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ARTICLE

Analysis of sugarcane productivity convergence by spatial regimes for brazilian microregions

Análise da convergência da produtividade da cana-de-açúcar por regimes espaciais para as microrregiões brasileiras

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Abstract: The objective of this research is to evaluate whether there was convergence in land productivity for sugarcane between 2006 and 2017, and to verify the contribution of some variables to this convergence. To achieve the objective, the methodology adopted was spatial econometrics, which seeks to control spatial dependence, performs absolute and conditional convergence tests. Convergence models considering the heterogeneity of the sample, called spatial regimes, were also tested. The results proved that a process of absolute and conditional convergence of sugarcane productivity occurs for Brazilian microregions, that is, differences in productivity are decreasing over time. The regression by spatial regimes using the SDEM model was shown to be the most appropriate among the tests, through which it was possible to observe that there was convergence for all major Brazilian regions, even if the processes and intensities were different. Some explanatory variables that were significant and positive for the model were: use of fertilizer and mechanical harvesting for the Midwest; women leaders and workforce for the Northeast; manager's education and women leaders for the North; tenant producer for the Southeast; manager's education and technical orientation for the South; among other variables.

Keywords: convergence, spatial econometrics, heterogeneity, productivity.

Resumo: O objetivo desta pesquisa é avaliar se houve convergência na produtividade da terra para a cana-de-açúcar entre 2006 e 2017, e verificar a contribuição de algumas variáveis nessa convergência. Para atingir o objetivo, a metodologia adotada foi a econometria espacial, que busca controlar a dependência espacial, realizando os testes de convergência absoluta e condicional. Testou-se os modelos de convergência considerando a heterogeneidade da amostra, chamados de regimes espaciais. Os resultados comprovaram que está ocorrendo um processo de convergência absoluta e condicional da produtividade da cana-de-açúcar para as microrregiões brasileiras, ou seja, as diferenças de produtividade estão se reduzindo ao longo do tempo. A regressão por regimes espaciais pelo modelo SDEM se mostrou a mais adequada dentre os testes, por meio da qual foi possível observar que houve convergência para todas as grandes regiões brasileiras, mesmo que os processos e as intensidades tenham sido diferentes. Algumas variáveis explicativas, significativas e positivas para o modelo, foram: uso de adubação e colheita mecânica para o Centro-Oeste; mulheres dirigentes e mão de obra para o Nordeste; escolaridade dos dirigentes e mulheres dirigentes para o Norte; produtor arrendatário para o Sudeste; escolaridade do dirigente e orientação técnica para o Sul; dentre outras variáveis.

Palavras-chave: convergência; econometria espacial; heterogeneidade; produtividade.

1 Introduction

Brazil stands out globally for its prominence in the primary sector, ranking among the largest producers and exporters of various agricultural commodities, such as soybeans and sugar. Bacha (2012) highlights the main roles played by the primary sector in the development process of nations, such as: the supply of food and raw materials, a consumer market for other sectors, the provision of labor, the transfer of capital to other sectors, and the generation of foreign exchange through exports.

Given its importance to society, the growth of rural production is essential, and productivity has stood out as a driving force behind agricultural growth, as it conserves factors such as labor, capital, and cultivated land. From an economic standpoint, productivity is the relationship between what is produced and the resources employed, that is, the ability to produce using a given amount of production factors. Thus, the more that is produced with the same amount of inputs, the higher the productivity, which can be assessed based on a specific production factor or the entire set of factors — referred to as partial productivity and total factor productivity, respectively (Lopes, 2004a).

In Brazil, the increase in agricultural productivity accounted for approximately 87% of total output growth between 2000 and 2007 (Gasques et al., 2008). Between 2006 and 2017, total factor productivity in Brazil grew at an average annual rate of 2.21%, while the global rate during the same period was 1.71% per year (Vieira Filho, 2022). This means that as agricultural growth results from factor productivity rather than from an absolute increase in inputs, the growth tends to spare the expansion of agricultural frontiers—an essential aspect in the development of rural areas (Alves, 2010).

Gollin (2010) points out that, since a large portion of the low-income population is concentrated in rural areas of underdeveloped countries, agricultural production (and thus productivity) becomes especially important for ensuring income and the survival of this segment of society. It is also essential for countries with a primary export base, such as Brazil, as it generates foreign exchange, which contributes to economic growth.

Confirming the importance of productivity in Brazilian agriculture, many studies have addressed this topic, such as: Gasques et al. (2004), Lopes (2004a), Almeida et al. (2008), Brigatte & Teixeira (2011), Felema et al. (2013), Raiher et al. (2016), Vieira Filho (2018, 2022), Baricelo (2019), Vedana et al. (2019), Machado et al. (2020), Hybner et al. (2020), Antunes (2021), Felema & Spolador (2023), among others. In addition to these, international studies have also focused on exploring absolute and conditional convergence, such as: Martin & Mitra (2001), Arbia & Paelink (2003), Mukherjee and Kuroda (2003a), Paudel et al. (2004a), Landiyanto & Wardaya (2005), Dall'erba (2005), Sanén et al. (2007), Hamulczuk (2015), Chatterjee (2017), Murtaza & Masood (2020), and Gong (2020).

The aim of this research is to assess whether there was a convergence in land productivity for sugarcane between 2006 and 2017, and to examine the contribution of certain variables to this convergence. To achieve this aim, the methodology adopted will be spatial econometrics, which aims to control spatial dependence. Convergence models will also be tested, considering sample heterogeneity, known as spatial regimes.

This research is divided into six sections, including this introduction (1). Next, a brief history and conceptualization of convergence is presented, along with its subdivisions, and a literature review that aims to contribute to the comparison of the results found here with previous studies, positioning this research in terms of similarities and differences within the existing literature (2). Section 3 presents the methodological procedures adopted, followed by the presentation and discussion of the results (4). The study concludes with the final considerations section (5).

2 Theoretical Foundation

This section allows for the identification of the evolution of convergence indicators (2.1), the historical development of the sugarcane sector (2.2), and empirical studies that highlight variables determining sugarcane productivity.

2.1 The convergence hypothesis

Convergence is a process of reducing differences over time between different locations for a given variable. Convergence may be driven by various factors, such as the implementation of public policies, structural changes in the production process, the diffusion of new technologies, integrative macroeconomic policies, among others (Lopes, 2004a).

The convergence hypothesis was first demonstrated in Solow's (1957) economic growth model, which predicted that poorer economies tended to catch up with richer ones, as differences would be eliminated over time. The Solow Model examined the behavior of capital and output across countries, considering that those with lower initial levels of output and capital would grow at a higher average rate than those with higher initial values for both variables. This led the group of countries toward convergence as they moved closer to a common steady state.

Building on this model, many researchers have sought to test the convergence hypothesis using different models and across various geographic contexts. Findings regarding the second half of the 20th century showed that relative income disparities between countries in Africa and Europe, for example, increased, which does not support the predictions of the Solow Model (Gordon, 2000).

In testing this hypothesis, Romer (1986, 1987) and Lucas (1988) refined the Solow Model by incorporating the implications of increasing returns and technological progress, as well as endogenous forms of growth. In addition, they highlighted the importance of human capital in the economic growth process of nations. Jones (1997) also explains that the transfer of technology between regions is one of the arguments that can help explain convergence.

The most current concept of convergence was discussed in three pioneering studies by Barro & Sala-I-Martin (1990, 1991, 1992), among other works by the same authors that addressed the topic. The authors propose three concepts of convergence: β-convergence, σ-convergence, and conditional β-convergence.

β-convergence is a type of total convergence, referred to as absolute convergence, because it estimates convergence (the reduction of differences) based on the initial condition of the variable. In this sense, the estimated regression uses as the dependent variable the natural logarithm (ln) of the ratio between the variable at its final point in time (Yt+n) and its initial point (Yt), and as the independent variable, the ln of the variable at the initial point in time (lnYt). The β-convergence hypothesis is confirmed if the coefficient associated with the lnYt parameter is negative and statistically significant. This is because, if the initial condition negatively affects the growth of the dependent variable, it means that the lower the initial condition, the greater the growth of the dependent variable.

Although β-convergence provides important analytical results, it does not account for factors that may be responsible for this convergence beyond the initial condition of each location. Conditional β-convergence seeks to address this limitation by adding structural variables that may indicate what drives the convergence process beyond the initial condition.

σ-convergence, on the other hand, examines the dispersion of the study variable as measured by the standard deviation of its natural logarithm, which decreases over time. Thus, β-convergence is a necessary condition for σ-convergence to occur, but it is not sufficient to indicate whether there is a reduction in the dispersion of the variable across locations. This model is used for panel data estimations, as it requires data from more than one period to indicate changes in dispersion.

2.2 Historical evolution of the sugarcane sector and productivity

The theoretical debate on convergence finds fertile ground for application in agriculture and has been discussed and studied across numerous countries and regions. In the case of India, Mukherjee & Kuroda (2003b) found that TFP convergence did not occur uniformly across states, being greater among those with better agricultural infrastructure. Similar results were found by Paudel et al. (2004a) in the United States, where human capital proved to be central to reducing disparities among states.

These studies align with the agricultural modernization process that began in Brazil in the 1960s, driven by the expansion of rural credit policies, technical assistance, and agricultural research, led by institutions such as Embrapa. In the specific case of sugarcane, the creation of the National Alcohol Program (Proálcool) in 1975 and the subsequent consolidation of the sugar-energy sector contributed to strengthening the production chain through the development of adapted varieties, mechanized harvesting, and production verticalization (Gazzoni, 2008; Martinelli & Filoso, 2008).

In this context, Azanha (2001, 2012) highlights that the modernization dynamics of the sugarcane sector occurred unevenly across Brazilian regions, being strongly influenced by the institutional organization of the agroindustry, the presence of public policies, and the structure of contracts between independent producers and mills. His analysis shows that productivity gains result not only from technological innovation but also from the coordination among economic agents and the qualification of the rural workforce. This reinforces the importance of considering institutional and social variables in convergence models.

Additionally, Guedes (2011) analyzes land concentration and the agro-industrial model of sugarcane as factors contributing to regional disparities in productivity and income. The author argues that agricultural productivity is influenced by the organization of production (ownership versus leasing) and by the investment capacity of production units.

Emphasizing these other authors, Terci (2010) contributes with analyses on the impacts of the modernization of the sugar-energy sector on labor relations and the productive organization of sugarcane-producing regions. The spatial reconfiguration of sugarcane production, with its expansion into the Savannah and decline in traditional areas of the Northeast, reflects processes of productive and economic restructuring that directly impact productivity. The author emphasizes that regional public policies, logistical infrastructure, and access to technical services are key variables determining whether regions are included in or marginalized by the sector's new dynamics.

Agricultural research focused on sugarcane played an important role in the agricultural modernization process, with notable contributions from institutions such as the IAC (Agronomic Institute of Campinas) and the CTC (Sugarcane Technology Center), which were responsible for developing cultivars with greater resistance, productivity, and regional adaptability (Landell et al., 2012). This dynamic favored the concentration of production in the Southeast and Center-West regions, where soil and climate, and logistical conditions are more favorable, intensifying regional disparities in productivity, as studied by Terci (2010), Guedes (2011), and Azanha (2001, 2012).

However, the advancement of mechanized harvesting — driven by environmental legislation that mandated the end of straw burning — posed an additional challenge for regions with lower investment capacity, such as the Northeast. Studies such as those by Gasques et al. (2010) indicate that total factor productivity in Brazilian agriculture grew unevenly, with more intense growth in regions with higher technological and institutional density, which has direct implications for the dynamics of convergence.

In search of other variables that determine productivity in the specifically sugarcane sector, Marin & Sentelhas (2011) investigated the impacts of climate change on the potential productivity of sugarcane in the Southern region of Brazil. They used agro-climatic models based on historical meteorological data series and scenario simulations. They concluded that precipitation and temperature are strongly correlated with productivity, especially in regions with low irrigation capacity.

Marin et al. (2008) also evaluated the efficiency of sugarcane production in different regions of Brazil, demonstrating that soil availability and quality, the level of mechanization, the adoption of adapted varieties, and the type of management (such as mechanized or manual harvesting) have a direct impact on productivity. The study reinforces that more technologically advanced regions — such as São Paulo and Mato Grosso do Sul — exhibit higher average productivity and lower interannual variability, suggesting greater stability and potential for convergence among similar microregions. Logistical infrastructure and local human capital are also important variables highlighted by Marin et al. (2013) in production efficiency, indicating that the technical qualification of workers is an essential factor for the effective adoption of new technologies.

2.3 Literature review

Numerous researchers have addressed the process of productivity convergence in both national and international contexts, seeking to demonstrate the convergence of agricultural productivity across countries, regions, states, and/or specific crops.

Internationally, the study by Mukherjee & Kuroda (2003a) explores total factor productivity convergence in agriculture across 14 Indian states between 1973 and 1993. It was observed that there was no single level of productivity convergence. For this reason, the states were grouped according to their productivity performance level. In this way, the results showed that high-performing states exhibit a more stable convergence pattern, while low-performing states experience greater volatility in this process. For the low-performing group, the variables that were significant included irrigation infrastructure, electricity, roads, and research and extension services, suggesting that government action can help reduce agricultural productivity inequality in the country. There was no evidence that productivity differences between the two groups were decreasing, which demonstrates the persistence of regional inequalities in India.

Expanding the analysis of agricultural productivity to a different context, Paudel et al. (2004b) examined 48 U.S. states from 1960 to 1996 and found no evidence of a generalized convergence process. The authors identified distinct regional patterns but attributed a central role to human capital in explaining productivity disparities, supporting the findings of Mukherjee & Kuroda (2003b). This emphasis on workforce qualification as a determining factor reinforces the importance of structural and institutional variables, broadening the discussion beyond the simple analysis of physical inputs.

This institutional perspective is further explored by Landiyanto & Wardaya (2005), who examined the sugarcane industry in Southeast Asia between 1961 and 2000, focusing on key countries in the sector such as Indonesia, Malaysia, Thailand, Cambodia, Laos, Myanmar, the Philippines, and Vietnam. Conducting a panel analysis, they concluded that there is an absolute convergence process within the group, with a convergence speed of 4% per year. They argued that the development of the sugar industry in each country depends on the economic policies implemented, such as import restrictions and subsidies for production and processing, which create distortions in productivity. It becomes evident that there is substantial room for productivity growth, as international benchmarks show higher productivity levels.

Complementing this discussion, Dall'erba (2005) evaluated the evolution of labor productivity convergence between 1980 and 1996 across 48 regions of Spain. Although evidence of aggregate convergence was found, the author emphasized that this pattern did not hold when analyzing the agricultural, industrial, and service sectors separately. The relevance of spatial dependence, captured through the spatial error model, indicates the influence of neighboring regions on productive performance. This contribution is fundamental, as it suggests that spatial factors must be considered in convergence analyses, otherwise the results may be biased or incomplete.

This is also reinforced by Chatterjee (2017), who tested productivity convergence in Indian agriculture between 1967 and 2010, determining that convergence exists and that there is significant spatial dependence in agricultural productivity. The significant and positive variables in the conditional convergence model were roads, electricity, irrigation, crop diversification, and the quality of human capital (rural education). The author concludes that promoting infrastructure incentives and improvements in human capital can lead to a reduction in regional disparities in India through spatial spillovers. Similarly, Dall'erba (2005), Chatterjee (2017) suggests that spatial spillovers are important for understanding the regional dynamics of productivity in rural areas, reinforcing the relevance of spatial models.

Following this methodological approach, Murtaza & Masood (2020) also confirmed the existence of both conditional and absolute convergence in Indian agriculture between 1971 and 2010. The structural factors that contributed to convergence — fertilizers, irrigation, machinery, road access, and number of livestock — align directly with previous findings and reinforce the thesis that overcoming productivity inequalities is closely tied to the availability and use of modern productive resources, as well as infrastructure.

Gong's (2020) research expands the analysis to China, testing agricultural productivity convergence and the variables that condition this convergence across 31 provinces and 23 agricultural products between 1978 and 2015. In contrast to previous studies, it was concluded that, out of the total, 23 provinces and 19 products showed no evidence of convergence. However, the variables that may contribute to increasing productivity in less developed provinces — irrigation, education, and public spending — are consistent with the determinants identified in other international experiences, reaffirming the importance of public policies.

Bringing the debate into the Brazilian context, the convergence hypothesis has been tested for different crops, for specific factors, or even for total factor productivity. In this regard, several studies are presented with the aim of comparing similar research to the results of the study proposed here, both in terms of methodology and the crop analyzed — in this case, sugarcane.

Lopes (2004a) analyzed absolute and conditional land productivity convergence for 11 crops, including sugarcane, over the period from 1960 to 2001, and found that this crop exhibited absolute convergence but not conditional convergence. One of the author's suggestions is that economic policies could improve convergence, which would help to homogenize productivity through the modernization of Brazilian agriculture.

In the same vein, Almeida et al. (2008) evaluated evidence of land productivity convergence across Brazilian microregions between 1991 and 2003. They used spatial econometric tools and found that absolute convergence exists; however, the rate is slow. This means that although productivity growth is undergoing a convergence process, it is happening slowly, leaving room for regional disparities. The authors, like those in the previously discussed studies, suggest that public policies should be designed to increase the rate of convergence.

More recent studies, such as that of Raiher et al. (2016), investigated the evolution of agricultural productivity in the microregions of Southern Brazil between the Agricultural Censuses of 1995 and 2006. The methodology used was spatial econometrics, and the results confirmed the existence of both absolute and conditional productivity convergence in the region studied. The results of conditional convergence show that structural characteristics — such as the percentage of inputs per hectare and the percentage of tractors per hectare, in addition to the cultivated area — are responsible for driving this convergence. These findings corroborate international results, which highlight the importance of structural factors in reducing productivity inequalities.

Complementing the study conducted by Raiher et al. (2016) with updated data from the 2017 Agricultural Census, Hybner et al. (2020) estimated total factor productivity (TFP) for the microregions of southern Brazil between the 2006 and 2017 Agricultural Censuses, aiming to identify productivity convergence. Using spatial econometrics, the results showed a trend of absolute convergence in TFP growth rates for this region. For conditional convergence, the results indicated that the inclusion of structural variables, such as storage infrastructure, accelerates the convergence process. In addition, credit and education variables were positive and significant. This study aligns with the findings of other research by highlighting the relevance of institutional and structural factors.

In the Northeastern context, Albuquerque (2020) estimated productivity convergence for the agricultural sector in the microregions of the Northeast region and for the municipalities of Ceará between 1996 and 2017. Using spatial econometrics to obtain the results, the study found evidence of both absolute and conditional convergence, for both the Northeast region and the state of Ceará. In addition, there is a process of spatial dependence among the microregions, indicating that geographic space influences productivity growth. The variables that were significant in the conditional convergence model were technical assistance, total cultivated area, labor, and the number of tractors. These findings align with the national and international literature presented, reaffirming the relevance of the productive and institutional structure.

Considering Brazil's ecological and productive heterogeneity, Antunes (2021) studied agricultural productivity convergence by applying spatial regimes based on biomes, covering the period from 1995 to 2017. The author concluded that there is a process of absolute and conditional convergence for the Brazilian microregions of the Amazon, Savannah, and Atlantic Forest. The factors that were significant for productivity convergence, according to the model, were credit, number of tractors, labor (negative), soil conservation, and the Gini Index (negative). The model captured both spatial dependence and spatial heterogeneity, controlling them through the spatial regimes model.

Finally, Castro (2022a) evaluated the absolute convergence of sugarcane productivity across Brazilian microregions and calculated the convergence speed for the period between 1980 and 2019. The results showed that absolute convergence occurred, but its magnitude decreased over time, as did the speed of convergence — findings also reported by Almeida et al. (2008). Castro (2022b) does not apply conditional convergence and suggests that it would be necessary to test variables that may affect productivity convergence beyond its initial condition.

In summary, the review of empirical studies reveals a scarcity of research that has specifically addressed the sugarcane crop in relation to productivity convergence, especially for more recent periods. In addition, no studies were found that analyzed the sugarcane sector by modeling spatial heterogeneity together with spatial dependence, for example, through the use of spatial regimes.

Therefore, this research distinguishes itself from previous studies by aiming to fill this gap, testing absolute and conditional productivity convergence for this specific sector and seeking to identify and analyze whether there is a spatial pattern of convergence, examining the existence of differences among Brazilian regions.

3 Methodology

This section will present the methodological procedures used to carry out this research. The approach is quantitative, based on secondary data.

The convergence models presented here are based on pioneering studies such as Barro & Sala-I-Martin (1990, 1991, 1992), as well as more recent works such as Lopes (2004a), Almeida et al. (2008), Raiher et al. (2016), and Antunes (2021). These studies employed concepts of absolute convergence and conditional convergence in their estimations. Absolute convergence (β-convergence) is estimated through a regression in which the natural logarithm (ln) of the ratio between final productivity (PTt+n) and initial productivity (PTt) is the dependent variable, and the ln of initial productivity (lnPTt) is the independent variable, as shown in Equation 1:

$$\ln\left(\frac{PT_{t+n}}{PT_t}\right)=\alpha+\beta lnPT_t+\mu \quad (1)$$

Where α and β are the parameters to be estimated in the regression, and μ is the random error term. For convergence to be confirmed, the coefficient associated with the β parameter must be negative and statistically significant, which supports the hypothesis that, over time, productivity differences tend to decrease.

Conditional convergence (β-conditional convergence) considers that convergence depends on the structural and specific characteristics of each location, and not only on its initial state, as is the case with absolute convergence. In this way, convergence would not occur toward a single steady-state point, but rather toward relative steady-state positions that are conditioned by a vector of structural variables X, as shown in Equation 2:

$$\ln\left(\frac{PT_{t+n}}{PT_t}\right)=\alpha+\beta_1 lnPT_t+\beta_2 lnX+\mu \quad (2)$$

As specified by Almeida (2012) and Raiher et al. (2016), the models in Equations (1) and (2) are estimated using Ordinary Least Squares (OLS). However, if there is spatial dependence among the regions under analysis, these estimates would be inconsistent and/or inefficient. Therefore, it is necessary to test for the existence of spatial dependence in order to account for these possibilities.

In this way, the following procedures are carried out:

a) Estimate the non-spatial model using OLS for various spatial weight matrices and analyze whether spatial dependence exists and which matrix captures the strongest spatial dependence relationship.
b) If spatial dependence is present, the spatial weight matrix that captures the greatest residual spatial dependence is selected. Then, the following models are estimated based on the matrix defined in the previous step: Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), Spatial Durbin Error Model (SDEM), and Spatial Lag of X Model (SLX).
c) The residuals of all spatial regressions from the previous step are tested to determine which model best eliminates or reduces spatial dependence. This serves as an indicator of the most suitable model. Almeida (2012) also recommends selecting the model with the lowest Akaike and Schwarz information criteria values.

d) Subsequently, the possibility of estimating regressions by spatial regimes will be tested using the spatial Chow test. If the test shows statistical significance, it suggests that the best model is the one that divides the data into subsamples representing spatial regimes. In the case of this research, these correspond to the major Brazilian regions (Center-West, Northeast, North, Southeast, and South).

e) If the best model is the one based on spatial regimes, steps (b) and (c) are repeated to select the most appropriate model.

The model to be used will consider the procedures described here for obtaining the results and determining the most appropriate model. If the model with spatial regimes is found to be appropriate, the estimation of the regressions, as well as the spatial lag in the models with spatial regimes, follows the same specifications indicated for models without spatial regimes, as detailed in Almeida (2012).

The data will be collected from the IBGE Automatic Recovery System (SIDRA) for the years 2006 and 2017, based on the two most recent available Agricultural Censuses. This database was used considering that specific data on sugarcane production at the national level, disaggregated by microregions, are not commonly available, and the Agricultural Censuses are able to meet this need.

The choice of the period and cross-section analysis considered data limitations, as the variables used by IBGE underwent changes between the 1995/96, 2006, and 2017 Agricultural Censuses. Therefore, it was not possible to capture the necessary variables to perform tests using panel data estimation. The software used for the estimation of spatial regressions and spatial regime models will be GeoDa Space.

The geographic unit adopted will be the Brazilian microregions. Municipalities were initially considered; however, many Brazilian municipalities do not engage in sugarcane production, which would make the analysis unfeasible. The use of geographic mesoregions was also tested; however, it significantly reduces the degrees of freedom in the estimations, especially for regressions with spatial regimes.

To capture the characteristics and specificities of the sector, variables that could condition productivity were identified based on the previously cited literature. The sugarcane sector in Brazil presents productive and institutional characteristics that set it apart from other agribusiness chains, standing out due to its complex integration between agriculture and industry, its strategic role in the biofuels market, and its profound regional disparities. The expansion of sugarcane, especially from the 1970s onward with the creation of the Proálcool Program, contributed to the consolidation of a vertically integrated agro-industrial system in the Southeast and Center-West regions, where large-scale farms, high levels of mechanization, logistical integration, and greater technological density prevail (Gazzoni, 2008; Martinelli & Filoso, 2008; Marin et al., 2008). In these regions, productivity is driven by efficient management systems, access to credit, transportation infrastructure, and proximity to processing mills. In contrast, the Brazilian Northeast, although historically significant in sugarcane cultivation, faces structural limitations such as smaller production scale, low mechanization, greater climate vulnerability, and logistical challenges, which negatively impact productivity levels and the stability of the sector (Guedes, 2011; Terci, 2010; Marin & Sentelhas, 2011).

In addition to regional fragmentation, there is significant heterogeneity among the actors involved in sugarcane production. The coexistence of large agro-industrial groups with independent and tenant producers results in varying capacities for investment, access to innovation, and market integration strategies (Azanha, 2001, 2012). This structural diversity directly influences the observed productivity patterns, as small and medium-sized producers face greater constraints in adopting modern technologies, hiring technical assistance, or complying with environmental and contractual requirements imposed by the mills (Terci, 2010; Lopes, 2004b). In addition, factors such as the education level of managers, gender, use of modern inputs, and participation in technical assistance networks influence the productive performance of units, shaping a sector characterized by multiple trajectories and unequal access to production factors (Marin et al., 2013; Albuquerque, 2020; Guedes, 2011). This reality justifies the importance of incorporating structural and spatial variables in analyses aimed at understanding sugarcane productivity and regional convergence in Brazil.

Table 1 presents the variables used in this research. The variables were used in percentage format to allow for comparisons across regions of different sizes without losing the intensity of each variable in its respective location.

Table 1 – Description of the variables used, their respective acronyms, year, and expected sign

Acronym	Variable	Year	Expected Sign
Y	Land productivity (quantity produced / harvested area) for 2017 divided by land productivity for 2006.	2017/2006	
X1	Land productivity (quantity produced / harvested area) for 2006.	2006	–
X2	Percentage of sugarcane produced (tons) that was sold	2006	+
X3	Percentage of harvested sugarcane area (ha) that used chemical or organic fertilization	2006	+
X4	Percentage of harvested sugarcane area (ha) that used only mechanical harvesting	2006	+
X5	Percentage of total agricultural establishments (units) that produce sugarcane	2006	+
X6	Percentage of harvested sugarcane area (ha) that used pesticides	2006	+
X7	Percentage of sugarcane-producing agricultural establishments where the manager (producer or administrator) has at least completed high school	2006	+
X8	Percentage of sugarcane-producing agricultural establishments receiving technical assistance	2006	+
X9	Percentage of sugarcane-producing agricultural establishments with female managers	2006	+ or –
X10	Percentage of sugarcane production (tons) used for human or animal consumption	2006	–
X11	Percentage of sugarcane production value (BRL) from tenant producers	2006	+
X12	Number of workers (man-equivalent units)	2006	+
X13	Land Gini Index	2006	+ or –
X14	Dummy for Center-West region	—	+ or –
X15	Dummy for Northeast region	—	+ or –
X16	Dummy for Southeast region	—	+ or –
X17	Dummy for South region	—	+ or –
X18	Spatial regimes – identification of Brazilian regions	—	

Source: Prepared by the authors.

The dependent variable (Y) is the ratio of productivity in the final year (2017) to that in the initial year (2006). Productivity was calculated by dividing the quantity of sugarcane produced (tons) by the harvested area (ha). This variable represents the proportion of change that occurred between the initial year (2006) and the final year (2017).

The independent variables are expressed by their acronyms from X1 to X18. The initial productivity condition (X1) is important for determining convergence, which is the aim of this research. The purpose of this variable is to indicate whether locations with lower initial productivity experienced greater growth compared to those with higher initial productivity. For this reason, the expected sign of the variable is negative, as a negative sign indicates that the higher the initial productivity, the lower the proportional growth in productivity relative to the final position, as explained by Barro & Sala-I-Martin (1990, 1991, 1992).

For variable X2, it is expected that the greater the proportion of production intended for sale[1], the higher the productivity. This is because when producers allocate their output for sale, they tend to focus on achieving the highest possible quality and profitability, which also indicates greater market integration, as analyzed by Terci (2010) and Azanha (2012). It is also expected that the greater the use of fertilization (X3), mechanical harvesting (X4), and pesticides (X6), the higher the productivity, considering that these elements contribute to soil maintenance, speed up the harvesting process, and help minimize losses related to pests (Marin et al., 2008; Lopes, 2004b).

For variable X5, which represents the proportion of establishments producing sugarcane relative to the total number of establishments in the microregion, it is assumed that in areas with a concentration of sugarcane-producing municipalities, knowledge spillovers as well as the development of supply chains, processing, and related services are more likely to occur — fostering production and increasing productivity. It may also reflect possible regional specialization (Guedes, 2011; Terci, 2010).

Variable X7 encompasses the education profile of the managers of sugarcane-producing establishments. The proportion of establishments whose managers had at least completed high school was considered, including those with technical education, undergraduate, and postgraduate degrees. As indicated by Marin et al. (2013) and Chatterjee (2017), human capital is essential for the adoption of technologies and the efficient management of agricultural operations.

The availability of technical guidance related to production is also a means of increasing output within the same geographic area. This variable, analyzed and considered important by authors such as Albuquerque (2020) and Lopes (2004b), promotes technological diffusion and the proper use of inputs. With this in mind, variable X8 was included to account for the proportion of sugarcane-producing establishments that receive technical guidance in relation to those that do not.

For variable X9, the intention is to test the possibility of differences in productivity based on whether the manager is female or male, as suggested in the studies by Terci (2010). Variable X10 represents the proportion of production intended for human or animal consumption on the establishments, as opposed to the portion allocated for processing or seedling production. Variable X10 is expected to have a negative sign, as observed in the analyses by Terci (2010) and Lopes (2004b), since a higher share of production for human or animal consumption tends to indicate that the establishment manager is less concerned with the quality or productivity of the sugarcane. It also suggests lower market integration and reduced productive specialization.

[1] "Production sold" refers to the variable name used in the 2006 Agricultural Census and includes: sold or delivered to cooperatives; sold directly to industries; delivered to an integrating company; sold directly to intermediaries; sold, delivered, or donated to the government; sold directly to consumers; sold as seed; exported; sold for human or animal consumption; and sold for processing or refining.

Seeking to determine whether there are differences related to the producer's land tenure status, variable X11 will also be tested. This variable expresses the proportion of production in which the producer is a tenant, as opposed to those who own the land. A positive sign is expected for this variable, as tenants must pay part of their production to the landowner in addition to securing their own profit. Therefore, they tend to seek the most effective means to increase productivity and land yield. A characteristic of sugarcane production in Brazil is the leasing of land by agro-industries to produce their own sugarcane. Therefore, this variable is also important, given its potential to influence productivity growth (Terci, 2010; Lopes, 2004b).

To understand the labor-related production factor, variable X12 includes the workforce in units, which was converted into man-equivalent (ME) units, calculated according to the method proposed by Silva & Kageyama (1983). This variable was used in absolute numbers rather than in proportion like the others, as the share of labor relative to the total in most microregions represented very small percentages, which hinders the accuracy of the estimates. As studied by Marin et al. (2008) and Raiher et al. (2016), it can be assumed that the greater the labor force, the higher the productive capacity — provided it is accompanied by efficient mechanization.

The Land Gini Index (X13) was included to test the relationship between land concentration and productivity growth. The Gini Index ranges from 0 to 1, with values closer to 1 indicating greater land concentration and values closer to 0 indicating lower land concentration. Guedes (2011), Antunes (2021), and Azanha (2012) suggest that high land concentration is associated with productive inefficiency. However, in the sugarcane sector — which requires large amounts of capital to enter the market — it can be assumed that productive concentration leads to specialization and greater economies of scale. Thus, this relationship is tested with the possibility of the parameter having either a positive or negative sign.

Understanding that there may be differences among Brazil's major regions in terms of productivity, dummy variables were included to represent the regions (X14, X15, X16, and X17), with the North region omitted to avoid perfect multicollinearity. Variable X18 also represents the regions, but it will be used specifically to test the regressions using spatial regimes.

In total, there are 558 microregions in Brazil. However, it was necessary to exclude 51 microregions (31 from the Northeast, 1 from the North, 8 from the Southeast, and 11 from the South) due to the absence of data on sugarcane production or harvested areas, which made it impossible to calculate the dependent variable. As a result, 507 observations remained in the sample.

4 Results and Discussion

Initially, tests were conducted using classical regressions (non-spatial estimated by OLS) in order to identify signs of spatial dependence in both absolute and conditional convergence (Appendix A). Based on the Moran's I test on regression residuals, it was possible to confirm the presence of spatial dependence, indicating the need to incorporate it into the model. Thus, the SAR, SEM, SDM, SDEM, and SLX models were tested for both absolute convergence (Appendix B) and conditional convergence (Appendix C). It was determined that the most appropriate model for both types of convergence was the SDEM, as it presented the lowest values for the Akaike and Schwarz information criteria. In addition, the SDEM model reduced spatial dependence as measured by Moran's I test on regression residuals, confirming that the estimated models were able to account for at least part of the spatial dependence.

Moreover, it was reasonable to assume that, in addition to spatial dependence, there was sample heterogeneity within the geographic scope used, considering that the sugarcane sector presents significant disparities in production and productivity, as previously observed in studies such as Vedana et al. (2019).

Thus, the spatial Chow test was conducted for both absolute convergence (p-value < 0.01) and conditional convergence (p-value < 0.01), indicating that the model with spatial regimes was more appropriate in both cases compared to the global model without spatial regimes. Furthermore, it was demonstrated — through the statistically significant Moran's I test on regression residuals (p-value < 0.01 for both absolute and conditional convergence) — that the spatial regimes model also captured spatial dependence, which needed to be incorporated into the model alongside heterogeneity.

Therefore, the absolute and conditional convergence models were estimated using spatial regime specifications: SAR (Appendices D and H), SEM (Appendices E and I), SDM (Appendices F and J), SDEM, and SLX (Appendices G and K). Among them, the SDEM model was once again the most appropriate for both cases, based on the reduction of the information criteria values as well as the reduction in Moran's I test on regression residuals.

The results of the SDEM model for absolute convergence with spatial regimes confirmed the existence of a productivity convergence process, as indicated by the negative and statistically significant coefficients of the variable representing the initial condition (X1) across all Brazilian regions. It is possible to identify that each region exhibits a different spatial dependence process, with varying intensities, as indicated by the coefficients of variable X1 (Appendix L).

In this model, the effect of global dependence is represented by the global λ, which was statistically significant at the 5% level and had a positive parameter sign, indicating a similarity relationship among microregions as captured by the model's residuals. The lag of the explanatory variable (WX1) was positive and significant for the Northeast, Southeast, and South regions, indicating that productivity growth in the microregions of these areas was influenced by the initial conditions of neighboring microregions.

For the estimation of the SDEM model for both absolute and conditional convergence, the hypothesis of no multicollinearity among the independent variables was assumed, given that the condition number diagnostic presented values within acceptable thresholds.

For each of the regimes, results were adjusted according to the necessary corrections: the Center-West, Southeast, and South regions showed non-normal errors (Jarque-Bera test) and heteroscedasticity in the residuals (Koenker-Bassett test). Thus, the estimation method used was GMM (Generalized Method of Moments), which does not require the assumption of error normality. Heteroscedasticity correction will be performed using the KP HET method. The Northeast region exhibited non-normal errors; however, it did not present heteroscedasticity. Thus, the estimation method used was GMM. The North region, in turn, showed normal errors and no heteroscedasticity; therefore, the model was estimated using the maximum likelihood method (Kelejian & Prucha, 1999; Arraiz et al., 2010).

Table 2 presents the results of the SDEM model for conditional convergence by spatial regimes, which was considered the most appropriate, as it achieved the greatest reduction in the Akaike Information Criterion (from 806.534 to 789.131) and the Schwarz Criterion (from 1102.529 to 1059.980), as well as the largest reduction in Moran's I test on regression residuals (from 0.0830 to 0.0503) after accounting for spatial dependence.

Table 2 – Results of the SDEM model for conditional convergence by spatial regimes

Variables	Center-West	Northeast	North	Southeast	South
Constant	3.1767**	2.3788**	3.6955**	2.2106***	2.6560*
X1	-0.8447*	-0.9167*	-0.9031*	-0.8612*	-0.9416*
X2	0.1491*	-0.0266	-0.1005*	0.0542	0.0941*
X3	0.1414**	0.0078	0.0270***	-0.0091	-0.0234***
X4	0.0485**	-0.0004	0.0337	0.0007	-0.0238**
X5	-0.2635**	0.0065	0.0395	0.0015	0.1011
X6	-0.0505	0.0059	-0.0426*	0.0019	0.0046
X7	-0.1056	0.0021	0.0273***	0.0250	0.0288**
X8	-0.0882	-0.0121	0.0452	0.0560	0.0875**
X9	-0.0314	0.0319***	0.0702*	-0.0826	-0.0091
X10	-0.0094	-0.0294***	-0.0406	-0.0594**	-0.0176
X11	0.0299**	0.0094	-0.0544	0.0159**	0.0307*
X12	-0.0116	0.0268**	0.0425**	-0.0047	0.0097
X13	0.1655	-0.7075	-0.0467	-0.2553	-0.3150
WX1	-0.4375	0.0727	0.0908	0.1481	0.0449
WX2	0.2100	0.1111**	-0.1312	0.0956	0.0557***
WX3	0.1748	-0.0347	0.0267	0.0399	-0.0205
WX4	-0.1425*	-0.0645**	-0.0025	0.2460	-0.0735*
WX5	0.0235	0.0017	-0.1730	-0.0887	-0.1570*
WX6	0.0755	0.0847*	-0.0421	-0.0372	0.0097
WX7	-0.4445***	0.0147	-0.0556	-0.0370	-0.1153**
WX8	0.2451	0.0203	-0.0580	0.1143	0.1091
WX9	0.0128	-0.0458	0.1704**	-0.0020	-0.0635***
WX10	0.0692	0.0287	0.0631	0.0192	0.0471
WX11	0.0064	-0.0070	0.1817	0.0349**	0.1133*
WX12	0.0991**	0.0185	0.0459	-0.0357***	0.0313***
WX13	-1.5442	0.4149	-2.1042***	0.8747	0.2936
λ global	**0.1701****				

Source: Prepared by the authors based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 789.131; Schwarz Criterion: 1059.980. Moran's I test on regression residuals: 0.00503 (p-value 0.036).

Variable X1 showed a negative and statistically significant sign for all Brazilian regions, confirming the existence of a productivity convergence process for sugarcane among Brazilian microregions. The global spatial dependence parameter, λ, was significant and showed a positive sign, indicating that a random shock — captured by the model's residuals — spreads from one region to another, contributing positively to productivity growth. These results are similar to those obtained by Raiher et al. (2016) and Antunes (2021), who evaluated agricultural productivity as a whole, both in terms of the most appropriate model (SDEM) and the sign and significance of variable X1 and the λ parameter.

The different parameters capturing convergence and the varying estimated coefficients of the explanatory variables for each region confirm that distinct convergence processes exist, and that each region has specific significant factors influencing productivity growth. Considering this, it would not be appropriate to analyze sugarcane productivity convergence across Brazilian microregions without incorporating the spatial heterogeneity represented by each major region into the model.

This is consistent with the findings of other studies — even those focused on different sectors or variables (given the scarcity of research specifically addressing sugarcane productivity and testing convergence through spatial regimes) — which have highlighted the importance of regional differences in convergence analysis, such as Mukherjee & Kuroda (2003a), Paudel et al. (2004b), Dall'erba (2005), and Antunes (2021).

Variable X2 (percentage of production that was sold) was statistically significant and positive for the Center-West and South regions, as expected, given the effort and need to improve productivity when production is intended for sale and, consequently, determines the producer's income. However, the North region showed a negative and significant sign, indicating that the greater the proportion of production sold, the lower the productivity growth. Although this result contrasts with other findings and insights in the literature, such as those by Terci (2010) and Azanha (2012), it may be related to the convergence process itself. In those locations where production was already being sold in the initial year of analysis (2006), productivity levels were likely already higher and, therefore, experienced less growth compared to areas that had lower initial productivity.

Variable X3 (percentage of harvested area with fertilization) was positive and significant for the Center-West and North regions, as expected, since the use of chemical or organic fertilizers in the production process tends to increase land productivity. This aligns with the findings of Raiher et al. (2016) for agricultural productivity as a whole and with the results of the study conducted in India by Murtaza & Masood (2020). They are also similarly mentioned in studies such as Marin et al. (2008) and Lopes (2004b). However, the South region showed a negative coefficient (significant at the 10% level). Based on this result, the hypothesis arises that it may be related to the edaphoclimatic conditions of the region, which, for the most part, are not favorable for sugarcane cultivation (especially in Santa Catarina and Rio Grande do Sul). This may require greater use of fertilizers, which might not yield sufficient compensatory effects to generate higher productivity levels.

For the percentage of harvested area using only mechanical harvesting (X4), the coefficient was significant and positive for the Center-West, and negative for the South. Murtaza & Masood (2020) found positive results for the use of machinery in Indian agricultural production. Raiher et al. (2016) demonstrated similar findings through the percentage of tractors per hectare for agriculture in Southern Brazil, as did the studies by Albuquerque (2020) and Antunes (2021). The Center-West and South regions have considerable differences in terrain: the Center-West features flatter landscapes, which facilitate the adoption of mechanical harvesting, while the South has more rugged terrain, making the use of mechanical harvesting more difficult. Thus, the South region possibly relies on a combination of mechanical and manual harvesting, or solely on manual harvesting. The average use of mechanical harvesting for sugarcane in the South was 5.02%, while in the Center-West it was 12.47%.

According to the proposition by Guedes (2011) and Terci (2010), productive specialization can lead to higher productivity. In this regard, variable X5 (the proportion of establishments producing sugarcane) was included and proved statistically significant only for the Central-West region, with a negative sign. This result contrasts with the findings of Albuquerque (2020) for agricultural productivity in the Northeast and Raiher et al. (2016) for agricultural productivity in the South. The result found for the Center-West region in this study is possibly linked to the fact that regions with productive agglomerations of sugarcane tend to have greater productivity homogenization, leading to lower growth. This process is specified by convergence itself, which establishes that locations with lower initial productivity tend to experience greater growth compared to those that already had high productivity levels.

The variable X6 (percentage of harvested area that used pesticides) was significant and negative only for the Northern region. Although this result contradicts the expected sign of the variable, it is considered that areas requiring higher amounts of pesticides are also more prone to pest attacks, which can significantly reduce productivity in certain harvests. In the case of the convergence test conducted here, the use of pesticides refers to the initial condition (2006), while the productivity growth relates to the comparison between the reference harvests of the 2006 and 2017 Agricultural Censuses.

The educational level of the establishment manager was represented by variable X7, which refers to the proportion of establishments where the manager had at least completed high school. It was statistically significant and positive, as expected, for the North and South regions, suggesting that the higher the level of education in these regions, the greater the increase in productivity. The conditions of education are expected to have a positive effect, as they provide greater access to productive knowledge and technologies, as supported by national and international research, such as: Marin et al. (2008), Chatterjee (2017), Paudel et al. (2004b) for agricultural productivity in the United States; Chatterjee (2017) for agricultural productivity in India; Gong (2020) for agricultural productivity in China; and Hybner et al. (2020) for total factor productivity in southern Brazil.

The percentage of establishments receiving technical assistance (X8) showed a positive and statistically significant coefficient at the 5% level for the South region, similar to the results obtained by Albuquerque (2020) and Lopes (2004b). This means that, for this region, those microregions that, in the initial period, had a higher proportion of establishments receiving technical assistance experienced greater productivity growth between the initial and final periods. This was expected, as technical assistance provides important production guidance that can improve various stages of the production chain. The positive relationship between technical assistance and higher productivity was also observed in the studies by Albuquerque (2020), for the microregions of Northeastern Brazil, and by Mukherjee & Kuroda (2003a), for total factor productivity in Indian agriculture.

Terci (2010) highlights the possibility of differentiation in rural areas based on gender. Considering this aspect, variable X9 (percentage of female managers) was included, and it showed a positive and significant result for the Northeast and North regions. This variable did not have a predefined expected sign, as the objective was to test whether there was any difference based on whether the manager was male or female. A noteworthy result is the positive impact on the growth of sugarcane productivity when the property was managed by a woman. This may be explained by women's educational attainment, which has shown an increasing trend, as noted by Vicente et al. (2005). The authors highlight that, in rural settings, women are typically responsible for seeking information — such as prices, expenses, and investment alternatives — which contributes to their role in decision-making and enables them to make more assertive choices. Camargo (2018) also finds evidence that women working in agriculture tend to have higher levels of education and are more inclined to introduce new management approaches, participate in training courses, and adapt to market demands. Furthermore, the Northeast and North regions have percentages of female managers above the Brazilian average, with 10.5% and 9.3%, respectively, compared to the national average of 9.08%, while the other regions fall below this average.

For the percentage of production intended for human or animal consumption (X10), the Northeast and Southeast regions showed negative and significant coefficients, corroborating the findings of Terci (2010) and Lopes (2004b). Therefore, the greater the proportion of production intended for consumption in the microregion, the lower the productivity growth. This result was expected, as production intended for human or animal consumption does not require high productivity and is generally allocated as a supplement for producers.

The variable X11 (percentage of production under leasehold arrangements) showed positive and significant behavior for the Center-West, Southeast, and South regions, indicating that the higher the proportion of production by tenant farmers, the greater the productivity growth. It was assumed that this variable would have a positive sign, primarily due to the Brazilian context in which the sugar mills themselves lease land to produce their raw material (Terci, 2010). Secondly, because producers who use land as tenants need to ensure that production is sufficient not only to cover the cost of the lease but also to generate productive profits. In this way, it is expected that the producer will make efforts to maximize land productivity, whether it is a mill or an individual farmer.

Labor (X12) was positive and significant for the Northeast and North regions, indicating that these regions relied on the labor production factor to increase productivity during the period analyzed. Meanwhile, the Center-West region, for example, showed productivity growth mainly through mechanical harvesting, which partly reflects the incorporation of capital into the production process. The positive relationship between labor and productivity growth was also observed in the study by Albuquerque (2020) regarding agricultural productivity in the microregions of Northeastern Brazil. It was also proposed by the studies of Marin et al. (2008) and Raiher et al. (2016).

The Gini Index for land (X13) was a variable tested to understand whether there was a relationship between land concentration and greater or lesser productivity growth, according to Guedes (2011), Antunes (2021), and Azanha (2012). However, it was not statistically significant for any region; therefore, it cannot be stated that it has any negative or positive impact on productivity within the scope of this research.

The lagged independent variables, represented by the acronyms WX1 to WX13, express the local effect of these variables — averaged across neighboring regions — on the dependent variable in the microregion under analysis. Thus, they can be interpreted similarly to the non-lagged variables, with the understanding that when they are significant and positive, the productivity growth of a microregion — within that larger region — is positively influenced by the growth of the explanatory variable in the average of neighboring regions. In turn, when they present a negative sign, they are interpreted as having a negative influence on the productivity growth of the reference municipality, when the explanatory variable increases in the average of the surrounding microregions.

Table 3 provides a summary view of the results from the final model, which captures both spatial dependence and spatial heterogeneity for absolute and conditional convergence. It is possible to observe the relationship between the dependent variable and the explanatory variables that were statistically significant for each of the major Brazilian regions. It is also possible to analyze the sign of each variable's coefficient and the relationship of the variables in the model, whether they are explanatory or spatially lagged explanatory variables. The first conclusion is that there is a convergence process in sugarcane productivity in Brazil when observing the microregions, both for the model as a whole and for the regions individually.

It is important to emphasize that each region had different significant variables, which is precisely captured by the analysis through spatial regimes. In a general analysis of the variables by region, it can be understood that productivity growth in the Center-West is focused on production for processing, based on capital investment in production, such as the use of mechanical harvesting and fertilization. The Northeast, in turn, shows a positive relationship between productivity growth and labor, as well as female managers of the establishments, which indicates a productivity pattern oriented toward the labor production factor.

Table 3 – Summary of results expressed by the relationship between the dependent variable and the significant explanatory variables in the conditional convergence model by spatial regimes

Region / Relationship with the dependent variable	Positive for explanatory variables	Negative for explanatory variables	Positive for lagged explanatory variables	Negative for lagged explanatory variables
Center-West	– Sold production. – Use of fertilization. – Mechanical harvesting. – Tenant producer.	– Initial productivity. – Establishments that produce sugarcane.	– Labor.	– Mechanical harvesting. – Manager's education level.
Northeast	– Female managers. – Labor.	– Initial productivity. – Production for consumption.	– Sold production. – Use of pesticides.	– Mechanical harvesting.
North	– Use of fertilization. – Manager's education level. – Female managers. – Labor.	– Initial productivity. – Sold production. – Use of pesticides.	– Female managers.	– Land Gini Index.
Southeast	– Tenant producer.	– Initial productivity. – Production for consumption.	– Tenant producer.	– Labor.
South	– Sold production. – Manager's education level. – Technical assistance. – Tenant producer.	– Initial productivity. – Use of fertilization. – Mechanical harvesting.	– Sold production. – Tenant producer. – Labor.	– Mechanical harvesting. – Establishments that produce sugarcane. – Manager's education level. – Female managers.

Source: prepared by the authors based on the research results.

Highlighting the main results for the Northern region, it is evident that the education level of the establishment manager had a positive relationship with productivity growth. In contrast, the use of pesticides showed a negative relationship with productivity, possibly due to the fact that the need for pesticide use may indicate potential productivity losses caused by pest infestations.

In the South, it is worth noting that it was the only region where the variable technical assistance was statistically significant, contributing to productivity growth, in addition to other variables previously discussed.

5 Conclusions

It was therefore concluded that, in addition to the spatial relationship observed in the growth of sugarcane productivity across Brazilian micro-regions, it is also necessary to consider the inherent regional differences within this sector. Historically, it has been a sector with specific dynamics in each location, shifting the production center from the Northeast to the Southeast, with the Southeast taking the lead in the development and implementation of technologies.

Production in the Southeast eventually spilled over into Paraná and the Central-West region, the latter demonstrating strong suitability for sugarcane cultivation.

In this context, productivity convergence is important as it drives regions toward high-performance production standards, leading to improvements in rural producers' income. Even when considering the specific production characteristics of each Brazilian region, this research makes it possible to affirm that productivity differences in sugarcane cultivation have been decreasing among Brazilian micro-regions. Moreover, this reduction is especially associated, in the Central-West region, with the use of fertilizers and mechanical harvesting — variables that can be encouraged to further reduce these disparities.

In the Northeast region, productivity growth can be stimulated by increasing the proportion of production that is processed/sold/industrialized (considering the negative relationship with variable X10). In the North, productivity improvement is linked to variables such as the use of fertilizers and education, which can also be encouraged through government initiatives, for example. In the Southeast region, the country's largest producer, production for consumption also negatively affects productivity, just as it does in the Northeast region. And, in the South, education and technical guidance are important tools for reducing sugarcane productivity disparities.

It is understood that there is scope for both governmental and private initiatives aimed at enhancing productivity and, consequently, rural income, by fostering the variables previously identified. Nonetheless, it is essential to acknowledge that such measures must be tailored to the specific conditions of each Brazilian region.

This study aimed to contribute to the literature on sugarcane productivity by testing convergence and its explanatory variables, while also accounting for Brazil's regional differences through spatial regimes. This approach was adopted considering the absence of studies that applied such tests for the period, the chosen geographic scope, and the employed methodology.

It is recommended that future research be conducted using different geographic scopes, with a particular focus on testing other factors that may be influencing the reduction of sugarcane productivity disparities. Moreover, focused field research can also contribute to identifying new factors that promote convergence.

Authors' contributions:

RC: Conception/design of the study, Data collection, Analysis and interpretation, Writing of the manuscript. PFAS: Conception/design of the study, Data collection, Analysis and interpretation, Critical review. ALS: Data collection, Analysis and interpretation, Critical review.

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APPENDIX A – RESULTS OF THE NON-SPATIAL MODEL FOR ABSOLUTE CONVERGENCE

Variables/Tests	Coefficient
Constant	1.8886*
X1	-0.5576*
R^2	0.4513
Multicollinearity (Condition Number)	6.423
Jarque-Bera	44.690*
Breusch-Pagan	8.147*
Koenker-Bassett	6.362**
White	8.307*
Moran's I of the residuals	0.2572*
Akaike Information Criterion	972.157
Schwarz Criterion	980.614

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%.

APPENDIX B – ESTIMATION RESULTS FOR THE SAR, SEM, SDM, AND SLX MODELS FOR ABSOLUTE CONVERGENCE

Variables/Tests	Models			
	SAR	SEM	SDM	SLX
Constant	2.226*	2.3233*	0.5560	1.1845*
X1	-0.6385*	-0.6925*	-0.7520*	-0.7093*
W X1	–	–	0.5917*	0.3690*
λ	–	0.5393*	–	–
ρ	-0.9578*	–	0.5778***	–
Pseudo R^2	0.2617	0.4513	0.587	0.5204
Moran's I (residuals)	0.5379*	0.3521*	-0.0811*	0.2181*
Akaike Information Criterion	971.225	878.462	860.692	905.916
Schwarz Criterion	983.911	886.919	877.606	918.601

Source: Prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%.

APPENDIX C – ESTIMATION RESULTS FOR SAR, SEM, SDM, AND SLX MODELS FOR CONDITIONAL CONVERGENCE

Variables/Tests	Models			
	SAR	SEM	SDM	SLX
Constant	2.7236*	2.7518*	4.8511	2.7270*
X1	-0.8637*	-0.8702*	-0.9032*	-0.8993*
X2	0.0108	-0.0024	-0.0100	0.0097
X3	0.0008	0.0027	0.0061	0.0017
X4	0.0110	0.0133***	0.0255**	0.0093
X5	-0.0246	-0.0115	-0.0756	-0.0026
X6	0.0114	0.0050	0.0174	0.0034
X7	0.0195	0.0197	0.0295	0.0145
X8	0.0235	0.0207	-0.0037	0.0212
X9	0.0190	0.0191	0.0178	0.0208
X10	-0.0262**	-0.0277**	-0.0410**	-0.0296**
X11	0.0268*	0.0186*	0.0231*	0.0171*
X12	0.0216*	0.0200*	0.0229*	0.0134**
X13	-0.6322**	-0.4949***	-2.500	-0.4152
X14	0.2144	0.2692	0.3405	0.1892
X15	-0.0044	0.0312	0.0557	0.0541
X16	0.2691**	0.3412**	0.5658**	0.72407**
X17	0.0640	0.1232	0.5172	-0.0068
*W*X1	-	-	-0.5124	-0.0800
*W*X2	-	-	0.3063**	0.0859*
*W*X3	-	-	-0.0687	-0.0180
*W*X4	-	-	0.0221	-0.0264
*W*X5	-	-	-0.0778	-0.0545
*W*X6	-	-	0.0858*	0.0595*
*W*X7	-	-	0.1121	0.0222
*W*X8	-	-	0.0420	0.0195
*W*X9	-	-	-0.0644***	-0.0090
*W*X10	-	-	0.1037	0.0153
*W*X11	-	-	0.0034	0.0179
*W*X12	-	-	-0.0039	0.0083
*W*X13	-	-	4.6248	-0.4983
λ	-	0.3252*	-	-
ρ	-0.0497	-	-0.2349	-
Pseudo R^2	0.6092	0.6099	0.5162	0.6545
Akaike Information Criterion	822.628	801.942	789.331	800.084
Schwarz Criterion	902.970	878.055	924.644	931.0168
Moran's I (residuals)	0.1475*	0.1593*	0.0187*	0.1166*

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%.

APPENDIX D – ESTIMATION RESULTS OF ABSOLUTE CONVERGENCE BY SPATIAL REGIMES FOR THE SAR MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	1.3945*	1.9508*	2.3778*	2.4237*	1.8141*
X1	-0.4301*	-0.6466*	-0.9016*	-0.6234*	-0.5064*
global ρ	-0.5713*				

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 901.905; Schwarz Criterion: 948.418. Moran's I (residuals): 0.3884 (p-value 0.001).

APPENDIX E – RESULTS OF ESTIMATIONS OF ABSOLUTE CONVERGENCE BY SPATIAL REGIMES FOR THE SEM MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	1.7461*	2.2669*	2.4460*	2.4550*	1.9121*
X1	-0.5070*	-0.7544*	-0.9005*	-0.6417*	-0.5618*
global λ			0.4394*		

Source: Prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 854.180; Schwarz Criterion: 899.465. Moran's I (residuals): 0.2343 (p-value 0.001).

APPENDIX F – ESTIMATION RESULTS OF ABSOLUTE CONVERGENCE BY SPATIAL REGIMES FOR THE SDM MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	0.0351	0.1720	1.8397*	0.5728	0.7556
X1	-0.5191*	-0.7505*	-0.9021*	-0.7744*	-0.6016*
*W*X1			0.4954* 0.6812* 0.2029 0.6304* 0.3790		
global ρ	0.6249***				

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 839.223; Schwarz Criterion: 906.880. Moran's I (residuals): -0.1244 (p-value 0.001).

APPENDIX G – ESTIMATION RESULTS OF ABSOLUTE CONVERGENCE BY SPATIAL REGIMES FOR THE SLX MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	0.3608	0.4430	2.5168*	1.4230*	1.2610*
X1	-0.4750*	-0.7171*	-0.9048*	-0.7242*	-0.5626*
WX1	0.3334	0.5573*	-0.0339	0.3614*	0.2068**

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 864.622; Schwarz Criterion: 928.049. Moran's I (residuals): 0.1584 (p-value 0.001).

APPENDIX H – ESTIMATION RESULTS OF CONDITIONAL CONVERGENCE BY SPATIAL REGIMES FOR THE SAR MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	2.7658*	2.9039*	1.9646*	2.8825*	2.5714*
X1	-0.07468*	-0.8504*	-0.9466*	-0.8752*	-0.9457*
X2	0.1052**	-0.0155	-0.0502**	0.0696	0.0740*
X3	0.2043**	0.0012	0.0230***	-0.0180	-0.0126
X4	0.0270	-0.0048	0.0504*	0.0039	-0.0070
X5	-0.1098	-0.0224	-0.0393	-0.0058	0.0399
X6	-0.0321	0.0167	-0.0315**	0.0199	0.0176
X7	-0.2150*	0.0097	0.0368*	0.0991	0.0368*
X8	-0.1038	-0.0121	0.0815**	0.0597	0.1749*
X9	-0.0494	0.0301	0.0500*	-0.0786	-0.0372***
X10	-0.0719**	-0.0248	-0.0485**	-0.0385***	-0.0801
X11	0.0203	0.0144	-0.1127*	0.0233*	0.0360*
X12	0.0011	0.0416*	0.0378**	-0.0038	0.0050
X13	-1.0059	-0.0811	-0.4032	-0.0205	-0.296
global ρ	-0.0048				

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 806.643; Schwarz Criterion: 1102.529. Moran's I (residuals): 0.0850 (p-value 0.004).

APPENDIX I – ESTIMATION RESULTS FOR CONDITIONAL CONVERGENCE BY SPATIAL REGIMES FOR THE SEM MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	2.7583*	2.9714*	2.0684*	2.9009*	2.5648*
X1	-0.7458*	-0.8673*	-0.9546*	-0.8793*	-0.9431*
X2	0.1054**	-0.0299	-0.0516**	0.0677	0.0742*
X3	0.2022**	0.0084	0.0231	-0.0190	-0.0127
X4	0.0258	0.0044	0.0476**	0.0030	-0.0072
X5	-0.1062	-0.0200	-0.0311	-0.0007	0.0387
X6	-0.0287	0.0054	-0.0314***	0.0213	0.0176
X7	-0.2170*	0.0118	0.0421*	0.1008	0.0366*
X8	-0.1010	-0.0140	0.0782***	0.0516	0.1746*
X9	-0.0500	0.0346**	0.0391***	-0.0795	-0.0372***
X10	-0.0720**	-0.0265***	-0.0470***	-0.0392***	-0.0797
X11	0.0196	0.0114	-0.1102*	0.0217*	0.0364*
X12	0.0024	0.0399*	0.0406**	-0.0029	0.0051
X13	-0.9869	-0.1298	-0.3978	-0.0925	-0.2995
global λ			0.2473*		

Source: Prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 791.424; Schwarz Criterion: 1087.420. Moran's I (residuals): 0.1125 (p-value 0.001).

APPENDIX J – ESTIMATION RESULTS OF CONDITIONAL CONVERGENCE BY SPATIAL REGIMES FOR THE SDM MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	2.9087	2.1190***	3.0383***	2.2803	5.5487*
X1	-0.8110*	-0.9111*	-0.9022*	-0.8656*	-1.0639*
X2	0.1230*	-0.0221	-0.0930*	0.0564	0.0535
X3	0.1189	0.0062	0.0264**	-0.0094	-0.0533
X4	0.0431***	0.0001	0.0324	0.0011	-0.0052
X5	-0.2348***	-0.0021	0.0421	0.0001	-0.0515
X6	-0.0285	0.0058	-0.0413*	0.0194	-0.0064
X7	-0.0753	-0.0006	0.0319**	0.0241	0.0486*
X8	-0.0866	-0.0115	0.0455	0.0565	0.1444**
X9	-0.0494	0.0340	0.0688*	-0.0872***	0.0349
X10	-0.0026	-0.0328**	-0.0403	-0.0559**	-0.0818
X11	0.0286**	0.0103	-0.0578	0.0162**	0.0465**
X12	-0.083	0.0277**	0.0414**	-0.0046	0.0275
X13	0.1918	-0.7388	-0.0131	-0.2756	-0.3156
*W*X1			-0.2027 0.1131 0.2453 0.1089 -1.1273		
*W*X2	0.3341***	0.1157**	-0.1095	0.0902	0.1878**
*W*X3	0.2536***	-0.0479**	0.0282	0.0425	-0.0335
*W*X4	-0.1563*	-0.0610***	-0.0029	0.0252	-0.0907***
*W*X5	-0.0543	0.0130	-0.1863	-0.0886	-0.0908
*W*X6	0.0474	0.0774**	-0.0438	-0.0343	-0.0010
*W*X7	-0.5174***	0.0259	-0.0580	-0.0390	0.0045
*W*X8	-0.0909	0.0187	-0.0472	0.1345	0.5621***
*W*X9	-0.0252	-0.0287	0.1396**	0.0227	-0.0157
*W*X10	0.1666	0.0196	0.0795	0.0147	-0.1251
*W*X11	0.0186	-0.0119	0.1918	0.0339***	0.1339*
*W*X12	0.0935**	0.0169	0.0273	-0.0334	0.0189
*W*X13	-1.3275	0.1310	-2.2160**	0.8935	0.4385
global ρ	-0.0159				

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 792.276; Schwarz Criterion: 1067.353. Moran's I (residuals): 0.0773 (p-value 0.002).

APPENDIX K – ESTIMATION RESULTS OF CONDITIONAL CONVERGENCE BY SPATIAL REGIMES FOR THE SLX MODEL

Variables	Center-West	Northeast	North	Southeast	South
Constant	2.8712	2.0872**	3.5072	2.2508**	2.7877*
X1	-0.8108*	-0.9116*	-0.9011*	-0.8664*	-0.9781*
X2	0.1225	-0.0225	-0.0985**	0.0564	0.1044*
X3	0.1186	0.0063	0.0272	-0.0095	-0.0191
X4	0.0433***	0.0004	0.0337	0.0011	-0.0203
X5	-0.2347	-0.0018	0.0367	0.0004	0.1005***
X6	-0.0289	0.0056	-0.0420***	0.0196	0.0065
X7	-0.0745	-0.0004	0.0291	0.0239	0.0317
X8	-0.0879	-0.0116	0.0448	0.0558	0.0814
X9	-0.0496	0.0340***	0.0682***	-0.0877	-0.0080
X10	-0.0029	-0.0327**	-0.0395	-0.0555**	-0.0175
X11	0.0287	0.0102	-0.0554	0.0161**	0.0303***
X12	-0.0084	0.0276**	0.0419	-0.0046	0.0077
X13	0.1992	-0.7434	-0.0565	-0.2832	-0.2205
*W*X1	-0.1917	0.1245	0.1068	0.1192	0.0061
*W*X2	0.3351	0.1156**	-0.1255	0.0872	0.0574
*W*X3	0.2530	-0.0474***	0.0292	0.0431	0.0021
*W*X4	-0.1567**	-0.0609**	-0.0009	0.0251	-0.0598
*W*X5	-0.0519	0.0128	-0.01775	-0.0886	-0.1968**
*W*X6	0.0465	0.0771*	-0.0439	-0.0343	0.0047
*W*X7	-0.5135***	0.0255	-0.0544	-0.0397	-0.1251***
*W*X8	-0.0917	0.0190	-0.0516	0.1337	0.1254
*W*X9	-0.0274	-0.0295	0.1612***	0.0265	-0.0389
*W*X10	0.1670	0.0202	0.0682	0.0146	0.0179
*W*X11	0.0184	-0.0120	0.1796	0.0333***	0.1042*
*W*X12	0.0929	0.0163	0.0375	-0.0329	0.0289
*W*X13	-1.3239	0.1548	-2.1691	0.8981	0.0651

Source: prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 794.707; Schwarz Criterion: 1365.556. Moran's I (residuals): 0.0554 (p-value 0.026).

APPENDIX L – RESULTS OF THE SDEM MODEL FOR ABSOLUTE CONVERGENCE BY SPATIAL REGIMES

Variables/Tests	Center-West	Northeast	North	Southeast	South
Constant	0.3645	0.6098	2.7373*	1.4899*	1.4443*
X1	-0.4689*	-0.7132*	-0.9139*	-0.7203*	-0.6089*
*W*X1	0.3307	0.4969*	-0.1234	0.3403*	0.1960**
global λ	0.3455**				

Source: Prepared by the author based on the research results. Notes: * significant at 1%; ** significant at 5%; *** significant at 10%. Akaike Information Criterion: 835.796; Schwarz Criterion: 899.223. Moran's I (residuals): 0.1680 (p-value 0.001).