_var <- vcov(obj)
  class(obj) <- "Gmsar"
  obj$type <- "SARAR"
  obj$data <- as.vector(obj$model)
  obj$s2 <- obj$sigma2
  imp <- impacts(obj, tr = tr, R = R, ...)
}
```

Yet, upon some testing and looking on the behaviour of `impacts` root function, we have not found differences in impacts calculations, nor estimated errors for different values of those arguments. It seems that only four arguments are utilized in `impacts.splm` function, the estimated coefficients of each model, the variance covariance matrix of each model, the spatial weights, and the number of periods in the panel. Knowing this we can finally calculate impacts, and error estimates of our spatial GM models [1] as:

```
spatialGM_within <- spgm(y ~ x1 + x2, data = df,
                    listw = listw.wts, spatial.error= F,
                    lag = T, model = "within")
spatialGM_within$type <- "fixed effects GM"
imp1 <- spatialreg::impacts(spatialGM_within,
            listw = listw.wts, time = 9, R = 200)
summary(imp1, zstats=TRUE, short=TRUE)
```

A.2 IMPACTS FOR SPATIAL GM WITH ENDOGENOUS VARIABLES MODELS

The code of `function` places stops when `obj$endog` is not null, meaning, the algorithm is hard locked into not calculating impacts for spatial two staged GM models. This might be based on econometric theory, or just that developers here not sure if results would be correct. However if the user desires to calculate impacts it is possible by employing the solution as follows.

First lets have a look at "Spatial w2sls model with additional endogenous variables"as the `obj$type` calls a spatial lag-GM models with endogenous variables. Its function should be similar to:

```
GM_endog_lag <- spgm(y ~  x1, data = df,
                lag = T, spatial.error = F,
                endog = ~ x2, instruments = ~z,
                listw = listw.wts)
```

here the spatial model $Y_{it} = \alpha_i + \lambda WYit\beta_1 x_{1it} + \beta_2 \hat{x}_{2it} + \varepsilon_{it}$ is estimated, with fist stage equal $x_2 = \theta_i + \gamma_z z_{it} + \gamma_x x_{1it} + v_{it}$. The object generated by this function will have it's coefficient and covariance arguments organized in matrices by the order x_2, λ, x_1; however if we look at a simple spatial-GM model this organization will follow the λ, x_1, x_2 order. Therefore we identified the three changes that need to be made so our endogenous model can be accepted into `impacts.splm` function: change model `$type`, remove argument `$endog`; reorganize coefficient and covariance matrices.

```
GM_endog_lag <- spgm(y ~  x1, data = df,
                lag = T, spatial.error = F,
                endog = ~ x2, instruments = ~z,
                listw = listw.wts)
GM_endog_lag$type <- "fixed effects GM"
GM_endog_lag$endog <- NULL
GM_endog_lag$coefficients<-GM_endog_lag$coefficients[c(2,3,1)]
GM_endog_lag$vcov <- GM_endog_lag$vcov[c(2,3,1),c(2,3,1)]
```

[1]Assuming that our panel as 9 periods, and using the standard 200 repetitions on the bootstrap calculations of our errors.

```
imp2 <- spatialreg::impacts(GM_endog_lag , listw = listw.wts,
                             time = 9, R = 200)
summary(imp2, zstats=TRUE, short=TRUE)
```

It is important to notice that the order (2,3,1) is particular to this model, one need to look at their particular object first in order to know what specific order to set their coefficients and vcov matrices.

APPENDIX B – PRINCIPAL COMPONENTS ANALISYS

This appendix present the loading of each significant principal component relative to each variable used in their composition. Four tables are presented, one for each farmland class.

Tabela B.1: Farmland class-I Principal components composition

	PC1	PC2	PC3	PC4	PC5
Latitude	0.314	0.020	−0.308	−0.004	−0.006
Pivot area (ha)	−0.014	−0.066	0.324	−0.263	−0.566
Irrigated area (ha)	0.030	0.017	0.322	−0.225	−0.517
Population density	−0.101	0.558	−0.048	−0.040	−0.048
Railroad density	−0.171	0.225	−0.071	0.160	−0.046
Street density	−0.132	0.510	0.036	0.137	−0.037
Highway density	0.221	0.050	−0.034	0.102	−0.321
Distance to São Paulo	0.393	0.073	−0.060	0.060	0.016
Distance to Curitiba	0.390	0.097	0.067	0.071	−0.026
Distance to Paranaguá	0.394	0.093	0.047	0.072	−0.011
Distance to Santos	0.394	0.075	−0.046	0.063	0.015
Distance to São Francisco	0.381	0.105	0.119	0.083	−0.025
ln Available Water Capacity	−0.024	−0.105	−0.585	−0.069	−0.332
Clay (%)	−0.044	−0.004	−0.558	−0.130	−0.271
ln GDP	0.135	0.040	0.007	−0.589	0.305
Urban Area (ha)	−0.085	0.546	−0.041	−0.048	−0.041
ln Credit Density	0.069	0.141	−0.064	−0.655	0.152
% Explained Variance	36.17	16.14	12.36	9.08	6.41

Tabela B.2: Farmland class-II Principal components composition

	PC1	PC2	PC3	PC4	PC5	PC6
Latitude	0.103	−0.354	0.362	0.179	−0.183	0.018
Pivot area (ha)	−0.027	0.036	−0.102	−0.409	−0.066	−0.766
Irrigated area (ha)	−0.041	0.127	−0.124	−0.077	−0.457	−0.282
Population density	0.194	0.372	0.391	−0.006	−0.012	−0.087
Railroad density	0.202	0.098	−0.004	−0.247	0.358	0.237
Street density	0.147	0.421	0.337	0.063	0.028	−0.016
Highway density	−0.037	0.120	−0.083	−0.406	0.501	0.064
Distance to São Paulo	−0.374	−0.061	0.284	0.099	−0.037	0.007
Distance to Curitiba	−0.417	0.094	0.090	−0.017	0.105	−0.023
Distance to Paranaguá	−0.418	0.080	0.117	−0.013	0.090	−0.016
Distance to Santos	−0.389	−0.035	0.256	0.079	−0.013	0.004
Distance to São Francisco	−0.408	0.144	0.047	−0.054	0.134	−0.022
ln Available Water Capacity	0.170	−0.420	0.287	−0.043	0.184	−0.168
Clay (%)	0.072	−0.367	0.340	−0.115	0.247	−0.233
ln GDP	−0.003	−0.001	0.163	−0.478	−0.458	0.356
Urban Area (ha)	0.198	0.372	0.389	0.006	−0.019	−0.092
ln Credit Density	−0.075	−0.168	0.156	−0.549	−0.169	0.217
% Explained Variance	31.37	16.18	14.01	7.84	6.82	5.93

Tabela B.3: Farmland class-III and class-IV Principal components composition

	PC1	PC2	PC3	PC4	PC5
Latitude	0.106	−0.223	−0.456	−0.242	−0.059
Pivot area (ha)	−0.034	0.005	0.072	0.407	−0.303
Irrigated area (ha)	−0.067	0.116	0.140	−0.016	−0.522
Population density	0.161	0.484	−0.261	−0.005	0.015
Railroad density	0.190	0.114	0.042	0.337	0.306
Street density	0.105	0.515	−0.182	−0.056	0.065
Highway density	0.045	0.056	0.243	0.360	0.517
Distance to São Paulo	−0.381	0.011	−0.256	−0.111	0.054
Distance to Curitiba	−0.418	0.087	−0.026	0.037	0.134
Distance to Paranaguá	−0.419	0.083	−0.059	0.032	0.127
Distance to Santos	−0.395	0.025	−0.223	−0.084	0.068
Distance to São Francisco	−0.409	0.120	0.029	0.079	0.147
ln Available Water Capacity	0.212	−0.294	−0.314	0.083	0.249
Clay (%)	0.071	−0.237	−0.456	0.100	0.093
ln GDP	−0.043	0.048	−0.198	0.461	−0.341
Urban Area (ha)	0.165	0.484	−0.260	−0.019	0
ln Credit Density	−0.099	−0.114	−0.267	0.520	−0.127
% Explained Variance	31.67	16.00	14.30	7.63	6.84