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Agricultural technology and land use: evidence for Brazil*

GT8. Pesquisa, inovação e extensão rural

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Resumo

A produção agrícola brasileira cresceu substancialmente nas últimas décadas. Pode-se dizer que o progresso tecnológico está no centro do crescimento do agronegócio brasileiro. Este boom teve consequências em termos de expansão de algumas culturas, adaptação de novas e mudanças geográficas nas fronteiras agrícolas. Também vale a pena mencionar o debate sobre a relação entre expansão agrícola e desmatamento. É possível estabelecer uma relação entre a adoção da tecnologia e o uso da terra agrícola e florestal. O método adotado aqui segue a estrutura dos Modelos de Equação Espacial Simultânea. Pode-se concluir que o uso de tecnologia, na forma de capital físico ou humano, estabelece uma relação positiva com a lavoura e uma relação negativa com a pastagem e a floresta. Uma possível explicação para isso é o aumento da produtividade/rentabilidade da terra destinada à agricultura como resultado do uso da tecnologia. Paralelamente a esse cenário, temos a não preservação de áreas florestais. Além disso, foi possível perceber a presença de *spillovers* tecnológicos na agricultura e como isso afeta as decisões de uso da terra.
Palavras-chave: tecnologia agrícola, difusão tecnológica, uso do solo, agricultura brasileira.

Abstract

Brazilian agricultural production has grown substantially in recent decades and it can be said that technological progress is at the center of the growth of Brazilian agribusiness. This boom has had consequences in terms of expansion of some crops, adaptation of new ones and geographical changes in agricultural frontiers. The debate about the relationship between agricultural expansion and deforestation is also worth mentioning. It is possible to establish a relationship between the adoption of technology and agricultural and forest land use. The method adopted here follows the structure of Simultaneous Space Equation models. It can be concluded that the use of technology, in the form of physical or human capital, establishes a positive relationship with tillage and a negative relationship with pasture and forest. One possible explanation for this is the increased productivity/profitability of land destined for farming as a result of the use of technology. Parallel to this scenario, we have the non-preservation of forest areas. In addition, the presence of technological spillovers in agriculture and how these affect land use decisions were noted.

Keywords: agricultural technology, technological diffusion, land use, Brazilian agriculture.

JEL Classification: O13, O33

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1 Introduction

Brazilian agricultural production has grown in enormously. In 1980, the grain harvest was 50.8 million tons, reaching 100.2 million in 2000 and finally 219 million in 2016 according to data from the National Supply Company (Conab). The country has become a major global player in the production of agricultural goods. No other nation has experienced such expressive variations in production. The sector stands out in the national accounts as the agricultural trade balance in 2016 was 71.3 billion dollars, while the total balance was 45 billion, according to the World Trade Organization (WTO). Brazil is among the world's largest exporters of sugar, soy, corn, orange juice, coffee, cotton, pork, poultry, and cattle.

The reasons for this success are several. The country has many natural advantages; the abundant availability of land and water, as well as favorable weather conditions. However, the key to success lies in the use of agricultural technology adapted to the Brazilian reality, the result of a partnership between the Brazilian Agricultural Research Corporation (Embrapa), research centers at universities and private initiatives with farmers and cattle ranchers. Thus, technological progress can be found at the center of the growth in Brazilian agrobusiness.

This agricultural boom has had consequences in terms of expanding some of the traditional areas for some crops, adapting new crops, and geographical changes in agricultural frontiers. It is also worth mentioning the debate about the relationship between agriculture and deforestation. It is possible to establish a relationship between the adoption of technology and the use of agricultural and forest land. However, the impacts of technology on land use remain controversial.

Some studies argue that agricultural research and, therefore, the use of agricultural technology can preserve areas of forest, limiting losses of biodiversity through increased productivity achieved by the agricultural sector (Green *et al.* 2005). Technologies that promote input efficiency enable farmers to overcome the constraints imposed by the low qualities of the land (Wu, 2014). Such dynamics significantly affect land prices to reduce the premium for higher quality land, which ultimately results in no need for deforestation. On the other hand, there are those who argue that increases in productivity from new technologies can increase the profitability of agriculture compared to alternative land uses (such as forest), encouraging the expansion of the agricultural frontier (Lambin *et al.* 2001; Southgate *et al.* 1991).

In addition, the effect of technological spillover from the spatial proximity should not be overlooked, that is to say, when using some type of technology the farmer can influence neighbors socially, including with regard to how the land is used. The works of Case (1992), Best *et al.* (1998), Holloway *et al.* (2002), Staal *et al.* (2002), Rounsevell *et al.* (2003), Bandiera and Rasul (2006), Conley and Udry (2010), Wright *et al.* (2013), and Wollni and Andersson (2014) run on this theme.

In view of the points presented, the questions that guide this study are: (i) what is the impact of technological elements (physical and human capital) on the use of agricultural and forestry land in Brazil? (ii) is there any influence of the neighboring areas in this relationship?

It is known that land resources are limited, and the decision about land use is interdependent and requires exclusivity of the space (i.e. choosing to plant a crop implies not choosing pasture or forest use and vice versa). Therefore, there is a problem of simultaneity of equations that explain land use. Therefore, the method adopted follows the structure of the Simultaneous Equation in Space models.

Empirical work related to land use modeling and its determinants can be found in literature. Aguiar *et al.* (2007) construct spatial regression models to evaluate the determinants of different land uses (i.e. forest, pasture, temporary and permanent agriculture) in four spatial partitions, namely: the entire Amazon; south and east of the Amazon, where most deforestation has occurred; Central Amazon, where the new borders are located; and the western Amazon, still preserved. The authors used data from the 1996 Agricultural Census. The results show that the pattern of concentrated deforestation in the south and east of the Amazon is related to the proximity of urban centers and roads, reinforced by the greater connectivity with the more developed regions of Brazil and more favorable climatic conditions in terms of the intensity of the dry season. The authors conclude that the heterogeneous occupation patterns of Amazonia can only be explained by combining several factors related to the organization of productive systems, favorable environmental conditions and access to local and national markets. Kirby *et al.* (2006), Laurance *et al.* (2002), Pfaff (1999) and Reis and Guzmán (2015) use the Amazon region as the scope of analysis.

Chakir and Le Gallo (2013) construct a model of land use participation using a spatial data panel and their observations referring to NUTS from France go from 1992 to 2003. This study considered the uses of agriculture, forest, urban and others. They investigated the relationship between land areas in different uses and economic-demographic factors that influence land use decisions. The authors found that a specification that control unobserved individual heterogeneity and spatial autocorrelation is better than any other specification, where these factors are ignored, in terms of predictive accuracy. Irwin (2010), Irwin and Geoghegan (2001) and Plantinga and Irwin (2006) are other references in land use modeling.

This work is innovative with respect to the literature on land use studies as firstly it takes into account the role of agricultural technology over agricultural and forestry uses, and secondly, it takes into account the interdependencies of land use and in a concomitant way, the spatial neighborhood effect, both elements, present in the System of Simultaneous Spatial Equations.

In addition to this introductory section, this article is divided as follows. The second section presents a discussion of the relationship between technology and land use, as well as notes on neighborhood effects in agriculture. The third describes the theoretical model, database, as well as the empirical implementation. The fourth section presents and discusses the results. The fifth section verifies the validity of the results, accomplishing, for that, tests of robustness. Finally, the sixth section presents the final considerations.

2 The relationship between agricultural technology and land use

The Green Revolution initiated in the USA and Europe in the 50s, spread "modern agriculture" to agricultural areas of the world through the creation of new products and practices[1]. The adoption of agricultural innovations drastically affected the use and values of land. The growth of new cultivated varieties as well as the expansion of existing crops are some of the results of this process (Wu, 2014). However, the impacts of technology on land use are still controversial.

Green *et al.* (2005) argue that agricultural research and consequently the use of technologies is able to maintain areas of forests, limiting losses of biodiversity by increasing the productivity achieved by the agricultural sector. In addition, the use of technologies has direct impacts on the control of damage such as the recovery of erosive or remaining lands from the cattle raising (Ervin and Ervin, 1982) and pest control (Lichtenberg and Zilberman, 1986). Technologies that increase the efficiency of input use allow farmers to overcome the constraints imposed by the low quality of the land (Wu, 2014). Such dynamics significantly affect land prices by reducing the premium for higher quality land, which ultimately results in no further deforestation.

On the other hand, there are those who argue that increases in productivity from the use of new technologies can increase the profitability of agriculture compared to alternative land uses (less profitable agricultural crops or forest), encouraging the expansion of the agricultural frontier. This second view is tied to the economic view of profit maximization by the decision-making agent. Angelsen and Kaimowitz (1999) synthesize the results of several studies that analyze the causes of tropical deforestation. Regarding the use of technology, evidence of a positive relationship between technological improvement and increased deforestation was found (Southgate *et al.* 1991). Lambin *et al.* (2001) argue that 4% of all forest deforestation cases are explained by agricultural expansion. Also in this study, the use of technology in the agriculture and logging sectors is considered to be responsible for 107 of the 152 cases of deforestation (70%). Angus *et al.* (2009), in a study done in the United Kingdom, predict that in the next 50 years the development of new agricultural technology markets for agricultural products will lead to considerable changes in land use. The increase in agricultural varieties from the Green Revolution can expand the amount of land allocated to agriculture, a process reinforced by the greater adoption of technology by small farmers influenced by their lower access prices (Sunding and Zilberman, 2001).

Based on the two views mentioned above, two antagonistic hypotheses are arrived at:

Hypothesis 1: the use of agricultural technologies can enable the maintenance of agricultural areas, while preserving forest areas by raising productivity and/or occupying previously unproductive areas.

If hypothesis 1 is confirmed, the sign of the coefficients that relate the technological variables (physical and human capital) and agricultural land use should be negative,

[1] The concept of agricultural technology must be understood as the application of knowledge, science and engineering in agricultural and animal production systems (Wu, 2014).

indicating an increase in productivity (i.e. an equal or greater quantity of agricultural goods is produced in a smaller geographic space) and forest use should be positive.

Hypothesis 2: the increase in productivity leads to an increase in profit, favoring the expansion of agricultural activity and land use destined to the same, to the detriment of forest use.

Therefore, a positive signal is expected for the coefficients that relate the technological variables and the uses of the tillage and pasture soil, indicating, therefore, an extensive agricultural and, inversely, to find a negative signal to the forest use. In addition, some studies report technological spillovers from geographically close agricultural activities. The work of Case (1992), Best *et al.* (1998), Holloway *et al.* (2002), Staal *et al.* (2002), Rounsevell *et al.* (2003), Bandiera and Rasul (2006), Conley and Udry (2010), Wright *et al.* (2013), and Wollni and Andersson (2014) are on this theme. Case (1992) proves the interdependence between farmers about decisions taken in relation to the adoption of new technologies in Indonesia by means of a microeconomic model. Wright *et al.* (2013) evaluate the existence of spatial spillovers in the adoption of irrigation technology in Texas (USA). They used SAR (spatial lag) and SEM (spatial autoregressive error) models and did not find evidence of the neighborhood effect. According to Wollni and Andersson (2014) organic farming can minimize the effects of soil erosion. The authors emphasize the role of the diffusion of biological technologies on the use of the soil for organic agriculture. Study areas in some regions of Honduras were used. It was found that the greater the information about these techniques present in the vicinity, the more they positively influenced the increase in the organic crop that broke a degradation spiral.

In turn, Pardey *et al.* (2010) highlight the characteristics of the use of technology in agriculture, which follows: (i) the atomistic nature of agricultural production, unlike the industrial sector in which agglomeration is more evident; (ii) the spatial specificity of agricultural technologies, due to the biological nature of agricultural production, where appropriate technologies vary with changes in climate, soil types, topography, latitude, altitude and distance from markets; and (iii) great heterogeneity among existing establishments, implying differences in demand for technologies and innovations. The meeting of these factors can act as a block to any neighborhood effect in agricultural activities.

Based on the above, the last hypothesis of this study is formulated:

Hypothesis 3: technological spillover in agriculture exists and its effects on land use should not be disregarded.

If hypothesis 3 is confirmed, the coefficients that relate spatially-lagged technological variables and the types of land use should be statistically significant.

3 Methodology

3.1 Theoretical model

Evenson and Alves (2009) and Féres *et al.* (2009) use microeconomic assumptions for soil use analysis. The theoretical model used in this study is based on their work. The production function for each land use category is described as:

$$y_i = \mathcal{F}(n_i, I_i, T_i, X_i), i = 1,2, \dots, m \tag{1}$$

where i is the land use category, y_i is the product of the origin of land type i, n area of land used type i, I vector of inputs used in land type i, T vector of technology variables, X is the vector of other control variables. The profit function (π_i) associated with production for each category of land use is given by:

$$\pi_i = \sum p_{yi} y_i - \sum p_{Fi} F_i = \pi_i(p_{yi}, p_{Fi}, F_i) \tag{2}$$

It is assumed that p_{yi} and p_{Fi} are constant (cash) and $F = \langle n, I, T, X \rangle$. It is possible to write the following problem of profit maximization conditioned to the total amount of land:

$$max_{n_1, n_2, \dots, n_m} \left(\sum_{i=1}^{m} \pi_i (n_i, F_i - n_i) \right) s.a \sum_{i=1}^{m} n_i = N \tag{3}$$

From the first order conditions extracted from (3), we can derive the optimal land allocations for each type of use i, represented by the symbol n_i^*. These optimal areas are determined by the total area of the establishment and by the vector of explanatory variables, i.e. $n_i^* = \mathcal{F}(N, F_i)$. Therefore, two optimal allocation equations are obtained for the various types of land use:

$$\sum_{i=1}^{m} \frac{\partial n_i^*(N, F_i)}{\partial N} = 1 \, ; \sum_{i=1}^{m} \frac{\partial n_i^*(N, F_i)}{\partial F_i} = 0 \tag{4}$$

The above expressions (4) can be interpreted as follows: if there is a one hectare increase in the establishment area, this additional area should be allocated in such a way that the area variations of the different types of use also add up to one hectare. On the other hand, if there are changes in the categories (F_i), area reallocations between types of use must compensate, resulting in a zero net effect.

3.2 Data

3.2.1 Dependent variable

Land use (N): Firstly (model 1) the uses of the soil are classified according to three types of use; tillage (tl), pasture (pt) and forest (ft), following Féres *et al.* (2009). Percentages of these uses were calculated in relation to the total[2]. Then, in a second approach (model 2), the

[2] The total area refers to the sum of crop area, pasture, forest and others (degraded areas, areas for the construction of properties and roads).

crop category is disaggregated, bringing to the analysis a greater level of detail, filling a gap in the literature. In this phase, eight crops with greater utilization of cultivated area were selected according to reports from the Ministry of Agriculture, Livestock and Supply (MAPA) and verified with data from the Agricultural Census (2006). They are: cocoa (coc), coffee (cof), cane (can), Brazil nuts (che), beans (bea), maize (mai), perishable foods[3] (per) and soy (soy). The data were extracted from the Agricultural Census of 2006 provided by the Brazilian Institute of Geography and Statistics (IBGE).

3.2.2 Variable of Interest

Agricultural technology (T): Two vectors make up the agricultural technology category. The first represents the use of physical agricultural technological capital (k). For this, the ratio between the number of tractors (with more than 100 hp) and the number of agricultural establishments was adopted as proxy. As source we used the 2006 Agricultural Census, made available by IBGE. The second represents agricultural human capital (h). The ratio between the total number of skilled workers in the agricultural sector (agricultural engineers, agronomy engineers and researchers in agronomic sciences) and agricultural establishments was used as a metric. The data used were provided by the Annual Social Information Report (RAIS), linked to the Ministry of Labor and Employment (MTE).

We assume, as Mendelsohn *et al.* (1994) and Evenson and Alves (2009) do, that changes in soil use as a function of technological variables (i.e. $\partial N/\partial T$) can be perceived using cross-section data[4].

3.2.3 Other Control Variables

Climatic conditions[5] *(C)*: The temperature and precipitation averages were selected in quarterly bands[6] to adapt climatic moments to the cultivation decisions. The climatic data constructed by the Climate Research Unit of University of East Anglia and compiled by the Institute for Applied Economic Research (IPEADATA) are results of a mean of temperature and precipitation variables for the period between 1961 and 1991. In this study, it is assumed that these averages are long-term and, in turn, capable of reflecting a climate pattern of Brazilian municipalities. In addition, it is expected that these values have not changed abruptly in the last two decades. Climatic variables are included to verify the influence of temperature and precipitation changes on land use.

[3] The category 'perishable' was created and represents food that rots rapidly and requires a more specialized transportation system. This group includes: avocado, pineapple, potato, onion, guava, orange, lemon, apple, papaya, mango, passion fruit, watermelon, pear, peach, tangerine, tomato and grape.

[4] The lack of statistical data in periods before or after 2006 precludes the use of a panel approach. There is data incompatibility between the Agricultural Census of 1996 and 2006, mainly in terms of disaggregated land use data.

[5] Decker *et al.* (1986), Adams (1989), Sanghi *et al.* (1997), Evenson and Alves (2009), Féres *et al.* (2009) and Faria and Haddad (2017) highlight the relationship between climatic variables and land use in Brazilian regions.

[6] They are: December/January/February (*djf*), March/April/May (*mam*), June/July/August (*jja*) and September/ October/November (*son*).

Edaphic conditions (E): Dummies related to Brazilian biomes[7] were used as proxy. Two reasons justify this: (i) the soil belonging to the same biome has similar edaphic characteristics, in order to help us explain how appropriate the crops are to a particular type of soil and (ii) to observe the role of biomes in relation to land use.

Spatial interdependence (S): Two spatial dependencies were used in this work and are actually the result of the interaction between the spatial weighting matrix (W) and the chosen variables: (i) WN which shows the average of the type n soil in the neighbors, Serving as an indicator of spatial patterns and (ii) technological interdependence in which we have Wk and Wh that symbolize the average use of some technology or technical knowledge in the neighborhood, serving as a proxy for spillovers.

For more details about the variables used, contact the authors. Due to the difference between the units of measurement of the variables, it was decided to standardize them[8]. The results should, therefore, be interpreted as the standard deviation. 5507 Brazilian municipalities are considered as the unit of spatial analysis.

3.3 Exploratory analysis of spatial data: spatial autocorrelation tests

The presence of spatial autocorrelation was tested globally and locally. The Moran Index (*I de Moran*) and the LISA index were used respectively. The existence of spatial patterns was verified for the dependent variables (land use) and the technology variables, which later will be useful to test the hypothesis of technological spillovers. Moran's I coefficients were calculated and their values are reported in Table 1.

Given the statistical evidence shown in Table 1, the null hypothesis of spatial randomness below a significance level of 1% is rejected. Coefficient I provides a clear indication that the 'uses' of the soil and the variables of technology are auto-correlated in space throughout the Brazilian municipalities. The magnitude of the statistic informs us that the variables soy (*soy*), cocoa (*coc*) and cane (*can*) present a strong spatial concentration.

The LISA indicator (Local Indicator of Spatial Association), proposed by Anselin (1995), has the capacity to capture local patterns of spatial autocorrelation. The local Moran coefficient I (I_i) breaks down the global autocorrelation indicator in the local contribution of each observation into four categories HH - high/high, LL - low/low, HL - high/low and LH - low/high (Almeida, 2012; Anselin *et al.*, 2013). The generated clusters maps are shown

[7] They are: Amazon (*damz*), Cerrado (*dcer*), Atlantic Forest (*dmatl*), Caatinga (*dcaa*), Pampa (*dpmp*) and Pantanal (*dptn*). The base category adopted will be Amazon (*damz*).

[8] In this case it is useful to obtain regression results when all variables involved, dependent as well as all independent variables are standardized, for two reasons. First, the unit of measurement of the variables becomes irrelevant, making them equal so that the estimated coefficients (denominated as standard coefficients or beta coefficients) will be given in terms of units of standard deviation, facilitating the interpretation of the results. Second, it is possible to rank the importance of the explanatory variables from the magnitudes of the standardized coefficients, or rather, the larger the standardized coefficient, the “more important” the variable will be compared to the other variables (Wooldridge, 2015).

below. Expectations about the distribution of variables in space were satisfied (Figure 1), demonstrating the reliability of the data used. In addition, we verified that the variables used are not randomly distributed in space, but spatially grouped. This suggests that econometric analysis incorporates geographic neighborhood effects.

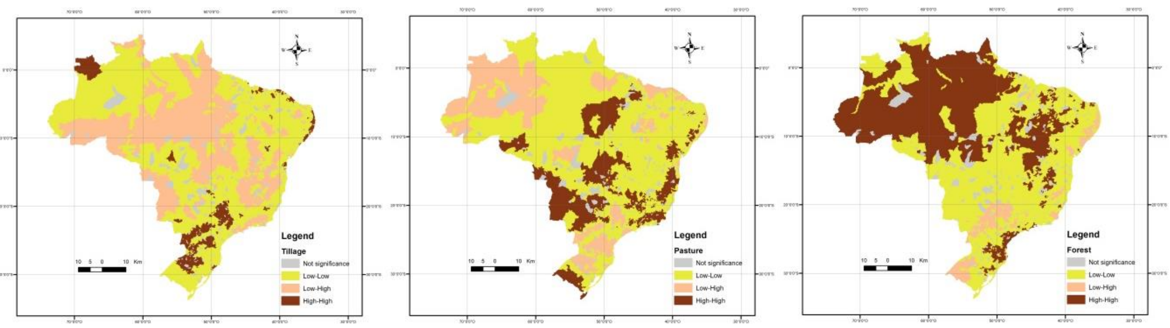
Table 1. Spatial autocorrelation statistics - Moran's I*

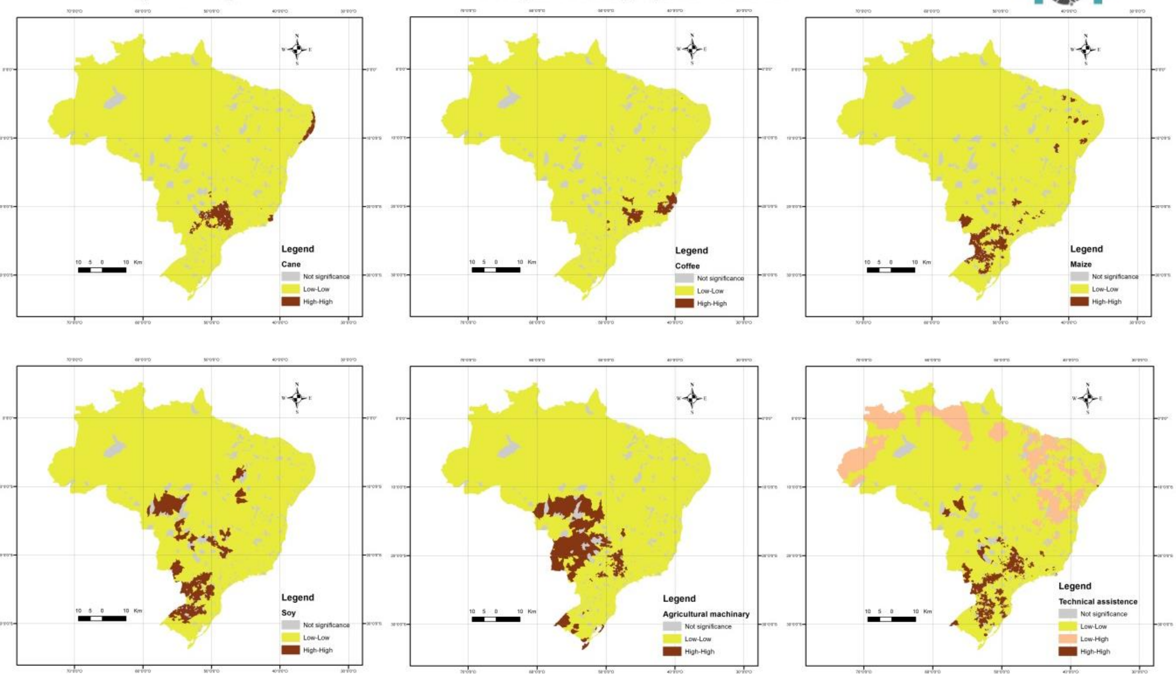
Variable**	Moran's I	E(I)	*p*-value***
Tillage (*tl*)	0.6602	-0.0002	0.001
Pasture (*pt*)	0.6200	-0.0002	0.001
Forest (*ft*)	0.5234	-0.0002	0.001
Cocoa (*coc*)	0.7409	-0.0002	0.001
Coffee (*cof*)	0.6626	-0.0002	0.001
Cane (*can*)	0.7127	-0.0002	0.001
Brazil nuts (*che*)	0.4233	-0.0002	0.001
Bean (*bea*)	0.5464	-0.0002	0.001
Maize (*mai*)	0.6226	-0.0002	0.001
Perishable foods (*per*)	0.2804	-0.0002	0.001
Soybean (*soy*)	0.7553	-0.0002	0.001
Physical capital – Agricultural machinery (*k*)	0.2617	-0.0002	0.001
Human capital – Technical assistance (*h*)	0.5154	-0.0002	0.001

Notes: (1) * The neighborhood matrix $k15$ was chosen using the criterion set forth in Stakhovych and Bijmolt (2009). (2) ** The variables are expressed in relation to the total. (3) *** The empirical pseudo-significance is based on 99,999 random permutations.

Source: Authors' calculations, using the software GeoDa.

Figure 1. Map of LISA clusters for selected variables*





Note: (1) * The scale value must be multiplied by 100.

Source: Authors' calculations, using the R software, ArcView 3.2 and ArcMap 10.3.

3.4 Empirical Implementation

Land resources are limited, and any decision about its use is interdependent and requires space exclusivity. Thus, if one chooses to plant crops on land, this implies not choosing pasture or forest and vice versa. This produces a potential correlation in terms of error (ε) of the equations belonging to the system. Therefore, there is a problem of simultaneity of equations that explain land use and the detection of spatial autocorrelation. Note the presence of a crossed spatial lag, indicating that the average of the variable of interest in neighbors explains the basic endogenous variable, in addition to the feedback simultaneity, formalizing a concept of circular causation. When using the Simultaneous Spatial Equation System framework, two problems are avoided: (i) a simultaneous estimation method takes into account the correlation between these errors. Methods that estimate each equation alone ignore the correlation between the equations and are therefore not efficient; and (ii) it prevents the omitted variable bias when not excluding the aspect of spatial dependency.

This study will show two models. Model 1 makes use of the dependent variables in an aggregate way, that is to say, tillage, pasture and forest, and follows the structure presented in

$$\begin{cases} tl_i = \beta_{01} + \beta_{11}Wtl_i + \beta_{21}N'_{1i} + \beta_{31}WN'_{1i} + \beta_{41}T_i + \beta_{51}WT_i + \beta_{61}C_i + \beta_{71}E_i + \varepsilon_1 \\ pt_i = \beta_{02} + \beta_{12}Wpt_i + \beta_{22}N'_{2i} + \beta_{32}WN'_{2i} + \beta_{42}T_i + \beta_{52}WT_i + \beta_{62}C_i + \beta_{72}E_i + \varepsilon_2 \\ ft_i = \beta_{03} + \beta_{13}Wft_i + \beta_{23}N'_{3i} + \beta_{33}WN'_{2i} + \beta_{43}T_i + \beta_{53}WT_i + \beta_{63}C_i + \beta_{73}E_i + \varepsilon_3 \end{cases} \quad (5)$$

where i is the 5507 Brazilian municipalities analyzed, W is the spatial weighting matrix of neighbors (k-15), which when multiplied by the variables tl, pt and ft represent, respectively, the averages of the tillage, pasture and forest areas in the neighbors. N'_{1i}, N'_{2i} and N'_{3i} represent the use of the other soil types, respectively, which are the vectors $\langle pt, ft\rangle$, $\langle tl, ft\rangle$ and $\langle tl, pt\rangle$ resulting in two parameters estimated by the equation. These were spatially lagged and composite WN'. The technology variables are represented by T and their spillovers (WT). In C the vectors of the climatic variables (temperature and precipitation, or their interaction) are found. In E we find the vectors of edaphic variable.

Model 2 breaks down the tillage use into eight different types of crops already mentioned, besides the pasture and forest categories to achieve a greater level of detail in the information obtained. Its structure is as follows (6).

$$\begin{cases} coc_i = \beta_{01} + \beta_{11}Wcoc_i + \beta_{21}N'_{1i} + \beta_{31}WN'_{1i} + \beta_{41}T_i + \beta_{51}WT_i + \beta_{61}C_i + \beta_{71}E_i + \varepsilon_1 \\ cof_i = \beta_{02} + \beta_{12}Wcof_i + \beta_{22}N'_{2i} + \beta_{32}WN'_{2i} + \beta_{42}T_i + \beta_{52}WT_i + \beta_{62}C_i + \beta_{72}E_i + \varepsilon_2 \\ can_i = \beta_{03} + \beta_{13}Wcan_i + \beta_{23}N'_{3i} + \beta_{33}WN'_{3i} + \beta_{43}T_i + \beta_{53}WT_i + \beta_{63}C_i + \beta_{73}E_i + \varepsilon_3 \\ che_i = \beta_{04} + \beta_{14}Wche_i + \beta_{24}N'_{4i} + \beta_{34}WN'_{4i} + \beta_{44}T_i + \beta_{54}WT_i + \beta_{64}C_i + \beta_{74}E_i + \varepsilon_4 \\ bea_i = \beta_{05} + \beta_{15}Wbea_i + \beta_{25}N'_{5i} + \beta_{35}WN'_{5i} + \beta_{45}T_i + \beta_{55}WT_i + \beta_{65}C_i + \beta_{75}E_i + \varepsilon_5 \\ mai_i = \beta_{06} + \beta_{16}Wmai_i + \beta_{26}N'_{6i} + \beta_{36}WN'_{6i} + \beta_{46}T_i + \beta_{56}WT_i + \beta_{66}C_i + \beta_{76}E_i + \varepsilon_6 \\ per_i = \beta_{07} + \beta_{17}Wper_i + \beta_{27}N'_{7i} + \beta_{37}WN'_{7i} + \beta_{47}T_i + \beta_{57}WT_i + \beta_{67}C_i + \beta_{77}E_i + \varepsilon_7 \\ soy_i = \beta_{08} + \beta_{18}Wsoy_i + \beta_{28}N'_{8i} + \beta_{38}WN'_{8i} + \beta_{48}T_i + \beta_{58}WT_i + \beta_{68}C_i + \beta_{78}E_i + \varepsilon_8 \\ pt_i = \beta_{09} + \beta_{19}Wpt_i + \beta_{29}N'_{9i} + \beta_{39}WN'_{9i} + \beta_{49}T_i + \beta_{59}WT_i + \beta_{69}C_i + \beta_{79}E_i + \varepsilon_9 \\ ft_i = \beta_{010} + \beta_{110}Wft_i + \beta_{210}N'_{10i} + \beta_{310}WN'_{10i} + \beta_{410}T_i + \beta_{510}WT_i + \beta_{610}C_i + \beta_{710}E_i + \varepsilon_{10} \end{cases} \quad (6)$$

The disaggregated model operates similar to the previous one presented. The difference is the variable N'(and therefore WN') that expresses all of the land uses, except the dependent variable, so that for this vector nine parameters are estimated by the equation.

Based on spatial econometric models, we attempt to verify Hypotheses 1 and 2 related to the coefficients estimated for the k and h variables, as well as Hypothesis 3, with coefficients associated to the variables Wk and Wh. In addition, we consider the idea of spillovers by means of the spatial lag of the independent variables (WX). The Spatial Durbin Model assumes the existence of a spatial diffusion process related to the dependent variable, justifying the inclusion of the spatially lagged endogenous variable (WN).

The Kelejian and Robinson (1993) estimator was used to generate the results. Its implementation follows the steps presented in Rey and Boarnet (2004). First, the adjusted values of the endogenous variables are shown on the right side of the equation ($pr\ N$) and were obtained by OLS regression of the dependent variable on the explanatory variables (X) and their spatial lags (WX). Then, the adjusted values of the additional endogenous variables ($pr\ WN$) were regressed by these variables against the explanatory variables (X) and their spatial lags (WX). Third, the adjusted values were replaced in the original system, estimated by OLS, using robust standard errors in order to correct heteroskedasticity. The KR estimators are considered to be consistent. This seems insufficient when working with finite samples, however, this is still superior to the alternative MQ2EE (Rey and Boarnet, 2004).

Furthermore, two other specifications were used as tests of robustness. The first, following Huang *et al.* (2017) and Ma *et al.* (2014) estimates the coefficients using the function in its translog format. Unlike the traditional Cobb-Douglas and CES (Mal *et al.*, 2011; Manjunatha *et al.*, 2013), the translog function imposes no restriction on the values of the elasticity of substitution, nor does it assume homogeneity of the function (Wilson *et al.*, 1998). Thus, it is convenient to use the translog function in the measurement of non-neutral technological modifications. The second specification follows a spatial cross-regression model (SLX). From this, the direct, indirect and total effects of the explanatory variables of the model could be calculated (Anselin *et al.*, 2013; LeSage and Pace, 2009). The main results of these tests are presented in section 5 (Tables 4 and 5).

4 Econometric Results

Table 2 shows the results of the aggregate model composed of three endogenous variables, namely: tillage, pasture and forest[9]. The coefficients associated to the use of physical (k) and human (h) technological capital were positive and statistically significant for the category of tillage. In this case, the interpretation is that if physical agricultural capital (k) increases by a standard deviation, on average, tillage varies by about 0.043 standard deviation, whereas, if agricultural human capital (h) increases by one standard deviation, cropping areas extend by 0.067 standard deviation. In turn, it can be observed that the use of technological physical capital (k) establishes a negative relationship with forest use (-0.027), as well as human agricultural capital (-0.077). These conclusions are in line with the validation of Hypothesis 2 (described in section 2), that is, the use of agricultural technology in the form of physical capital (agricultural machinery), as well as in the form of human capital (technical assistance), allows greater productive efficiency, translated into greater profitability and expansion of agricultural areas. It is also possible to observe a negative relationship between physical/human capital and land use for pasture. In other words, the results show in part that technology is encouraging the expansion of agricultural areas. Note that this does not mean that Brazilian agriculture is of the extensive type, but that the cultivated area is positively linked to the adoption of agricultural technologies. The evidence seen in this paragraph follow the line of reasoning seen in Angelsen and Kaimowitz (1999) and Lambin *et al.* (2001), who found evidence of a positive relationship between the adoption of technology and deforestation.

In addition, in Table the technological neighborhood effect can be seen, expressed by the variables Wk and Wh. That is, the use of agricultural technology by neighbors influences the way the local soil is used. This validates Hypothesis 3 described in section 2. It can be seen that the agricultural technology, now adopted under the influence of neighbors, leads to a relative reduction in the domestic soil for agricultural or pasture purposes. For example, if the agricultural physical capital of the neighborhood (Wk) increases by a standard deviation, on average, tillage and pasture will vary respectively by -0.127 and -0.058 standard deviation. Such evidence corroborates the works of Case (1992), Wollni and Andersson (2014) and Wright *et al.* (2013) who also found signs of technological spillovers in agricultural activities. Some channels may explain this technological spillover. The best known is explained by the epidemiological models (see Griliches, 1957; Mansfield, 1961) that report the existence of a contagious effect or "word-of-mouth" communication. By realizing the gains of their neighbors (e.g. productivity increase), economic agents, in this case, farmers seek to adopt a similar technology in order to enjoy the same benefits. It should be noted that this contagion

[9] All model 1 results can be obtained by contacting the authors.

effect occurs between agents from the same region and between regions (e.g. municipalities), the latter being explained by the variables Wk and Wh. The economic literature identifies two other basic approaches to technological diffusion, namely, the models of balanced diffusion (David, 1969; Davies, 1979; Stoneman and Ireland, 1983) and evolutionary models (Iwai, 1984a, 1984b; Metcalfe, 1998; Nelson and Winter, 1982; Silverberg *et al.*, 1988).

Table 2. Determinants of agricultural and forest land use for model 1: estimation by System of Simultaneous Equations in Space (2006).

Explanatory variables	Tillage (*tl*)	Pasture (*pt*)	Forest (*ft*)
	Coef.	Coef.	Coef.
Dependent variable spatially lagged (*prWN*)	1.330***	0.752***	0.822***
	(0.090)	(0.070)	(0.088)
Physical capital (*k*)	0.043***	-0.024***	-0.027***
	(0.006)	(0.006)	(0.008)
Human capital (*h*)	0.067***	-0.080***	-0.077***
	(0.008)	(0.008)	(0.010)
Spatially lagged physical capital (*Wk*)	-0.127***	-0.058**	0.004**
	(0.031)	(0.024)	(0.021)
Spatially lagged human capital (*Wh*)	-0.112***	-0.040*	0.000
	(0.019)	(0.022)	(0.019)
Other control variables			
Climatic variables	Yes	Yes	Yes
Edaphic variables	Yes	Yes	Yes
Variables of spatial interdependence	Yes	Yes	Yes
Instrumental variables (time-lag land use)	Yes	Yes	Yes
AIC	4602.09	5676.93	7963.42
R-squared	0.865	0.836	0.752

Notes: (1) The estimated standard errors are robust and presented in parentheses. (2) *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Source: Authors' calculations, using R software.

However, an aggregate model may omit relevant information about the behavior of different crop types and therefore, a disaggregated model is required[10]. Or rather, despite the evidence from the aggregate model showing that the area devoted to agriculture establishes a positive relationship with the variables of agricultural technology (particularly for human capital in Table 2), there may be some crops that behave differently, that is, the use of technology causes there to be a reduction in its cultivated area. Cocoa, coffee, sugarcane, maize and soybeans presented coefficients associated with the use of positive and statistically significant physical and/or human technological capital (Table 3). This favors Hypothesis 2 (see section 2), which assumes that the use of technologies increases the productivity and profitability of agricultural activities, thus determining the extent of land allocated to these activities. In turn, there was a negative relationship between the use of agricultural technology and the cultivation of perishable food. This fact meets Hypothesis 1 or can be interpreted as the change of use for more profitable and/or less risky activities such as sugarcane, corn and soy. Also in Table 3, it can be observed that for some types of cultivation the effect of technological diffusion in agriculture was found, reaffirming Hypothesis 3.

[10] All model 2 results can be obtained by contacting the authors.

Table 3. Determinants of agricultural and forest land use for model 2: estimation by System of Simultaneous Equations in Space (2006)

Explanatory variables	Cocoa (*coc*)	Coffee (*cof*)	Cane (*can*)	Brazilian nuts (*che*)	Bean (*bea*)	Maize (*mai*)	Perishable (*per*)	Soy (*soy*)	Pasture (*pt*)	Forest (*ft*)
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Dependent variable spatially lagged (*prWN*)	3.606***	-2.841***	1.407***	-3.307***	1.477***	1.929***	1.875***	1.777***	0.738***	0.782***
	(0.869)	(0.548)	(0.158)	(0.578)	(0.116)	(0.146)	(0.316)	(0.099)	(0.066)	(0.090)
Physical capital (*k*)	-0.003	-0.013	0.040***	-0.009	-0.003	0.009	-0.019	0.053***	-0.026***	-0.034***
	(0.006)	(0.008)	(0.007)	(0.007)	(0.010)	(0.008)	(0.015)	(0.006)	(0.007)	(0.008)
Human capital (*h*)	0.014**	0.065***	-0.016**	-0.009	0.004	0.046***	-0.032**	0.072***	-0.091***	-0.082***
	(0.007)	(0.010)	(0.009)	(0.010)	(0.013)	(0.010)	(0.018)	(0.008)	(0.008)	(0.010)
Spatially lagged physical capital (*Wk*)	0.001	-0.057**	-0.147***	-0.043**	0.143***	-0.001	-0.058	-0.026	-0.025	-0.002
	(0.017)	(0.024)	(0.048)	(0.021)	(0.029)	(0.023)	(0.057)	(0.021)	(0.028)	(0.007)
Spatially lagged human capital (*Wh*)	-0.006	0.149***	-0.010	0.079***	-0.001	-0.157***	-0.001	-0.098	0.046**	-0.008
	(0.017)	(0.027)	(0.023)	(0.021)	(0.026)	(0.039)	(0.038)	(0.018)	(0.023)	(0.008)
Other control variables										
Climatic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Edaphic variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Variables of spatial interdependence	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrumental variables (time-lag land use)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	3858.03	6944.02	6475.66	6574.02	9660.63	7547.26	13518.79	4463.78	5669.36	8000.36
R-squared	0.882	0.795	0.811	0.808	0.664	0.771	0.323	0.869	0.837	0.751

Notes: (1) The estimated standard errors are robust and presented in parentheses. (2) *** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Source: Authors' calculations, using R software.

5 Robustness Tests

In order to verify the validity of the results presented in section 4, tests of robustness were implemented. The first one estimates the coefficients of the model using the translog format. The second follows an SLX specification[11]. Table 4 shows the results of the coefficients using a translog specification. A first aspect to be noted is the degree of fit of the model, indicated by R-squared, which presented lower values compared to the other models presented previously, with specifications that followed a Cobb-Douglas structure. In spite of this, the positive and statistically significant effect of the use of agricultural physical capital on tillage can be seen. Regarding forest use, a negative relationship is found again, reinforcing the validity of Hypothesis 2.

Table 4. Determinants of agricultural and forest land use for model 1: estimation by System of Simultaneous Equations in Space using Translog function. Period: 2006.

Explanatory variables	Tillage (*tl*)	Pasture (*pt*)	Forest (*ft*)
	Coef.	Coef.	Coef.
Physical capital (k)	0.854***	-1.879***	-1.479***
	(0.304)	(0.219)	(0.277)
Human capital (h)	-0.174	-0.164	-0.071
	(0.586)	(0.379)	(0.540)
Physical capital (k) × Physical capital (k)	-0.043	-0.054	-0.055
	(0.087)	(0.037)	(0.049)
Human capital (h) × Human capital (h)	-0.060	-0.076	-0.075
	(0.425)	(0.306)	(0.399)
Physical capital (k) × Human capital (h)	0.044	0.040	0.040
	(0.151)	(0.406)	(0.077)
Other control variables			
Climatic variables	Yes	Yes	Yes
Edaphic variables	Yes	Yes	Yes
Variables of spatial interdependence	Yes	Yes	Yes
R-squared	0.391	0.391	0.239

Notes: (1) The estimated standard errors are robust and presented in parentheses.

(2) The other results, referring to the disaggregated model can be obtained by contacting the authors.

(3) *** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Source: Authors' calculations, using R software.

Table 5 shows the negative direct effect of the variable of human capital on the uses of pasture and forest, and the positive effect for tillage. In this case, the interpretation is that if domestic human capital (h) increases by a standard deviation, on average, tillage, pasture and forest uses will respectively vary by +0.033, -0.064 and -0.060 standard deviation. For this variable, we also found a negative and statistically significant indirect effect related to the uses of pasture and forest. If the agricultural human capital of the neighborhood (Wh)

[11] All robustness test results, including estimates for the disaggregated model, are available upon request from the authors.

increases by a standard deviation, on average, pasture and forest uses will vary respectively by -0.103 and -0.041 standard deviation, validating again Hypotheses 2 and 3.

Table 5. Determinants of agricultural and forest land use for model 1: estimation by System of Simultaneous Equations in Space using spatial cross-regression model (SLX). Period: 2006.

Explanatory variables	Tillage (*tl*)	Pasture (*pt*)	Forest (*ft*)
	Coef.	Coef.	Coef.
Physical Capital (*k*)	0.049*** (0.004)	-0.023*** (0.005)	-0.013** (0.006)
Human Capital (*h*)	0.033*** (0.005)	-0.064*** (0.006)	-0.060*** (0.008)
Spatially Lagged Physical Capital (*Wk*)	0.273*** (0.012)	-0.183*** (0.013)	0.061 (0.017)
Spatially Lagged Human Capital (*Wh*)	0.120*** (0.011)	-0.103*** (0.012)	-0.041*** (0.015)
Other control variables			
Climatic variables	Yes	Yes	Yes
Edaphic variables	Yes	Yes	Yes
Variables of spatial interdependence	Yes	Yes	Yes
Instrumental variables (time-lag land use)	Yes	Yes	Yes
AIC	2011.45	2732.05	5829.84
R-squared	0.916	0.904	0.832
Direct and indirect effects			

Explanatory variables	Dependent variable: Tillage (*tl*)		
	Direct (I)	Indirect (II)	Total (III)
Physical capital (*k*)	0.049***	0.273***	0.322***
Human capital (*h*)	0.033***	0.120***	0.154***
Climate - December, January and February (*cdjf*)	0.218***	-0.261***	-0.042***
Climate - March, April and May (*cmam*)	0.036	0.258***	0.294***
Climate - June, July and August (*cjja*)	-0.099***	-0.088**	-0.188***
Climate - September, October and November (*cson*)	-0.066	0.340***	0.273***
Climate - December, January and February squared (*cdjf2*)	-0.060	-0.204***	-0.265***
Climate - March, April and May squared (*cmam2*)	-0.055	0.107**	0.051**
Climate - June, July and August squared (*cjja2*)	0.076***	-0.048*	0.027***
Climate - September, October and November squared (*cson2*)	0.002	-0.136**	-0.134*
Biome - Caatinga (*dcaa*)	0.022	-0.041	-0.018
Biome - Cerrado (*dcer*)	0.132**	0.027	0.160*
Biome - Pampa (*dpmp*)	-0.044	-0.467***	-0.511***
Biome - Pantanal (*dptn*)	-0.060	0.085	0.025
Biome - Atlantic Forest (*dmatl*)	0.120*	0.029	0.150
Pasture (*pt*)	-0.446***	0.255***	-0.190***
Forest (*ft*)	-0.294***	0.128***	-0.165***
Dummie for residuals outliers	0.461***	0.452***	0.914***
Time-lag dependent variable (*Nt-1*)	0.256***	0.311***	0.568***

Explanatory variables	Dependent variable: Pasture (*pt*)		
	Direct (IV)	Indirect (V)	Total (VI)
	Direct	Indirect	Total
Physical capital (*k*)	-0.023***	-0.183***	-0.207***
Human capital (*h*)	-0.064***	-0.103***	-0.167***
Climate - December, January and February (*cdjf*)	-0.105	-0.445***	-0.551***
Climate - March, April and May (*cmam*)	-0.209***	0.190***	-0.018***

Climate - June, July and August (*cjja*)	-0.096***	-0.228***	-0.325***
Climate - September, October and November (*cson*)	-0.042	0.111	0.068
Climate - December, January and February squared (*cdjf2*)	0.090	0.453***	0.543***
Climate - March, April and May squared (*cmam2*)	0.181***	-0.227***	-0.046***
Climate - June, July and August squared (*cjja2*)	0.043**	0.157***	0.200***
Climate - September, October and November squared (*cson2*)	-0.053	-0.037	-0.087
Biome - Caatinga (*dcaa*)	-0.075	-0.207**	-0.282**
Biome - Cerrado (*dcer*)	-0.219***	-0.117*	-0.337***
Biome - Pampa (*dpmp*)	0.293***	0.383***	0.676***
Biome - Pantanal (*dptn*)	0.202	0.941*	1.144*
Biome - Atlantic Forest (*dmatl*)	-0.112*	-0.054	-0.166*
Tillage (*tl*)	-0.507***	0.255***	-0.251***
Forest (*ft*)	-0.337***	0.124***	-0.212***
Dummie for residuals outliers	0.528***	0.508***	1.037***
Time-lag dependent variable (*Nt-1*)	0.210***	0.316 ***	0.526***
	Dependent variable: Forest (*ft*)		
Explanatory variables	Direct (VII)	Indirect (VIII)	Total (IX)
Physical capital (*k*)	-0.013**	0.061	-0.007**
Human capital (*h*)	-0.060***	-0.041***	-0.102***
Climate - December, January and February (*cdjf*)	-0.209**	0.324***	0.115***
Climate - March, April and May (*cmam*)	-0.131**	-0.096	-0.228**
Climate - June, July and August (*cjja*)	0.014	0.153***	0.168***
Climate - September, October and November (*cson*)	0.319***	0.262**	0.582***
Climate - December, January and February squared (*cdjf2*)	0.183**	-0.333***	-0.150***
Climate - March, April and May squared (*cmam2*)	0.161***	0.046	0.207***
Climate - June, July and August squared (*cjja2*)	-0.036	-0.062**	-0.099*
Climate - September, October and November squared (*cson2*)	-0.295***	-0.069	-0.364**
Biome - Caatinga (*dcaa*)	0.234**	-0.128	0.106**
Biome - Cerrado (*dcer*)	0.181**	-0.051	0.129**
Biome - Pampa (*dpmp*)	-0.045	-0.305**	-0.351*
Biome - Pantanal (*dptn*)	-0.206	0.057	-0.148
Biome - Atlantic Forest (*dmatl*)	-0.063	-0.066	-0.130
Tillage (*tl*)	-0.600***	0.314***	-0.285***
Pasture (*pt*)	-0.643***	0.320***	-0.322***
Dummie for residual outliers	0.635***	0.317***	0.953***
Time-lag dependent variable (*Nt-1*)	0.148***	0.477***	0.626***

Notes: (1) The estimated standard errors are robust and presented in parentheses.

(2) The other results, referring to the disaggregated model can be obtained by contacting the authors.

(3) *** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Source: Authors' calculations, using R software.

Table 5, columns (I) to (IX), reports the estimates of the direct, indirect and total effects, derived from the SLX model. Firstly, the values of the direct and total effects indicate that the use of physical capital (k) in a given region will expand the land use for tillage (+0.049; +0.322), but will reduce for pasture areas (-0.023; -0.207) and forest areas (-0.013; -0.007). These results point towards Hypothesis 2. The indirect effects are also significant, reinforcing these results. For tillage and pasture, the values obtained were +0.273 and -0.183, respectively, and for forest use +0.061 (not significant). This indicates that the use of agricultural physical capital by neighbors is capable of influencing the way local soil is used. In all these cases, the magnitude of the indirect effect (spillover) is greater than the direct effect. This goes towards the confirmation of Hypothesis 3.

6 Conclusion

This article attempted to understand the relationship between the adoption of technology and agricultural and forest land use in Brazilian municipalities. The questions that guided this study are: (i) what is the impact of technological elements (physical and human capital) on the use of agricultural and forest land in Brazil? and (ii) is there any influence of the neighborhood in this relationship? To answer these, the variables of agricultural and forest land use were regressed in relation to physical and human technological capital variables. In addition, other factors were considered in the equations, such as climatic conditions, soil conditions, and spatial interdependence.

Since land as a resource is limited, the decision about its use is interdependent and requires exclusivity of the space (i.e. when choosing to plant crops, this implies not choosing pasture or forest and vice versa). Therefore, there is a problem of simultaneity of equations that explain land use. Therefore, the adopted method follows the structure of the Simultaneous Space Equation System models.

Three results are worth highlighting.

First, in general, the results show a positive relationship between the variables of agricultural technology (physical and human capital) and land use for tillage and a negative relationship between technology variables and land use for pasture and forests, towards the validation of Hypothesis 2. One possible explanation for this is the increased productivity/profitability of the land dedicated to farming as a result of the use of technology. Parallel to this scenario, we have the non-preservation of forest areas.

Second, we observe that the relationship between agricultural technology (machines and technical assistance) and use of soil for tillage depends on the crop analyzed. Cocoa, coffee, sugarcane, maize and soybeans presented coefficients associated with the use of positive and statistically significant technological and/or human technological capital, reaffirming Hypothesis 2. In turn, a negative relationship was found between the use of agricultural technology and the cultivation of pasture and perishable foods.

Third, as the models incorporate spatially-lagged technological variables, we could perceive the presence of technological spillovers in agriculture and how these affect land use decisions, validating Hypothesis 3. The robustness tests, which estimated the coefficients of the model using a SLX type specification, reaffirmed the main results of this study.

This article contributes to the empirical literature on the impacts of agricultural technology on agricultural and forest land use in Brazil, opening a new debate on this research topic. Future related work could consider other proxies for the agricultural technology variable in addition to testing other levels of disaggregation for the dependent variable. In addition, this study serves to motivate future work that may advance this theme, investigating the impacts of technology on biome areas.

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