Adoption of No-Tillage System and Brazilian natural areas:
What can a Spatial Propensity Score Matching analysis tell us?

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Abstract

Agrotechnology adoption has a direct impact on land use management. In this article we analyze the causal effect of adopting the No-Tillage System (NTS) on natural and cultivated areas in Brazilian municipalities using the Spatial Propensity Score Matching method. We perform econometric models using different treatment definitions. Our statistical results show that the adoption of NTS had a positive effect on the natural and cultivated agricultural areas of the treated municipalities. The evidence from this case study indicates that the use of soil management technology can lead to environmental preservation, confirming Borlaug's hypothesis. We believe that the recovery of eroded land and the increase in agricultural productivity may partially explain these results.

Resumo

A adoção de agrotecnologias têm impacto direto na gestão do uso da terra. Neste artigo, analisamos o efeito causal da adoção do Sistema de Plantio Direto (NTS) em áreas naturais e cultivadas em municípios brasileiros utilizando o método Spatial Propensity Score Matching. Realizamos modelos econométricos usando diferentes definições de tratamento. Nossos resultados estatísticos mostram que a adoção de NTS teve um efeito positivo nas áreas agrícolas naturais e cultivadas dos municípios tratados. As evidências deste estudo de caso indicam que o uso de tecnologia de manejo do solo pode levar à preservação ambiental, confirmando a hipótese de Borlaug. Acreditamos que a recuperação de terras erodidas e o aumento da produtividade agrícola podem explicar parcialmente esses resultados.

Keywords

No-Tillage System, Natural Areas, Spatial Propensity Score Matching

JEL code

Q15, Q55

1. Introduction

Brazil is the largest producer of agricultural goods in the world. According to data from the National Food Supply Company (Conab), in 1980 production was 50.8 million tonnes (Mton) and reached 123.1 Mton in 2000 and 237.6 Mton in 2017. Other data show the trajectory of the expansion of Brazilian agriculture through the extension of planted areas. Also, according to data from Conab, in 1980 40.1 Mha of land were used and about 60.8 Mha in 2017. Much of the agricultural production serves foreign markets. The agricultural trade balance in 2018 totaled 81.6 billion dollars, while the total balance was 50.9 billion, according to the World Trade Organization (WTO). Sugar, soy, corn, orange juice, coffee, cotton, pork, poultry, and cattle are the main products exported.

In addition to the natural advantages (e.g., availability of agricultural land, water and adequate climatic conditions), the use of agricultural technology in the form of products and more efficient practices explain the increase in production and productivity in Brazilian agriculture. The synergy created from the 1970s, which involves the participation of the Brazilian Agricultural Research Corporation (Embrapa), research centers at universities, and farmers are at the center of this process (Suzigan & Albuquerque 2011).

The adoption of technology and the consequent economic-productive advancement of agriculture has direct effects on the management of land use. The recovery of previously non-agricultural soils, the possibility of switching to more profitable crops (e.g., soybeans, corn) are examples of agricultural technology acting on space. However, the relationship between agriculture and natural areas is certainly a most worrying point, in view (i) of the greater need to reduce Greenhouse Gases (GHG), directly related to global climate change (Miles & Kapos 2008, Reay et al. 2012, Schmitz et al. 2012, Havlík et al. 2013, Lamb et al. 2016, Mayer et al. 2018), (ii) the need to avoid changes in hydrological cycles (Pielke Sr et al. 2007, Sterling et al. 2013, Bagley et al. 2014), and (iii) the preservation of the biodiversity present in natural areas (Reidsma et al. 2006, Oliver & Morecroft 2014, Kehoe et al. 2017, Marques et al. 2019, Fastré et al. 2020).

The concept of agricultural technology must be understood as the application of knowledge, science, and engineering in agricultural and animal production systems (Zilberman et al. 2014). According to Rocha et al. (2020), this term can represent the adoption of agricultural machinery, equipment, and products (tractors, harvesters, irrigation pivots, fertilizers, and pesticides), planting systems (conventional, no-tillage system, integrated systems) and genetic engineering, biotechnology techniques, and nanotechnology.

NTS is a way of soil management that involves techniques recommended to increase agricultural land productivity. The main techniques used in the NTS are: minimal soil turning, soil cover with straw and crop rotation. In NTS, straw and residues from other crops are kept on the soil surface, ensuring coverage and protection against harmful processes, such as erosion. The soil is manipulated only at the time of planting, when furrows are opened where seeds and fertilizers are deposited. The most important control in this cultivation mode is that of weeds through integrated pest management. Finally, for the success of the system, crop rotation is necessary.

According to the 2017 Brazilian Agricultural Census available from the Brazilian Institute of Geography and Statistics (IBGE), NTS is adopted by about 19% of farmers. Higher productivity, the label “less environmental impact” and the incentive of government agricultural agencies (Ministry of Agriculture, State Agricultural Institutes, etc.) drive the growing adoption of NTS in Brazil.

Soil erosion and the consequent loss of productivity and increased costs are the main motivations for farmers to adopt NTS. However, the practice of NTS was included in the Sectoral Plan for the Mitigation and Adaptation to Climate Change for the consolidation of a Low-Carbon Economy in Agriculture (ABC Plan). More details about the ABC Plan are available at Brazilian Ministry of Agriculture (2016). This plan is an important part of the commitment to reduce GHG emissions, undertaken by Brazil at the 15th Conference of the Parties (COP15), held in 2009. The relationship between the adoption of NTS and a reduction in GHG must include: (i) its ability to retain carbon dioxide in the soil (via straw remaining in the soil), (ii) less use of agricultural machinery, and (iii) less use of fertilizers and pesticides (via crop rotation).

Certainly, each agrotechnology establishes a relationship with land use management. This article is limited to analyzing the relationship between the adoption of the No-Tillage System (NTS) and its effects on land use in Brazil, paying special attention to its impacts on natural and cultivated areas.

In view of this purpose, our article is close to the work of Rudel et al. (2009), Ngoma & Angelsen (2018), Pelletier et al. (2020) and Rocha et al. (2020) that assess the economic and environmental impact of conservation agriculture practices. Our work innovates by seeking causation effects between NTS adoption and land use in Brazil, using the statistical approach of Spatial Propensity Score Matching. This discussion of impacts of agricultural practices gains importance when we analyze the Brazilian case where there is the presence of an economically relevant agricultural sector and there is a need to preserve tropical natural areas.

In addition to this introductory section, this article is divided as follows. The second section presents a literature review on the relationship between agricultural technology and land use management. The third describes the Spatial Propensity Score Matching method and database used in the empirical models. The fourth presents and discusses the main results. Finally, the fifth section concludes.

2. Literature

The relationship between adoption of agrotechnologies, land use and conservation of natural areas is widely discussed in the literature. At the center of this debate are the dissonant approaches of Borlaug and Jevons.

The idea of Borlaug's hypothesis is that the adoption of agricultural innovation is the key to "land-sparing", through increasing productivity (Hertel 2012). In this case, there is the possibility of greater food production without the need to open new agricultural frontiers. Thus, agrotechnologies would be able to conserve natural areas. Ervin & Ervin (1982), Southgate (1990), Holden (1993), Faminow (1998), McNeely & Scherr (2001), Shively & Pagiola (2004), Green et al. (2005), Kazianga & Masters (2006), Burgess & Morris (2009), De Souza et al. (2013), Corbelle-Rico et al. (2015), Assunção et al. (2020), Pelletier et al. (2020) and Rocha et al. (2020) are examples of works that find evidence linked to this line of thought.

De Souza et al. (2013) analyze the relationship between agricultural technology and deforestation rates in the Brazilian Amazon. Thus, they create an agricultural technology index for the region's municipalities. They conclude that areas where agriculture and livestock have a low level of technology coincide with areas of high deforestation in the Amazon.

Corbelle-Rico et al. (2015) make argument that agricultural technology and policy (in this case a market integration policy) can mean shifts in land use systems. The authors make a case study for Spain. The results indicate that the driver of economic policy was more important than technological changes. These two channels led to a reduction in agricultural area and a notable increase in forest area.

Assunção et al. (2020) assess the impact of a stricter agricultural credit concession policy on deforestation in the Brazilian Amazon. They show that credit restriction has led to a substantial reduction in deforestation. This indicates that the region's economic activities are land intensive and use little agricultural technology.

Pelletier et al. (2020) assess the impact of using inorganic fertilizers and improved maize seeds on deforestation, using Zambia as a case study. The use of modern agricultural inputs are able to improve food security while conserving natural areas.

Rocha et al. (2020) evaluate the relationship between agricultural technologies and land use in Brazilian municipalities. In this case, the use of agricultural machinery and the presence of technical assistance in the region are considered as technology. The results indicate that the use of agricultural technologies can lead to the maintenance of agricultural areas while preserving forest areas. The authors still find evidence of technological spillovers in agriculture.

Based on this literature review, we tested the following hypothesis:

HYPOTHESIS 1 (H1): Adoption of NTS can maintain cultivated areas while avoid the reduction of natural areas. This is linked to Bourlag's idea that agricultural technology leads to land-sparing.

H1 is validated if both coefficients that relate NTS adoption and natural and cultivation areas are null or positive.

On the other hand, the Jevons' paradox suggests that an increase in agricultural productivity will be accompanied by a reduction in costs and a consequent increase in profitability, thus promoting an expansion of agricultural areas (Hertel 2012). In the absence of effective environmental conservation policies, increased production can stimulate loss of vegetation cover (Rudel et al. 2009) via direct agricultural invasion or displacement of other uses (Arima et al. 2011, Lambin & Meyfroidt 2011). Fearnside (1987), Ehui & Hertel (1989), Fearnside (2002), Geist & Lambin (2002), Pretty (2002), Margulis (2003), Perz (2003), Arima et al. (2005), Rudel et al. (2009) and Ngoma & Angelsen (2018) find evidence of the Jevons type.

Rudel et al. (2009) note the relationship between agricultural intensification and cultivated area. They analyze long-term land use trends from different regions of the world. Reductions in cultivated area occurred infrequently at regional and global scales. Increases in agricultural yields and cultivated areas are more common. This is similar to Jevons' paradox.

Ngoma & Angelsen (2018) assess minimum cultivation as an agricultural conservation practice. In other words, they look at the relationship between minimal cultivation and protection of natural areas. Information from smallholders in Zambia is used. No evidence was found that the adoption of minimal cultivation and reduced deforestation. The authors make argument that practices aimed at improving agricultural yields must be complemented along with environmental conservation measures, seeking to avoid deforestation.

Thus, we have the following hypothesis:

HYPOTHESIS 2 (H2): Adoption of NTS can lead to the expansion of cultivated agricultural areas, then reducing natural areas. This is related to the Jevons' paradox.

To validate H2, the coefficient relating NTS and natural areas must be positive and the coefficient for cultivated area must be negative.

3. Method

3.1. Spatial Propensity Score Matching

There are several reasons why adopting NTS can affect land use. But how can we be sure that the degradation or conservation of natural areas is caused using NTS? Ideally, using experimental data could provide us with counterfactual information, which would solve the problem of causal inference. This is not our case because observed data (Blundell & Costa Dias 2000). With observational data some statistical solution is used to make a causal inference (Blundell & Costa Dias 2000, Abadie & Imbens 2006, Caliendo & Kopeinig 2008). This has to do with the problem of self-selection, i.e., when farmers decide to adopt a new technology (in particular NTS) it will be related to the benefits/losses of this adoption and this is directly related to the land use decision. In other words, there may be a two-way relationship between NTS and the conservation/degradation of natural areas. That said, we proceed with the description of the Spatial Propensity Score Matching (Spatial-PSM) procedure, that will be used in our estimates of the impact of NTS adoption on land use. The existence of spatial dependence is considered in the estimates due to the spatial nature of the units analyzed (i.e., municipalities).

Matching methods seek to obtain a control group statistically similar to the treatment group in terms of specific observable covariates (X). Thus, in comparing two groups of municipalities with the same observable characteristics, the only factor that differentiates them is the existence or the expectation of the presence of adoption of NTS in their territory ($T = 1$ if treated or $T = 0$ otherwise) (Dehejia & Wahba 2002). Therefore, we can write the average treatment effect on the treated (ATT) as:

$$ATT = E\{E[Y^1 - Y^0 | T = 1, X]\} \tag{1}$$

where Y^1 is the potential outcome of the variable of interest under treatment and Y^0 is the potential outcome of the variable of interest in the absence of treatment.

To ensure that the PSM estimators identify and consistently estimate the treatment effect, we assume: (i) unconfoundedness, i.e., assignment to treatment is independent of the conditional outcomes on the covariates (X) - $(Y^0; Y^1) \perp T|X$. This implies that the selection of NTS adoption is random and is not correlated with the land use pattern, as we control for the vector of observed variables and (ii) common support condition, i.e., the probability of assignment is bounded away from 0 and 1 $[0 < p(T = 1|X) < 1]$. This hypothesis shows that, if NTS adoption is random, we can compare the land use pattern (e.g., proportion of natural area) from similar municipalities with different NTS adoption status (i.e., treatments and controls), defining similar municipalities according to the values of X. However, due to the high size of X, the PSM method reduces the dimensionality of the problem by comparing municipalities with the same probability of adopting NTS, given the controls X (Rosenbaum & Rubin 1983, 1984, 1985a, 1985b). This conditional probability is the propensity score, which we use to identify similar municipalities. In this article, we estimated the propensity score using a general probit model, such that:

$$p(T = 1|X) = \Phi(X\beta) \tag{2}$$

where Φ is the cumulative distribution function of the standard normal distribution and β is the estimated parameter vector associated with covariates X.

However, with the existence of spatial effects (this is due to the geographical nature of the data), conventional models for estimating the propensity score are not adequate. The possibility of spatial dependence between the observed units should be considered in the propensity score estimation through the implementation of a spatial propensity score. Based on Chagas et al. (2012) we consider the spatial dependence when inserting a spatial lag term in the treatment variable, obtaining a SAR-Probit model. Formally, the spatial model is represented by:

$$\begin{gathered} T = \Phi(Z\gamma) + \epsilon \\ Z = [WT, X] \;\; \gamma = (\rho, \beta) \\ \epsilon \sim (0, \sigma_\epsilon^2 I) \end{gathered} \tag{3}$$

where T is the treatment binary variable ($T = 1$ for treated municipalities and $T = 0$ for control municipalities). Φ is the cumulative distribution function of the standard normal distribution. Z matrix contains WT which represents the treatment variable spatially lagged by the spatial weight matrix W and X which are the covariates. γ is a matrix of parameters composed of ρ that represents the parameter that indicates spatial dependence, so that if $\rho \neq 0$ we have a SAR-Probit and $\rho = 0$ we return to the general probit (LeSage & Pace 2009), β is the set of parameters linked to covariates. Finally, ϵ represents the random error term *i.i.d* with a zero mean and constant variance.

After estimating the propensity score, it is possible to identify for each treated municipality (i.e., adopts NTS) a twin municipality in terms of observable characteristics but that differs in the treatment situation, i.e., does not adopt NTS. Finally, it is possible to calculate an estimate of the effect of NTS use on land use from the average difference between each pair of municipalities combined. The effect of adopting NTS for municipalities with scores of similar propensity can be rewritten as:

$$ATT = E\{E[Y^1 - Y^0 | T = 1, p(Z)]\} \tag{4}$$

In other words, the Spatial-PSM estimator is a difference in the average of outcomes in relation to common support, properly weighted by the distribution of the spatial propensity score.

The statistical implementation of the models took place in the R environment using essentially the "Matching" (Sekhon, 2011), "rbounds" (Keele, 2010), "spatialprobit" (Wilhelm 2015), and "spdep" (Bivand et al. 2011) packages. Codes are available upon request.

3.2. Data description

3.2.1. Variable of interest

Land use: We observed the effect of adopting NTS on natural and cultivated areas. For that, we calculated the share of these uses in relation to the non-urban area of the municipality. These variables are represented by "*NaturalAreas*" and "*CultivatedAreas*", respectively. We use data from 4448 municipalities present in the 2017 Brazilian Agricultural Census provided by the Brazilian Institute of Geography and Statistics (IBGE).

3.2.2. Treatment and control groups

We perform econometric models using different treatment definitions. In the main model, we consider as treaties, the municipalities that use NTS above the national average. In this case, municipalities with values above 8.86 NTS farms per 1000 ha are selected. The remaining municipalities are in control group. Other treatment definitions were used to assess the robustness of the estimates. Thus, we consider the thresholds of 1, 5, 10, 15, 20, 25 and 50 NTS farms per 1000 ha. For this, we used data from 4448 Brazilian municipalities extracted from the 2017 Agricultural Census provided by the IBGE.

Table 1 shows the sample of treated municipalities and control municipalities for each of the econometric experiments. In the main model, 994 municipalities are considered treated and 3454 are controls. As the treatment definition becomes more rigid (i.e., when the number of NTS farms per 1000 ha increases), the treated group decreases while the control group increases.

Table 1. Treated and control groups

Treatment Definition	*T=1*	*T=0*
Mean (8.86 NTS farms per 1000 ha)	994	3454
1 NTS farm per 1000 ha	2197	2251
5 NTS farms per 1000 ha	1261	3187
10 NTS farms per 1000 ha	936	3512
15 NTS farms per 1000 ha	753	3695
20 NTS farms per 1000 ha	630	3818
25 NTS farms per 1000 ha	506	3942
50 NTS farms per 1000 ha	180	4268

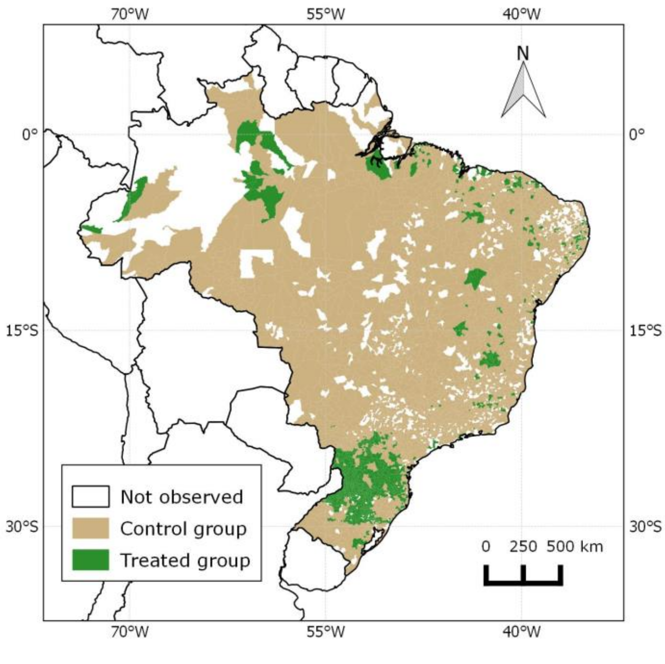

Figure 1. Treated and control municipalities

Figure 1 shows the geographic distribution of the treated and control municipalities. Most of the municipalities classified as treated (≥ 8.86 NTS farms per 1000 ha) are located mostly in the southern region of Brazil. It is also possible to observe the use of NTS in the rest of the Brazilian territory, especially in the northeast, but more geographically dispersed. The NTS technique arrived in Brazil in the 1970s, being first applied in Rio Grande do Sul and Paraná (states in the southern region of Brazil). Embrapa has a fundamental role in the application, dissemination, and improvement of NTS in Brazilian agriculture (Salton et al. 1998). Thus, the geographic concentration seen in Figure 1 is the representation of the historical origin of NTS in Brazil.

3.2.3. Covariates

Farms characteristics: We selected the following variables to characterize the farms: (i) number of tractors by farm "*Tractor*", (ii) number of agronomists by farm "*AgriAdvice*", (iii) percentage of farmers with some education "*FarmSchool*", and (iv) percentage of farms using pesticides "*Pesticide*". The first expresses the use of physical agricultural technological capital. For this, the ratio between the number of tractors (with more than 100 hp) and the non-urban area of the municipality is considered. We used the 2017 Agricultural Census, available from IBGE. The second represents agricultural human capital. The ratio between the total number of skilled workers in the agricultural sector (agricultural engineers, agronomy engineers, and researchers in agronomic sciences) and the non-urban area of the municipality was used as a metric. The data were provided by the Annual Social Information Report (RAIS), published by the Brazilian Ministry of Labor and Employment (MTE) in 2017. In the third, we calculate the ratio between the number of farms whose owners who have attended school and the non-urban area of the municipality. Information from the 2017 Agricultural Census, provided by IBGE was used. The fourth variable assesses the use of pesticides by farms in the municipality. We calculated the ratio between the number of farms using pesticides and the non-urban area of the municipality. We use data from the 2017 Agricultural Census, provided by IBGE.

Socioeconomic aspects: The following variables were used to characterize the socioeconomic conditions of the analyzed municipalities: (i) rural population density "*RuralDensity*", (ii) total population density "*PopDensity*", (iii) indigenous population density "*Indigenous*", and (iv) municipal agricultural GDP per capita "*GDPpc*". In the first, we calculated the ratio between the number of rural residents and the non-urban area of the municipality. We use data from the 2017 Agricultural Census, available from IBGE. In the second, we calculate the ratio between the population and the total area of the municipality. We use data available from the 2017 Agricultural Census. In the third, we calculated the ratio between the indigenous population and the total population of the municipality. We collected 2017 data estimated by IBGE. Finally, municipal agricultural GDP per capita will show us how important agricultural activity is to the municipality. This information was extracted from the Brazilian Institute of Applied Economic Research (IPEA), with reference to 2017.

Historical characteristics: We collected historical information (about a decade ago) for all the covariates mentioned above. For that, we used the 2006 data provided by IBGE (2006 Agricultural Census), RAIS/MTE and IPEA. These variables are named as "*Tractor(06)*", "*AgriAdvice(06)*", "*FarmSchool(06)*", "*Pesticide(06)*", "*RuralDensity(06)*", "*PopDensity(06)*", "*Indigenous(06)*", and "*GDPpc(06)*".

Climate and edaphic conditions: Climatic conditions in the Brazilian municipalities will be represented by temperature and precipitation information. The temperature data are from the

NCEP-DOE Reanalysis 2 project (Kanamitsu et al. 2002), while the precipitation information is from the Climate Hazards group Infrared Precipitation with Station (CHIRPS) (Funk et al. 2015). The average annual and summer (December/January/February) precipitation and temperature were considered. These variables are represented by "*Temp*", "*SummerTemp*", "*Prec*", and "*SummerPrec*", respectively. Data were selected for the year 2017. In turn, the edaphic conditions were represented by a categorical variable of Brazilian biomes (Amazon Forest, Atlantic Forest, Cerrado, Caatinga, Pantanal, and Pampa). This variable is represented by "*Biomes*". The 4448 municipalities analyzed were classified into one of these categories.

Table 2 provides the descriptive statistics for the variables used in this study. The first column contains a summary name of the variables used in the econometric models. Column two provides the unit of measurement for the variables. Columns three to five provide basic statistics on mean, maximum and minimum value of variables. Column six shows the number of observations in the sample. Finally, column seven indicates the sources and the period of the information.

Table 2. Descriptive statistics

Variable	*Unit*	*Mean*	*Max*	*Min*	*Obs*	*Source*
NaturalAreas	ha/ha	0.272	0.990	0.000	4448	IBGE (2017)
CultivatedAreas	ha/ha	0.281	0.979	0.000	4448	IBGE (2017)
NTS ratio	(farms/ha)×1000	8.865	1825.243	0.000	4448	IBGE (2017)
Tractor	tractor/ha	0.009	0.186	0.000	4448	IBGE (2017)
AgriAdvice	workers/ha	0.009	0.280	0.000	4448	RAIS (2017)
FarmSchool	farms/ha	0.041	8.587	0.000	4448	IBGE (2017)
Pesticide	farms/ha	0.016	0.721	0.000	4448	IBGE (2017)
RuralDensity	people/ha	0.421	159.545	0.001	4448	IBGE (2017)
PopDensity	people/ha	58.830	7398.220	0.230	4448	IBGE (2017)
GDPpc	R$/people	324.300	351438.100	5.900	4448	IPEA (2017)
Indigenous	people/people	0.006	0.715	0.000	4448	IBGE (2017)
Temp	Kelvin	295.302	300.365	291.197	4448	IBGE (2017)
SummerTemp	Kevin	296.783	301.268	293.536	4448	IBGE (2017)
Prec	millimeters	1265.218	3543.960	179.648	4448	IBGE (2017)
SummerPrec	millimeters	136.183	700.644	8.093	4448	IBGE (2017)
Biomes	categorical variable	4.183	6.000	1.000	4448	IBGE (2017)
Tractor (06)	tractor/ha	0.006	0.140	0.000	4448	IBGE (2006)
AgriAdvice (06)	workers/ha	0.010	0.177	0.000	4448	RAIS (2006)
FarmSchool (06)	farms/ha	0.027	3.396	0.000	4448	IBGE (2006)
Pesticide (06)	farms/ha	0.013	0.365	0.000	4448	IBGE (2006)
RuralDensity (06)	people/ha	0.324	109.154	0.001	4448	IBGE (2006)
PopDensity (06)	people/ha	52.660	6860.480	0.170	4448	IBGE (2006)
GDPpc (06)	R$/people	384.700	1100961.900	2.800	4448	IPEA (2006)
Indigenous (06)	people/people	0.005	0.479	0.000	4448	IBGE (2006)

4. Empirical results

4.1. Spatial propensity score

Before proceeding with the calculation of the spatial propensity score, we perform an analysis to verify the existence of spatial dependence. The geographical concentration related to the use of NTS (see Figure 1) indicates the possibility of spatial dependence. Moran's I statistic provides an indication of this dependency as it measures the spatial autocorrelation based on the product of the deviations of a variable in relation to its mean (Anselin 2001, LeSage & Pace 2009). Moran's I statistic is calculated for the treatment variable, i.e., the adoption of NTS. For this purpose, five matrices of spatial weight (W) of the type k-closest neighbors were used, k = 5, 10, 15, 20 and 25. The results are shown in Table 3.

Table 3. Moran's I test

W	*Moran I*	*p-value*
k = 5	0.349	0.000
k = 10	0.320	0.000
k = 15	0.297	0.000
k = 20	0.276	0.000
k = 25	0.265	0.000

With the statistical evidence shown in Table 3, it is possible to reject the hypothesis of spatial randomness at a significance level of 0.001%. For all types of W matrix it is possible to see a positive spatial autocorrelation, revealing a spatial similarity in terms of the adoption (or not) of NTS. That is, municipalities that adopt NTS are neighbors of municipalities that also adopt NTS. This also applies to the contrary, i.e., it does not adopt NTS. The highest value of Moran's I statistic was found using the matrix k = 5 closest neighbors, a value close to 0.349. This indicates a greater strength of the spatial autocorrelation.

Table 4 presents the results of the spatial propensity score using a SAR-Probit model (equation 3). We also present the results from a general probit model (equation 2). For both cases, the estimated coefficient, standard error, and p-value statistics are presented.

Table 4. Propensity score estimations

	Treatment Definition: Mean (8.86 NTS farms per 1000 ha)					
	Probit			*SAR-Probit (k=5)*		
Variable	*Coef.*	*Std. Error*	*p-value*	*Coef.*	*Std. Error*	*p-value*
Tractor	-0.058	0.025	0.019	-0.051	0.024	0.031
AgriAdvice	0.209	0.043	0.000	0.152	0.042	0.000
FarmSchool	0.272	0.094	0.004	0.094	0.084	0.262
Pesticide	0.012	0.040	0.759	0.008	0.036	0.830
RuralDensity	0.087	0.092	0.342	0.159	0.084	0.057
PopDensity	-0.833	0.289	0.004	-0.307	0.269	0.255
GDPpc	0.238	0.087	0.006	0.231	0.083	0.006
Indigenous	-0.010	0.009	0.277	-0.010	0.010	0.313
Temp	-420.050	30.132	0.000	-77.836	24.208	0.001
SummerTemp	499.790	37.034	0.000	89.188	28.692	0.002
Prec	0.539	0.122	0.000	0.317	0.083	0.000
SummerPrec	-0.209	0.062	0.001	-0.040	0.046	0.385
Biomes	0.120	0.028	0.000	0.053	0.021	0.013
Tractor(06)	0.044	0.019	0.017	0.043	0.018	0.016
AgriAdvice(06)	-0.058	0.046	0.209	-0.066	0.045	0.142

FarmSchool(06)	0.195	0.090	0.030	0.126	0.084	0.134
Pesticide(06)	0.117	0.036	0.001	0.071	0.035	0.043
RuralDensity(06)	-0.061	0.084	0.471	-0.067	0.080	0.404
PopDensity(06)	0.641	0.283	0.024	0.108	0.259	0.677
GDPpc(06)	-0.291	0.091	0.001	-0.240	0.086	0.005
Indigenous(06)	0.006	0.010	0.528	0.009	0.010	0.356
Intercept	-456.670	68.816	0.000	-65.318	52.679	0.215
Rho (ρ)				0.676	0.023	0.000
Obs	4448			4448		
Log Likelihood	-1217.682			-1209.830		
AIC	2479.363			2465.658		
BIC	2620.168			2612.862		

It is possible to infer from the Log-Likelihood, AIC, and BIC criteria that the SAR-Probit models have a better fit compared to the general probit models. This points to the importance of applying spatial econometric models when dealing with data of a geographical nature. We found the value of the spatial dependence parameter (ρ) statistically significant at 0.001% and with positive magnitude (0.676). This indicates that Brazilian municipalities whose immediate neighbors ($k \leq 5$) adopt NTS are statistically more likely to adopt it as well. The opposite (i.e., not adopting NTS) is also true.

In the characteristics of the farms, it is possible to see that the greater number of tractors per ha in the municipality leads to less chance of the municipality adopting the NTS (-0.051). In turn, greater technical support leads to a greater likelihood that the municipality will adopt NTS (0.152).

In socioeconomic variables, we found statistical significance in rural population density (0.159) and agricultural GDP per capita (0.231).

In the climatic variables, we found a negative coefficient for the average annual temperature (-77.836), and positive and statistically significant coefficients for average temperature in summer and average annual precipitation (89.188 and 0.317, respectively).

Finally, some historical variables were statistically significant. The increased use of tractors and pesticides, and higher education of farmers in the past (a decade ago) leads to the greater likelihood of the municipality adopting NTS (0.043, 0.071, and 0.126, respectively). On the other hand, the greater technical advice and the higher agricultural GDP per capita in the past leads to a less probability of the municipality adopting the NTS in the current period (-0.066 and -0.240, respectively).

4.2. Average treatment effect on the treated

The effects of adopting NTS in natural and cultivated areas are observed by estimating the average treatment effect on the treated (ATT). Table 5 presents these results. They were generated from the procedure for matching the propensity scores of the SAR-Probit (main results) and general probit models.

Table 5. Main results, ATT effects of NTS adoption on land use

	Treatment Definition: Mean (8.86 NTS farms per 1000 ha)					
	PSM Probit			*PSM SAR-Probit (k=5)*		
Dependent variable	*Coef.*	*Std. Error*	*p-value*	*Coef.*	*Std. Error*	*p-value*
Natural areas (log)	0.247	0.095	0.009	0.338	0.097	0.000
Cultivated areas (log)	0.279	0.088	0.002	0.214	0.092	0.020
All covariates	Yes			Yes		
Obs. Treated	994			994		
Obs. Control	3454			3454		
Obs. Total	4448			4448		

Matching algorithm characteristics:

(i) nearest neighbour criteria with replacement,

(ii) oversampling with 1 nearest neighbour,

(iii) weights for oversampling type Mahalanobis distance metric, and

(iv) maximum tolerance level = 0.00001.

Using a SAR-Probit model, we can see that ATT related to natural areas is positive. That is, municipalities that adopt NTS have a larger share of natural area than municipalities that do not. In this case, the ATT value is statistically significant and equal to 0.338. With an exponential transformation, we found that treated municipalities have 1.402 percentage points larger share of natural area than untreated municipalities. Something similar happens with cultivated land-use. We estimate an ATT of 0.214. With exponential transformation we infer that treated municipalities have a cultivated area share 1.239 percentage points greater than municipalities that have not adopted NTS. These results seem to follow Borlaug's hypothesis (Hertel 2012). In other words, the adoption of NTS can expand or maintain agricultural areas while preserving natural areas, validating H1.

What factors can link the adoption of NTS to the preservation of natural areas? We believe that the recovery of eroded land and the increase in agricultural productivity may partially explain these results.

Land use without conservation practices (Merten & Minella 2013, Panagos et al. 2015, Borrelli et al. 2017), lack of vegetation cover (Cerda 1999, Zhou et al. 2008, Zhongming et al. 2010), over adoption of heavy agricultural machinery (Schäffer 2007) and the natural action of water, wind and gravity (Mahmoodabadi & Sajjadi 2016, Kheirabadi et al. 2018, Guo et al. 2021) may explain the process of soil erosion.

The erosion process can make the use of land for agriculture and pasture economically unfeasible. Thus, farmers may decide to expand their activities towards natural areas, especially in a scenario of global food growth. Soil management practices that prevent erosion of agricultural soils, such as the use of NTS, can help in environmental conservation, saving natural areas.

The soil cover with a layer of straw and later its revolving, can dissipate the energy from the impact of rain on the soil (an important source of erosion). This serves as an obstacle to surface movement of excess water that has not infiltrated the ground and preventing the transport of land. That is the central idea of NTS.

Improvements in soil management can bring higher agricultural productivity (Shepherd & Soule 1998). This idea can be seen in the use of NTS. The steps of NTS (i.e., soil cover and crop rotation) allow the maintenance of organic components in the soil and prevent the emergence of pests and weeds - something quite common in traditional monoculture. Following Borlaug's hypothesis, higher productivity can translate into greater economic gains for farmers leading them to conserve natural areas. Thus, in their land-decision process, farmers are not encouraged to push the agricultural frontier toward natural areas. Such a process can reduce the risk of deforestation.

Figure 2 shows the ATT effects using different treatment definitions (thresholds between 1 and 50 NTS farms per 1000 ha). These econometric exercises assess the robustness of the main results as it tests different thresholds. In the case of natural areas, most of the estimated ATT coefficients are positive and statistically significant. The results are close to 0.2. In turn, the ATT coefficients for the cultivation area are mostly positive and statistically significant. In this case, the values are close to 0.3.

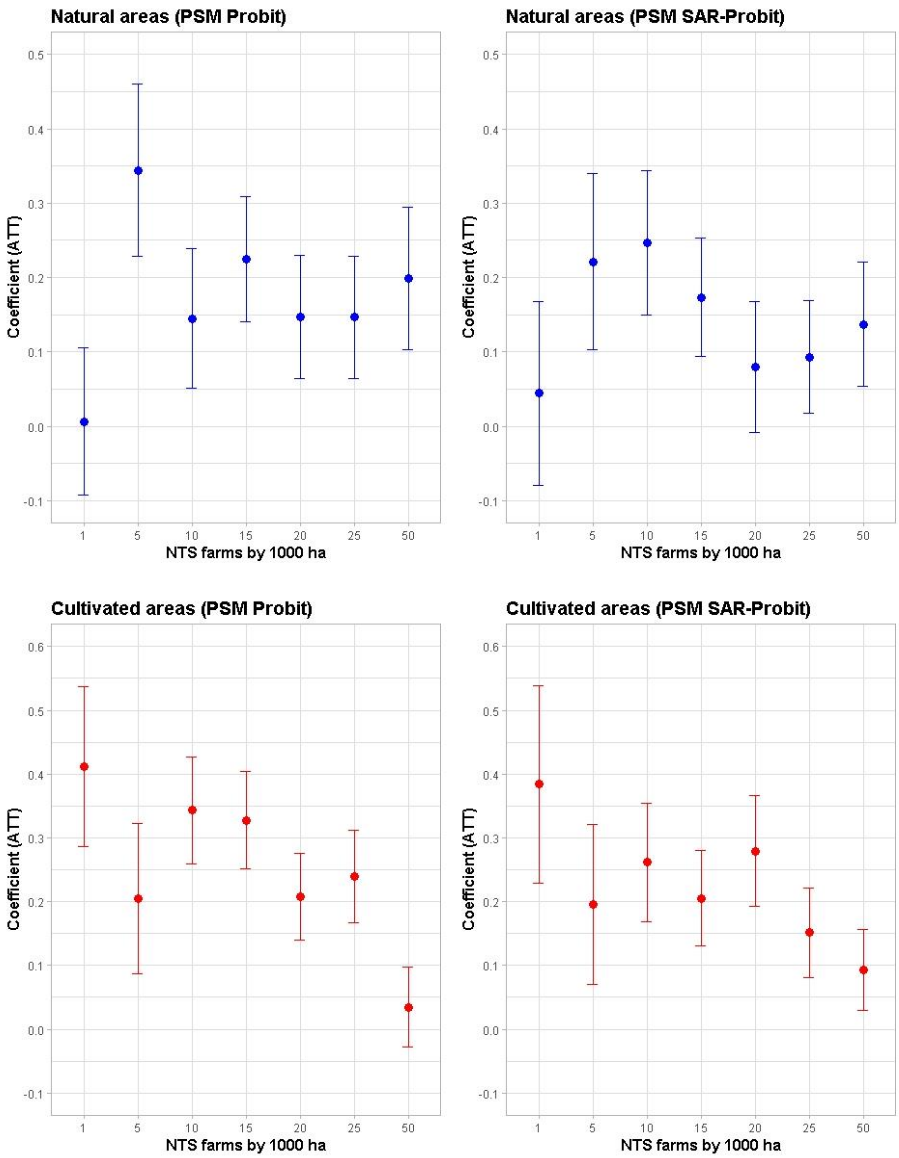

Figure 2. ATT effects with different treatment definitions

(thresholds = NTS farms per 1000 ha)

With this exercise, it was possible to see that regardless of the concentration of NTS farms in the municipality, the main results are maintained. That is, the estimated coefficients indicate that the use of NTS is related to a greater share of natural and cultivated land compared to untreated regions.

5. Conclusion

By 2050, the world population will reach 9.1 billion, which means that there will be a need for greater production of food. To reach a level of food security, cereal production will have to be around 3 billion tons/year, and meat production is expected to reach 470 million tons/year. This scenario could worsen if we consider natural resource restrictions and more severe climatic conditions (FAO 2009, 2013). In this context, the adoption of technologies is regarded as the main strategy for greater productivity in the agricultural sector.

It is necessary to discuss the consequences of adopting these technologies on the environment. That is, we need to assess its environmental sustainability. This article has attempted to better understand the effects of adopting NTS on natural areas in Brazil. Through a Spatial-PSM approach, we found evidence that the adoption of NTS can stimulate the preservation of natural areas.

The ABC Plan inserts NTS as an agricultural practice capable of reducing GHG emissions in the agricultural sector. By reducing erosion and retaining soil carbon, NTS is seen in Brazil as a way to help reduce GHG emissions from agriculture. Our article points to an indirect effect of the use of NTS for GHG emission control because it potentially helps in the conservation of natural areas (Powlson et al. 2014, Powlson et al. 2016, VandenBygaart 2016). Therefore, the presence of NTS in plan ABC seems to have been a correct measure.

Finally, we recommend the following actions to public policy makers: (i) creating ways to expand the use of NTS, it should be noted that only 19% of Brazilian farms adopt NTS - for that, it is necessary to design incentive mechanisms, (ii) provide material conditions for farmers to adopt NTS - this includes the training of farmers and the possibility of financing for the purchase of agricultural equipment, and (iii) to continuously monitor the actions of the farmers - for this, it is necessary to expand and improve deforestation monitoring through satellite images.

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