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Spatial Analysis of Sustainable and Agricultural Development in Southern Brazil

Fernanda Cigainski Lisbinski[1], Felipe André Oliveira Freitas[2] & Heloisa Lee Burnquist[1]

[1] Department of Economics, Administration and Sociology, "Luiz de Queiroz" College of Agriculture, University of São Paulo, Piracicaba, 13416-000, SP, Brazil

[2] Department Animal Science, "Luiz de Queiroz" College of Agriculture, University São Paulo, Piracicaba, 13416-000, SP, Brazil

Correspondence: Fernanda Cigainski Lisbinski, Department of Economics, Administration and Sociology, "Luiz de Queiroz" College of Agriculture, University of São Paulo, Piracicaba, 13416-000, SP, Brazil.

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Abstract

This study aimed to develop and analyze a Sustainable and Agricultural Development Index (SADI) for the municipalities of the Southern Region of Brazil. The methodology employed included factor analysis through principal component analysis, followed by exploratory spatial data analysis (ESDA) to examine the spatial distribution of the index. The results indicate a generally medium-low level of sustainable agricultural development, with the highest index value being 0.5885 and most others falling below 0.5. The ESDA revealed strong evidence of significant positive spatial correlation among the municipalities, as well as considerable disparities in sustainable and agricultural development across the region. These disparities highlight the need for targeted public policies and coordinated initiatives to improve infrastructure, promote technological innovation, and implement sustainable agricultural practices, aiming for balanced and inclusive growth in the region.

Keywords: agriculture, sustainability, factor analysis, Exploratory Spatial Data Analysis (ESDA)

1. Introduction

One of the greatest challenges today is to align the need for increased agricultural production with the promotion of sustainable development, the reduction of impacts on natural resource use, and support for social development. This motivation stems from international debates and social pressures that call for a new development model capable of reconciling economic growth, social development, and environmental preservation (Sambuichi et al., 2012).

According to Froehlich (2014), the theme of sustainability is gaining increasing prominence; however, it is a concept still under development and requires more detailed study for better understanding. Despite this, the most widely used concept of sustainable development is that presented in the Brundtland Report by the World Commission on Environment and Development (WCED, 1987), which states that sustainable development is a process of change in which the exploitation of resources, the direction of investments, technological development, and institutional changes are made consistent with both current and future needs. Sustainable development is defined based on several dimensions; the three most frequently indicated in the literature are economic, social, and environmental (Gehringer & Kowalski, 2024; Werbach, 2010; Pawlowski, 2008; Spangenberg & Bonniot, 1998; Sachs, 1993; Organisation for Economic Cooperation and Development [OECD], 1993).

The economic dimension pertains to macroeconomic planning, involving the efficient allocation and management of resources and a consistent flow of public and private investments from endogenous sources. This aims to expand access to resources and foster economic and social development. The social dimension focuses on achieving a standard of living adequate for both the present and the future, aligned with enhancing the quality of life through greater equity in income distribution, improvements in health and education, job creation, and related factors. The environmental dimension seeks the rational use of natural resources—including both renewable and non-renewable resources—and the management of fossil fuel consumption. It emphasizes reducing waste and pollutants, increasing research for the development of low-waste technologies that promote urban, rural, and industrial development, and establishing standards for environmental protection. This dimension necessitates solutions for production processes that consume large amounts of natural resources, aiming to reduce environmental degradation while meeting the demands of the global population without harming the environment (Sachs, 1993; Terra dos Santos et al., 2023; Hariram et al., 2023).

In this context, it is important to note that Brazil is essentially an agricultural country; therefore, this sector is extremely significant for generating wealth and income in the nation. However, the development of this sector has not occurred uniformly across regions and product specializations. According to Melo (2006) and the Organisation for Economic Co-operation and Development (OECD, 2015), this uneven development resulted from the evolution of the agricultural sector based on the formation of agro-industrial complexes. The emergence of these agro-industrial complexes generated wealth but was also accompanied by increased concentration of income and land ownership, rural exodus, unemployment, ecological imbalances, and the exclusion of the less privileged, since the capital invested over the years benefited large-scale producers more than small family producers (Pereira et al., 2004; Sergi et al., 2019).

Agricultural establishments occupy a total area of 351.3 million hectares, corresponding to about 41% of Brazil's territory, with significant discrepancies in the percentage of occupied area among Brazilian regions (Brazilian Institute of Geography and Statistics [IBGE], 2017). Because agriculture primarily utilizes land and natural resources in its production processes, the environmental impacts caused by this sector are considerable. These impacts directly or indirectly affect the climate, the hydrological cycle, and the quality of natural resources available in the country (Sambuichi et al., 2012). Consequently, a major concern arises: the search for growth and development patterns in the agricultural sector that are aligned with sustainable development.

In this context, the following questions arise: What is the contribution of agricultural development to economic, social, and environmental sustainability? How can these aspects be reconciled? What is the current situation in Brazil? Therefore, the objective of this study is to develop and analyze an index of sustainable agricultural development for the municipalities in the Southern Region of the country. The specific objectives are to create an indicator based on the dimensions of sustainability and the current agricultural situation in the region, and to analyze its spatial distribution, discussing the results obtained. The methodology employed includes factor analysis through principal component analysis, followed by Exploratory Spatial Data Analysis (ESDA) to examine the distribution of the indicator and the formation of clusters.

The justification for choosing this theme arises from the ongoing academic and social debate on the subject and the significant difficulty in reconciling sustainable and agricultural development. Therefore, this study aims to develop an indicator based on these two interrelated areas, examining the relationships among the variables involved in constructing the indicator. The choice of the region analyzed is justified by the fact that the Southern Region has the second-largest planted area in the country (22,320,494 hectares), behind only the Midwest Region (31,803,034 hectares). It is the largest producer of wheat (85% of national production) and rice (82%), and the second-largest producer of corn (22%) and soybeans (28.26%) in Brazil (Municipal Agricultural Survey—Brazilian Institute of Geography and Statistics [PAM-IBGE], 2021).

In addition, the agricultural sector holds significant prominence in the region and is a major generator of employment and income. Due to its geographical location, favorable climate, and abundant natural resources, the Southern Region has substantial potential for agricultural production. Finally, studying agriculture in this region, aligned with sustainable development principles, can aid in understanding how agricultural production can be conducted sustainably, preserving the natural resources and biodiversity of the area.

This study is divided into four sections, beginning with this introduction. Section two presents the methodology used; section three analyzes and discusses the results; and finally, section four presents the conclusions of the study.

2. Methodology

2.1 Statistical Foundations of the SADI

To capture the sustainable and agricultural development of the municipalities in the Southern Region, a wide range of variables was used. To reduce this broad set, factor analysis was employed, which transforms the variables into a reduced number of factors. This results in a more direct and parsimonious data reduction, facilitating interpretation and analysis. Factor analysis is a multivariate technique that groups variables exhibiting similar correlation behaviors; thus, from a selected group of variables, information is consolidated through factors or components (Hair Jr. et al., 2009). In this study, we use the principal components method to explain the factor analysis model, which extracts uncorrelated factors while maximizing their contribution to the common variance (Fávero & Belfiore, 2017).

The factor analysis model is given by the following equation (Mingoti, 2005):

$$X_i = \alpha_{ij} F_j + \varepsilon_i \tag{1}$$

where, $X_i = (X_1, X_2, X_3 \dots, X_p)^t$ = a transposed vector of observable random variables; α_{ij} = a matrix $(p \ x \ m)$ of fixed coefficients called factor loadings, which describe the linear relationship of X_i; $e \ F_j$; $F_j = (F_1, F_2, \dots, F_p)$ is a transposed vector $(m < p)$ is a transposed vector of latent variables, describing the unobservable elements of the sample used; $\varepsilon_i = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_p)$ represents a transposed vector of random errors, corresponding to measurement and variance errors not explained by common factors. Considering that the variables composing the indicator have different scales, and principal component analysis aims to maximize variance, it may be sensitive to these differing scales, potentially affecting the results. To address this issue, it is necessary to standardize the variables, expressing the data in comparable units (Lattin, 2011). This procedure can be achieved by the following equation:

$$Z = \frac{(X_i - \bar{X})}{S} \ , i = 1, 2, 3 \ \dots, n \tag{2}$$

where, Z is the standardized variable; X_i is the variable to be standardized; $\bar{X}$ is the arithmetic mean of the variable X; S is the sample standard deviation of the variable X. By standardizing the observable variables X_i, they can be replaced by a standardized variable vector Z_i, which resolves the issue of differing scale units.

The next step is to identify the appropriate number of factors to include in the model. This involves examining the eigenvalues, also known as characteristic roots, which express the total variance explained by each observed factor. The determination of the number of factors required to represent the data set is guided by Kaiser's Rule, which recommends retaining those principal components whose eigenvalues exceed one (Lattin, 2011).

To facilitate the interpretation of the factors, an orthogonal rotation using the varimax method is applied. This method simplifies the structure of the factor loading matrix by maximizing the variance of the squared loadings for each factor, thereby promoting a clearer and more interpretable factor structure (Hair et al., 2009).

According to Mingoti (2005), the factor scores are values corresponding to each observation in the sample, situating them within the space of the common factors. These scores are calculated using the following equation:

$$F_j = \sum_{j=1}^{k} b_i X_{ij} \ , \text{com i = 1, 2,…, p} \tag{3}$$

where, F_j denotes the factor scores; b_i are the regression coefficients representing the weights of the variables X_{ij} in the factor F_j ; X_{ij} are the values of the variables for the k-th observation in the sample.

Therefore, according to Mingoti (2005), the Sustainable and Agricultural Development Index ($SADI_m$) can be calculated using the following expression:

$$SADI_m = \sum_{i=1}^{p} \left(\frac{\sigma i^2}{\sum_{i=1}^{p} \sigma^2 i} F_{im} \right) \tag{4}$$

where σ^2 is the variance explained by fator i; p is the number of factors selected; $\sum_{i=1}^{p} \sigma^2 i$ is the sum of the variances explained by all p factors and F_{ie} is the factor score of the m-th municipality in the Southern Region of Brazil for fator i. The results are then standardized to facilitate comparison among municipalities. This normalization is achieved using the following formula:

$$SADI_m = \frac{SADI_{m(before)} - SADI_{min}}{SADI_{máx} - SADI_{min}} \tag{5}$$

where the individual values of $SADI_m$, along with the maximum and minimum values, are used to adjust the results to a scale between 0 and 1.

According to Fávero and Belfiore (2017), the results obtained can be evaluated using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. The KMO test is given by the following equation:

$$KMO = \frac{\sum_{l=1}^{k} \sum_{c=1}^{k} \rho_{lc}^2}{\sum_{l=1}^{k} \sum_{c=1}^{k} \rho_{lc}^2 + \sum_{l=1}^{k} \sum_{c=1}^{k} \varphi_{lc}^2} \tag{6}$$

where KMO values between 0.6 and 0.7 are considered reasonable; however, it should be noted that the closer the KMO value is to 1, the better the overall adequacy of the model. Bartlett's test of sphericity is given by the following equation:

$$X^2_{Bartlett} = \left[(n-1) - \left(\frac{2k+5}{6}\right)\right] \ln|D| \tag{7}$$

where the degrees of freedom are calculated as $\frac{k\ (k-1)}{2}$, with n being the sample size, k the number of variables, and D the determinant of the correlation matrix ρ. When the value of the test statistic exceeds the critical value, the null hypothesis that the correlation matrix is an identity matrix is rejected.

Thus, in the next section, we will describe the second methodology used in this work: Exploratory Spatial Data Analysis (ESDA). Following the presentation of the econometric procedure adopted for developing the proposed SADI and its spatial distribution, we will provide a description of the variables used, along with the data sources employed to compose the SADI for the municipalities in the Southern Region of Brazil.

2.2 A Synthesis of Exploratory Spatial Data Analysis (ESDA)

Exploratory Spatial Data Analysis (ESDA) examines the interaction of agents across space; that is, the value of a certain variable of interest in each region i depends on the values of this variable in neighboring regions j. Including spatial location in the study enhances the consistency of the results. According to Anselin (1999), spatial econometrics is a subfield of econometrics that deals with spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models.

Therefore, to obtain more consistent results, ESDA is used to verify whether there is spatial autocorrelation between municipalities and their neighbors and whether they influence the sustainable and agricultural development of the latter. Autocorrelation is measured using Moran's I statistic, which indicates the degree of linear association between the observed values and the weighted average of the neighboring values (Parré, 2014; Almeida, 2012). Moran (as cited in Almeida, 2012) states that the formula for this statistic can be expressed by the following equation:

$$I = \frac{n}{\Sigma\Sigma\,\omega_i} \frac{\Sigma\Sigma\,\omega_{ij}\ (y_i-\bar{y})(y_i-\bar{y})}{(\Sigma\, y_i-\bar{y})^2} \tag{8}$$

where, n is the number of observations (regions), y_i is the variable of interest; ω_{ij} is the spatial weight for the pair of spatial units i and j measure the level of interaction between them.

Considering this, spatial dependence is one of the main characteristics of spatial data. However, to determine the degree of spatial autocorrelation, one must consider the neighborhood structure intended for analysis. By adopting a neighborhood criterion, it is possible to construct a spatial weight matrix (Sabater, Tur, & Azorín, 2011). These matrices are based on contiguity and can be determined according to neighborhood, geographic or socioeconomic distance, or even by a combination of both (Almeida, 2012). The most common forms of spatial weight matrices used are the queen and rook contiguity conventions, as shown in Figure 1, where the neighbors of regions A and B are the highlighted regions. Regarding the queen contiguity convention, it considers as contiguous not only the boundaries with non-zero length but also the vertices (nodes) in the map representation. The rook contiguity, on the other hand, considers only the physical borders with non-zero length between regions (Almeida, 2012).

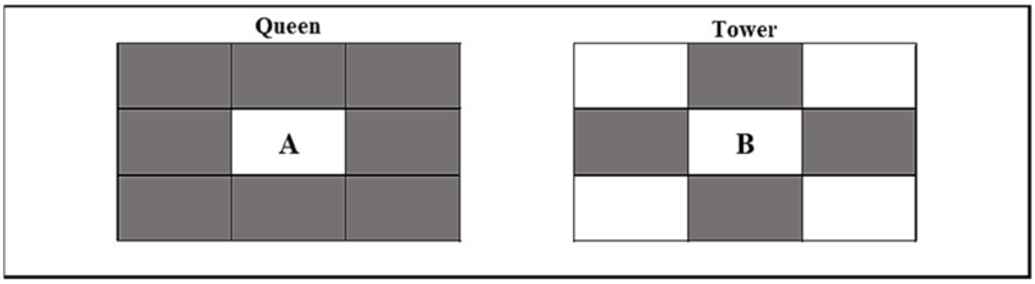

Figure 1. Space Weight Matrices

Source: Almeida, 2012, p. 77.

The values obtained for Moran's I statistic range between -1 and 1. Negative values indicate negative spatial autocorrelation, demonstrating dissimilarities between the values of the studied attribute and their spatial locations. Conversely, positive values indicate positive spatial autocorrelation, indicating similarities between the attribute values and their spatial locations (Lins et al., 2015).

Therefore, Figure 2 generically presents the scatter plot of Moran's I statistic, illustrating the possible types of clusters in spatial linear association. It is noteworthy that this dispersion analysis is valid for both univariate and multivariate Moran's I statistics.

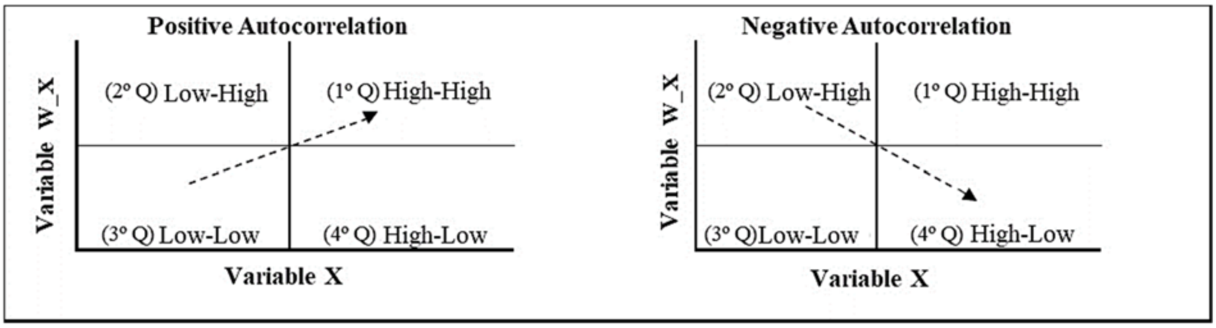

Figure 2. Moran's Scatter Plot

Source: Prepared by the authors based on Almeida (2012).

In the scatter plot, the variable of interest (X) is placed on the horizontal axis, and the spatial lag of the variable (W_X) is presented on the vertical axis. This setup allows for the examination of the data's concentration patterns, which are divided into four types of spatial associations corresponding to the four quadrants: Q1—High-High (HH), Q2—High-Low (LH), Q3—Low-Low (LL), Q4—High-Low (HL). If the spatial association is positive, the regression line will have a positive slope, and municipalities will tend to cluster in the first and third quadrants. Conversely, if the association is negative, the regression line will have a negative slope, and the units will predominantly cluster in the second and fourth quadrants (Almeida, 2012).

2.3 Variables and Data Source

The data employed in the multivariate model were obtained from the databases of the Brazilian Institute of Geography and Statistics (IBGE), the Department of Informatics of the Unified Health System (DATASUS), and the Transparency Portal of the Office of the Comptroller General of the Union. The sample includes 1,191 municipalities from the Southern Region of Brazil. Table 1 presents the list of variables used in the study.

Table 1. Variables Used in the Calculation of the Sustainable and Agricultural Development Index

Dimension	Variable	Description	Source	Year
Sustainable and social development	x1	Geometric Growth Rate	IBGE	2021
	x2	Birth Rate	Datasus and IBGE	2021
	x3	Number of hospital beds/thousand inhabitants	Datasus	2022
	x4	Illiteracy rate	IBGE	2017
	x5	Number of households with access to mains water supply/TF	Datasus	2015
	x6	Number of households with access to Garbage/TF collection	Datasus	2015
	x7	Number of households with other garbage disposal/TF	Datasus	2015
	x8	Number of households with access to the sewer/TF network	Datasus	2015
	x9	Number of households that do not have access to the sewer/TF network	Datasus	2015
Environmental	x10	Number of agricultural establishments with Springs or Streams - protected by forests/NE	IBGE	2017
	x11	Number of agricultural establishments with silviculture species/NE	IBGE	2017
	x12	Forestry production - planted forests/TA	IBGE	2017
	x13	Forest production - native forests/TA	IBGE	2017
	x14	Number of agricultural establishments that use chemical fertilization/NE	IBGE	2017
	x15	Number of establishments that use pesticides/NE	IBGE	2017
Economic Dimension	x16	Value of resources allocated to municipalities (Union and states)	Office of the Comptroller General of the Union	2022
	x17	GDP per capita	IBGE	2020
Agricultural	x18	Production of temporary/HV crops	IBGE	2017
	x19	Production of permanent crops/HV	IBGE	2017
	x20	Livestock and other animal husbandry/TA	IBGE	2017
	x21	Number of agricultural establishments that make use of Irrigation/NE	IBGE	2017
	x22	Number of tractors in agricultural establishments/NE	IBGE	2017
	x23	Number of agricultural establishments with employed staff/NE	IBGE	2017
	x24	Amount of expenses incurred by agricultural establishments with Medicines for animals/NE	IBGE	2017
	x25	Amount of expenses incurred by agricultural establishments with fuels and lubricants/NE	IBGE	2017
	x26	GVA of agriculture/TA	IBGE	2020

Note. TF = Total Families; TA = Total Area; NE = Number of Agricultural Establishments.

Source: Compiled by the authors, 2023.

Finally, following the description of the methodology used, the results are presented, analyzed, and discussed.

3. Analysis and Discussion of Results

3.1 Presentation and Interpretation of Factors

Upon analyzing the adequacy of the sample used, it was found that the Kaiser-Meyer-Olkin (KMO) test yielded a value of 0.6568, indicating good sample adequacy. The Bartlett’s test of sphericity was significant with a statistic of 26,528.302, leading to the rejection of the null hypothesis that the correlation matrix is an identity matrix. Based on the values obtained from these tests, it was concluded that the sample is appropriate for the factor analysis procedure, thus allowing the continuation of the study.

By performing factor analysis using the principal components method, seven factors with eigenvalues greater than one were extracted, effectively synthesizing the information contained in the twenty-six variables analyzed, as shown in Table 2. The contribution of these seven factors to the total variance of the indicators is substantial, accounting for 67.09% of the total variance in the dataset. According to Hair et al. (2009), an accumulated variance of 60% is considered satisfactory in the social sciences, thereby validating the adequacy of the extracted factors for this study.

Table 2. Characteristic Root, Percentage Explained by Each Factor, and Accumulated Variance

Factor	Characteristic Root	Variance explained by the factor	Cumulative variance
Factor 1	4.66137	18.65%	18.65%
Factor 2	3.26799	13.07%	31.72%
Factor 3	2.87585	11.50%	43.22%
Factor 4	1.86501	7.46%	50.68%
Factor 5	1.54686	6.19%	56.87%
Factor 6	1.4244	5.70%	62.57%
Factor 7	1.132	4.53%	67.09%

Source: Survey results, 2023.

After identifying the factors that constitute the constructed indicator, an orthogonal rotation of these factors was performed using the varimax method. Table 3 presents the factor loadings and communalities for the factors considered in this research. In the interpretation, only factor loadings with values above 0.5 (highlighted in bold italics) were considered, indicating the variables most strongly associated with each factor.

Table 3. Factor Loadings and Communalities after Orthogonal Rotation of Factors

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Commonalities
x1	0.0975	0.212	0.0128	**0.5292**	0.2588	0.0318	0.235	0.5422
x2	0.0521	0.1921	0.0853	0.0001	0.0303	**0.7754**	0.0482	0.3486
x3	0.1024	0.0161	0.0053	0.12	0.0414	**0.7737**	0.0537	0.3716
x4	-0.0248	0.0644	-0.0943	0.0572	-0.1544	-0.1544	**-0.6473**	0.5164
x5	**0.9901**	0.0312	0.0073	0.0217	0.0092	0.0324	0.0238	0.0165
x6	**0.99**	0.0383	0.0031	0.0314	0.0075	0.0401	0.0282	0.015
x7	**0.5477**	0.167	0.1686	0.3016	0.0799	0.0499	0.0302	0.6225
x8	**0.9321**	0.0058	0.0241	0.0092	0.0121	0.0752	0.0129	0.1246
x9	**0.6208**	0.0999	0.0645	0.0305	0.0618	0.3252	0.109	0.4781
x10	0.0465	0.3635	0.0403	**0.5714**	0.3192	0.1822	0.0316	0.4015
x11	0.0685	0.0494	0.1979	0.0004	**0.8918**	0.0064	0.0397	0.1568
x12	0.0952	0.274	**0.7204**	0.1874	0.1595	0.0106	0.1243	0.3207
x13	0.1093	**0.7879**	0.2081	0.2014	0.1083	0.029	0.2314	0.2173
x14	0.0371	**0.7983**	0.1175	0.0104	0.1548	0.0069	0.0591	0.3199
x15	0.0131	0.2874	0.0778	0.018	**0.8338**	0.0713	0.0922	0.202
x16	**0.7973**	0.1396	0.0426	0.2857	0.0476	0.1643	0.0729	0.2267
x17	0.0414	0.0999	0.2114	0.0701	0.0194	0.0224	**0.6688**	0.4906
x18	0.131	0.0428	0.0742	**0.7251**	0.0206	0.0648	0.0207	0.4447
x19	0.1485	**0.6159**	0.0451	0.3753	0.0587	0.0945	0.0687	0.4386
x20	0.0493	**0.7899**	0.0034	0.1803	0.2619	0.1031	0.2057	0.2196
x21	0.0071	**0.6469**	0.2533	0.3827	0.2416	0.012	0.2591	0.2452
x22	0.0074	0.1812	**0.7751**	0.1034	0.0288	0.0191	0.039	0.3529
x23	0.03	**0.5336**	0.3481	0.4139	0.0487	0.0132	0.007	0.4193
x24	0.0491	0.1259	**0.6215**	0.2062	0.0458	0.0115	0.2508	0.4878
x25	0.0106	0.0403	**0.7932**	0.0879	0.08	0.0253	0.0404	0.3528
x26	0.113	0.1057	0.1788	0.2122	0.1581	0.0144	**0.6803**	0.4111

Source: Survey results, 2023.

The commonality values indicate the extent to which each of the seven factors explains the corresponding variables, and a positive relationship is observed among the variables that constitute each factor. Communalities are presented alongside each factor loading. Specifically, Factor 1 is strongly associated with the following variables: Number of families with access to public water supply per total families (TF) (x5); Number of households with access to garbage collection per TF (x6); Number of households with alternative garbage disposal methods per TF (x7); Number of households with access to the sewer/TF network (x8); Number of households without access to the sewer/TF network (x9); and Transfers of public resources (x16). Factor 1 accounts for the highest explained variance, representing 18.65% of the total accumulated variance. This factor is related to public investment, infrastructure, and basic sanitation.

Factor 2 is associated with the following variables: Forest production from native forests per total area (TA) (x13);

number of agricultural establishments utilizing chemical fertilization per number of establishments (NE) (x14); production of permanent crops per TA (x19); livestock and other animal husbandry per TA (x20); number of agricultural establishments employing irrigation methods per NE (x21); and number of agricultural establishments with employed personnel per NE (x23). This factor pertains to technology and land use and accounts for the second highest explained variance, representing 13.07% of the total accumulated variance.

Factor 3 is related to the following variables: Forest production from planted forests per TA (x12); number of tractors in agricultural establishments per NE (x22); amount of expenses incurred by agricultural establishments on animal medicines per NE (x24); and value of expenses incurred by agricultural establishments on fuels and lubricants per NE (x25). This factor is associated with environmental degradation and accounts for the third highest explained variance, corresponding to 11.50% of the total accumulated variance.

Factor 4 includes the geometric growth rate (x1); number of agricultural establishments with springs or streams protected by forests per NE (x10); and production of temporary crops per TA (x18). This factor is linked to the increase in agricultural production and accounts for the fourth highest explained variance, amounting to 7.46% of the total accumulated variance.

Factor 5 comprises the number of agricultural establishments engaged in silviculture per NE species (x11) and the number of establishments utilizing pesticides per NE (x15). This factor is associated with pest control and management, representing the fifth highest explained variance with 6.19% of the total accumulated variance.

Factor 6 consists of the birth rate (x2) and the number of hospital beds per thousand inhabitants (x3). This factor relates to hospital and health infrastructure and accounts for the sixth highest explained variance, corresponding to 5.70% of the total accumulated variance.

Factor 7 includes the illiteracy rate (x4); GDP per capita (x17); and the Gross Value Added (GVA) of agriculture per TA (x26). Notably, variable x4 has a negative loading on this factor, indicating an inverse relationship with both agricultural productivity and per capita income. This factor is associated with income and explains the seventh highest portion of variance, amounting to 4.53% of the total accumulated variance.

The study identified seven key factors contributing to sustainable and agricultural development in the Southern Region of Brazil, as outlined in Table 4.

Table 4. Summary of Factors

Factor	Description	Variance Explained (%)
Factor 1	Public investment, infrastructure, and basic sanitation	18.65%
Factor 2	Technology and land use	13.07%
Factor 3	Environmental degradation	11.50%
Factor 4	Increase in agricultural production	7.46%
Factor 5	Pest control and management	6.19%
Factor 6	Hospital and health infrastructure	5.70%
Factor 7	Income	4.53%

Source: Compiled by the authors, 2023.

Collectively, these factors account for 67.09% of the total variance in the analyzed indicators, thereby providing a robust framework that aligns with existing literature on sustainable development and offers valuable insights into regional disparities in agricultural sustainability.

3.2 Analyzing and Discussing the SADI

From the factorial scores, the Sustainable and Agricultural Development Index (SADI) was constructed for the municipalities in the Southern Region of Brazil. This index ranges from 0 to 1, with values closer to 1 indicating a higher degree of sustainable and agricultural development within the municipality. The indicators revealed a medium-low degree of sustainable and agricultural development, as the highest value observed was 0.5885, while the remaining values were below 0.5. Consequently, the municipalities with the highest SADI values, reflecting the greatest degree of sustainable and agricultural development, were Curitiba (PR) (0.5885), Capivari do Sul (RS) (0.4541), and Paranapoema (PR) (0.4536). In contrast, the municipalities with the lowest SADI values, indicating a lower degree of sustainable and agricultural development, were Bombinhas (SC) (0.1843), Governador Celso Ramos (SC) (0.2170), and Matinhos (PR) (0.2172), as shown in Table 5.

Table 5. Sustainable and Agricultural Development Index (SADI) for Selected Municipalities in the Southern

Region of Brazil

Major Indicators				**Lower Indicators**			
Municipality	SADI	GDP (thousand USD)	GDP Agriculture (thousand USD)	Municipality	SADI	GDP (thousand USD)	GDP Agriculture (thousand USD)
Curitiba (PR)	0.5885	17602600.86	3277.99	Adrianópolis (PR)	0.2371	56.98	4.46
Capivari do Sul (RS)	0.4541	52.23	13962.88	Itaperuçu (PR)	0.2305	114.35	5.69
Paranapoema (PR)	0.4536	15.48	6873.11	Garopaba (SC)	0.2277	136.53	3.70
Turvo (SC)	0.4348	128.48	22505.38	Gravatal (SC)	0.2274	57.66	3.66
Ituporanga (SC)	0.4333	221231.86	51600.62	Pontal do Paraná (PR)	0.2256	118.68	0.81
Imbuia (SC)	0.4296	42.40	17631.16	Altamira do Paraná (PR)	0.2222	16.70	8.53
Faxinal do Soturno (RS)	0.4287	45.19	3520.97	Pescaria Brava (SC)	0.2173	21.46	1.06
Carazinho (RS)	0.4262	618106.56	25205.71	Matinhos (PR)	0.2172	163.97	0.38
Mafra (SC)	0.4240	419950.17	54590.97	Governador Celso Ramos (SC)	0.2170	75.70	9.94
Vacaria (RS)	0.4221	506691.12	95583.64	Bombinhas (SC)	0.1843	156.99	5.06

Source: Survey results, 2023.

The SADI values indicate that most municipalities exhibit a medium-low level of sustainable and agricultural development, highlighting areas where targeted interventions could enhance sustainability practices. Curitiba, as the municipality with the highest SADI, exemplifies effective integration of sustainable practices in agricultural development, whereas Bombinhas, Governador Celso Ramos, and Matinhos demonstrate the need for significant improvements in their sustainability and agricultural strategies.

Figure 3 illustrates the spatial distribution of the Sustainable and Agricultural Development Index (SADI) proposed in this study. The municipalities are color-coded based on their SADI values, with lighter shades representing those in the Southern Region of Brazil with lower SADI scores, and darker shades indicating municipalities with higher SADI scores.

Data from the Brazilian Institute of Geography and Statistics (IBGE, 2020) indicate that the Northwest Mesoregion of Rio Grande do Sul accounts for 41.89% of the state's agricultural Gross Value Added (GVA), making it the region with the highest agricultural production. In 2022, this mesoregion was also the largest producer of soybeans, contributing approximately 42.9% of the state's production. Additionally, it led in corn production, accounting for about 55.6% of the state's output, and dominated wheat cultivation with 75.7% of the state's production (PAM-IBGE, 2022).

In this context, Lisbinski et al. (2020) analyzed the degree of rural development in the Northwest Mesoregion and found that municipalities in the southern and midwestern areas exhibited higher concentrations of high and medium levels of rural development, while those in the northern areas demonstrated lower levels of development. These findings are consistent with the results of this study, as the map indicates that the highest concentrations of high SADI scores in Rio Grande do Sul are located within the Northwest Mesoregion.

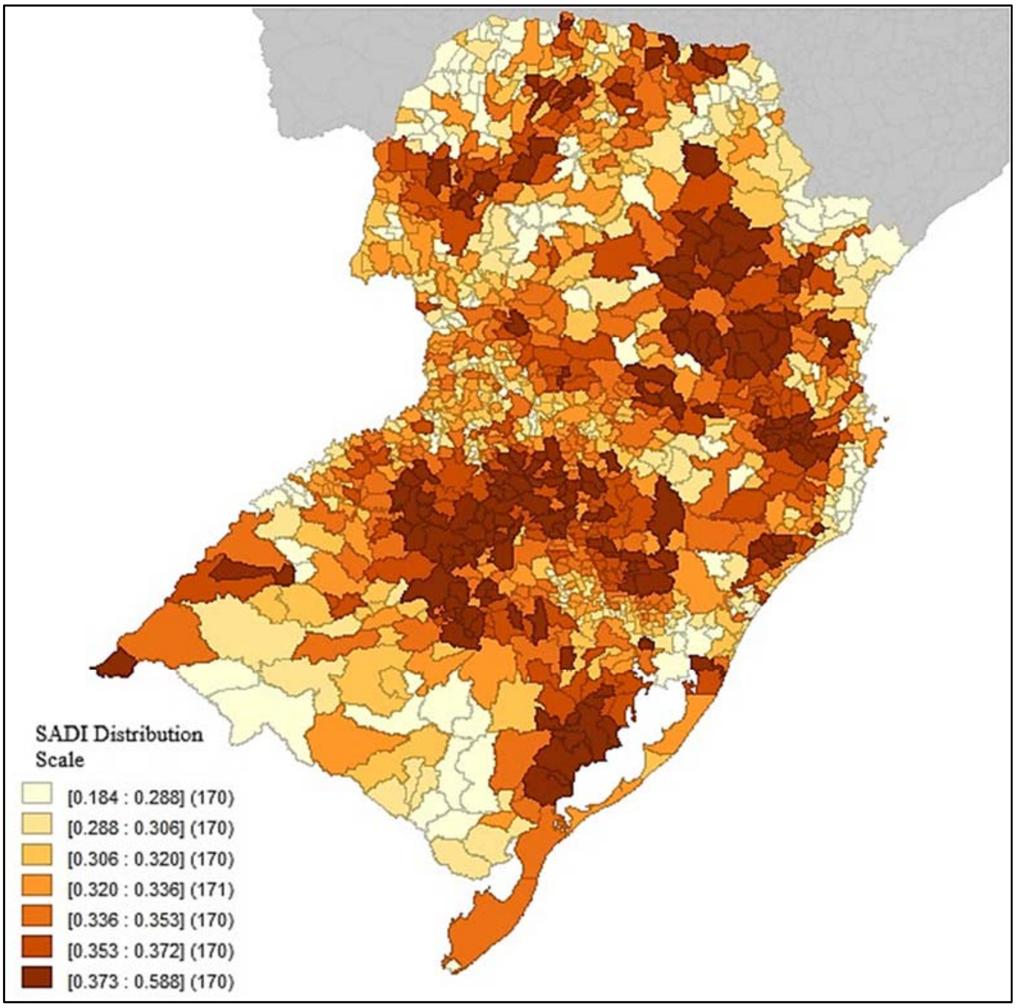

Figure 3. Spatial distribution of the Sustainable and Agricultural Development Index in the municipalities of the Southern Region of Brazil

Source: Survey results, 2023.

It was also observed that the municipality in the state of Rio Grande do Sul with the highest Sustainable and Agricultural Development Index (SADI) was Capivari do Sul (0.4541). This result corroborates the findings of Fujimoto et al. (2006), who, while developing an indicator of socioeconomic performance for the northern coast of Rio Grande do Sul and identifying environmental issues, identified Capivari do Sul as the municipality with the highest degree of development in the region. Additionally, the authors found that the municipality's Gross Value Added (GVA) is predominantly driven by agriculture and that its population is largely urban. However, according to IBGE data (2022), there was a population decrease of 1.36% between 2020 and 2021.

In Santa Catarina, the municipality of Turvo, located on the southern coast, exhibited the highest sustainable development indicator. Other high-performance indicators were observed in the Central Region, particularly in Alto Vale do Itajaí. Silva and Rosa (2020) evaluated sustainable development indicators across the state's mesoregions and found that the sustainable performance of all five mesoregions was classified as medium-low. The Itajaí Valley was the only mesoregion achieving a median performance, thereby corroborating the findings of this study. According to the authors, this scenario is attributable to low levels of environmental management, limited economic dynamism, and unequal wealth distribution. These factors highlight the necessity for public managers to place greater emphasis on the economic and environmental dimensions to enhance long-term sustainable development.

Thus, while some regions, such as Alto Vale do Itajaí, exhibit superior performance, the state as a whole still faces challenges, particularly in terms of weak environmental management and unequal wealth distribution. Regions with better indicators, such as the Itajaí Valley, often benefit from more structured local governance and greater integration into agricultural and industrial activities. However, challenges remain in balancing economic growth with environmental sustainability, underscoring the need for improvements in these areas to promote long-term sustainable development (de Oliveira Menezes & Vieira, 2019; Królikowska-Tomczak, 2021).

In the state of Paraná, the municipality with the highest Sustainable and Agricultural Development Index (SADI) within the observed sample was Curitiba. Additionally, the highest SADI values are located in eastern Paraná, particularly in municipalities proximate to Curitiba. Eberhardt and Lima (2012) analyzed the profile and stage of economic development of Paraná's regions and found similar results. They confirmed that among the analyzed regions, the micro-region of Curitiba exhibited the best performance, with its indicator surpassing those of other regions. Furthermore, the Curitiba micro-region was identified as the most economically dynamic when compared to other micro-regions within the state.

Turra and Lima (2018) developed a Sustainable Development Index (SDI) for the micro-regions of the state of Paraná. Their results indicated that the Micro-region of Curitiba ranked first, with its performance closely linked to the economic and institutional dimensions. This characteristic is typical of areas that have experienced significant urbanization. Conversely, the lowest indicators were found in micro-regions located within the Center-South Mesoregion of the state. This area is characterized by low temperatures and rugged terrain, which inhibit the cultivation of certain grain crops, such as soybeans and corn, and instead favor livestock activities and reforestation efforts.

These findings highlight the high degree of heterogeneity in the distribution of the Sustainable and Agricultural Development Index (SADI) among municipalities in the Southern Region of Brazil. According to Belik (2015), this existing heterogeneity, particularly within the rural sector, necessitates differentiated policies tailored to the specific needs of various clienteles. Consequently, adopting a uniform agricultural and sustainable development policy is impractical. It is important to recognize that the disparities are not solely due to technological gaps but also involve differences in access to services, transportation, commercialization, and income levels. Therefore, to promote sustainable development alongside Brazilian agribusiness, it is essential to implement policies that facilitate the adoption of more appropriate and sustainable technologies. Additionally, efforts should be directed towards developing markets for the products and services offered by rural producers.

3.3 Spatial Distribution of Data

The following section presents the Exploratory Spatial Data Analysis (ESDA), which investigates the spatial interactions among municipalities. Specifically, it evaluates whether the value of a particular variable in one municipality i is influenced by the values of the same variable in neighboring municipalities.

To conduct Moran's I autocorrelation test, both Queen and Rook spatial weight matrices were assessed. The Queen-type spatial weight matrix produced a higher statistic; consequently, the analyses were performed using this spatial configuration, as it more accurately represents the interactions between regions.

Moran's I autocorrelation test yielded a statistic of 0.870, providing robust evidence of positive spatial autocorrelation. The test was highly statistically significant, leading to the rejection of the null hypothesis and confirming the presence of spatial correlation among the municipalities in the sample.

Cluster analysis categorized the Sustainable and Agricultural Development Index (SADI) into five groups: High-High, Low-High, High-Low, Low-Low, and non-significant clusters. The analysis revealed that municipalities with high SADI values and neighboring municipalities with high SADI values (High-High clusters) are predominantly concentrated in the state of Rio Grande do Sul and the southern and center-south regions of Santa Catarina. This spatial pattern can be attributed to various structural and institutional factors that favor these regions.

Firstly, the favorable climate and soil conditions in these regions provide an ideal environment for cultivating key crops such as soybeans, corn, and wheat, thereby fostering high agricultural productivity. These areas are characterized by fertile soils and well-distributed rainfall patterns, both of which are essential for successful agricultural endeavors (Bergamaschi & Dalmago, 2004).

Moreover, technological innovation has been pivotal in enhancing agricultural productivity. Southern Brazil serves as a major hub for agricultural innovation within the country, hosting research institutions like Embrapa and numerous universities that collaborate in developing technologies aimed at improving the productivity and sustainability of farming practices (Martha & Lopes, 2023). The adoption of modern technologies, including precision agriculture and biotechnology, has enabled more efficient management of natural resources, resulting in increased productivity while simultaneously reducing environmental impacts (da Silva & Silva-Mann, 2020).

Another significant factor is the organization of farmers into cooperatives. These cooperatives are fundamental to the regional economy, as they allow small and medium-sized producers to access broader markets, higher quality inputs, and enhanced bargaining power. This cooperative model strengthens farmers' negotiating capabilities and facilitates access to advanced technologies and knowledge, thereby directly contributing to high indicators of sustainable development (Schneider, 2015).

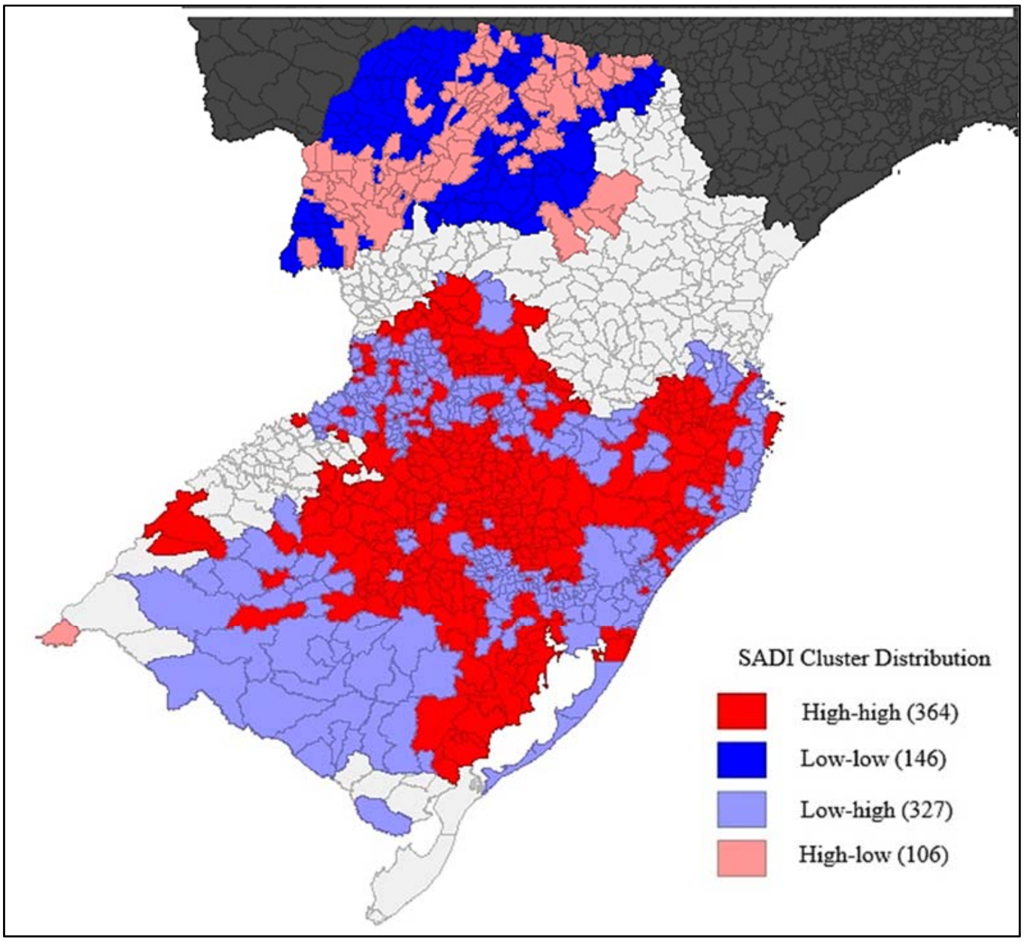

Figure 4. Map of clusters and their spatial correlations for municipalities in the Southern Region of Brazil

Source: Survey results, 2023.

Finally, the implementation of public policies targeted at the agricultural sector has been crucial for the sustainable development of these regions. Programs that offer tax incentives, rural credit, and technical assistance, promoted by both state and federal governments, provide the necessary support for modernizing agricultural practices and promoting sector sustainability (Grisa & Schneider, 2015). Additionally, access to rural extension services aids farmers in adopting more sustainable practices, thereby improving both the economic and environmental performance of the region (Lisbinski et al., 2020).

The Low-Low clusters, characterized by low development indicators surrounded by other municipalities with similarly low indicators, are predominantly concentrated in the Central and Western regions of Paraná. These areas continue to face significant challenges related to basic sanitation, as documented by Leiva (2018) and Gioia, Barros and Barros (2017). Limited access to sewage systems in these regions directly impacts the quality of life, particularly in rural areas, and hinders sustainable development. The absence of adequate sanitation infrastructure is a critical factor affecting public health and environmental preservation. Recent reports indicate that deficits in basic sanitation can diminish agricultural productive potential, thereby reducing the competitiveness of rural areas (Paraná Sanitation Company - Sanepar, 2024).

Another issue exacerbating the situation is the inadequate management of solid waste. Many cities in these regions continue to operate open-air dumps, which fail to comply with current environmental legislation. This practice can lead to the contamination of soil and water resources, further compromising local quality of life and economic development potential (de Lorena Diniz Chaves, dos Santos Jr & Rocha, 2014). Additionally, the presence of low-fertility soils in these areas, as noted by Tiecher (2016), poses a significant limitation, making it challenging to cultivate high-yield agricultural crops and necessitating greater investments in soil correction and advanced agricultural technologies.

Furthermore, these regions are vulnerable to adverse climate events, such as prolonged droughts and extreme heat, which directly impact agricultural production and increase the risk of crop loss. This unfavorable climatic scenario, combined with structural challenges such as low soil fertility and inadequate infrastructure, exacerbates the difficulties in achieving sustainable rural development in these areas (Zilli et al., 2020). Consequently, these regions require targeted public policies that focus on infrastructure improvements, environmental management, and climate impact mitigation to overcome these developmental barriers.

The Low-High clusters, characterized by low development indicators surrounded by municipalities with high indicators, are predominantly located in the states of Rio Grande do Sul and Santa Catarina. In contrast, High-Low clusters, which exhibit high development indicators surrounded by municipalities with low indicators, are mainly found in the state of Paraná. This distribution underscores the significant disparities in sustainable and agricultural development among the municipalities within these states.

Several factors contribute to these disparities. Firstly, geographical diversity—including variations in topography, climate, soil quality, and water availability—plays a crucial role in influencing soil fertility, agricultural productivity, and sustainable development (Medeiros, 2011). Additionally, infrastructure investment varies markedly among municipalities, resulting in unequal access to roads, storage facilities, and transportation networks. This uneven distribution of infrastructure investments affects the overall development potential of the regions (Gazolla & Schneider, 2013; Manica, 2017).

Furthermore, the Southern Region of Brazil encompasses municipalities with diverse economic activities, leading to differing propensities for sustainable development. Some municipalities are better positioned to achieve sustainable growth due to the nature of their economic activities (Rossato, File, & Lily, 2010; Fochezatto & Tartaruga, 2016). Lastly, there are significant differences in the implementation of public policies across municipalities. Those that prioritize access to health, education, and sanitation services, as well as sustainable agriculture and investments in agricultural research and technology, tend to exhibit higher levels of development (Schneider & Waquil, 2001; Smile, Gazolla, & Schneider, 2010).

Consequently, substantial regional inequalities exist both between and within the analyzed states, with some regions exhibiting the highest and lowest development indicators simultaneously. These disparities are attributable to the aforementioned factors. To address these challenges, a collaborative and coordinated effort among producers, government entities, and civil society is essential. Such efforts should focus on the implementation of sustainable agricultural practices, enhancement of infrastructure, increased investments in research and technology, and the promotion of public policies aimed at regional and social development.

4. Conclusion

This study aimed to construct and evaluate an index of sustainable and agricultural development for the municipalities within the Southern Region of the country. To achieve this, factor analysis was employed using principal component analysis (PCA) as the methodological framework. Subsequently, Exploratory Spatial Data Analysis (ESDA) was conducted to examine the distribution of the index and the formation of spatial clusters.

The primary findings indicated that the indicators exhibited a medium-low degree of sustainable and agricultural development, with the highest value recorded at 0.5885 and the remaining indicators presenting values below 0.5. Specifically, the municipalities with the highest indices were Curitiba (PR) (0.5885), Capivari do Sul (RS) (0.4541), and Paranapoema (PR) (0.4536). In contrast, the municipalities with the lowest indices, reflecting a lower degree of sustainable and agricultural development, were Bombinhas (SC) (0.1843), Governador Celso Ramos (SC) (0.2170), and Matinhos (PR) (0.2172).

The spatial analysis revealed robust evidence of positive and significant spatial autocorrelation among the analyzed municipalities. High-High clusters, characterized by municipalities with high development indicators surrounded by others with elevated indicators, were predominantly concentrated in the state of Rio Grande do Sul and the southern and center-south regions of Santa Catarina. Low-Low clusters, consisting of municipalities with low development indicators surrounded by others with similar indicators, were mainly located in the Central and Western regions of Paraná. Additionally, Low-High clusters were identified in the states of Rio Grande do Sul and Santa Catarina, while High-Low clusters were primarily found in Paraná. This spatial distribution underscores the significant disparities in sustainable and agricultural development among the municipalities within these states.

This study identified the municipalities facing challenges in sustainable and agricultural development and delineated the regions where these issues are concentrated. The findings suggest that public authorities should adopt more efficient and effective strategies to promote sustainable and agricultural development, aligning these efforts with broader developmental goals. Addressing these challenges is crucial for Brazilian agriculture, as it will facilitate the improvement of municipal infrastructure and the quality of life for local populations.

To minimize the observed disparities and promote sustainable and agricultural development, several coordinated actions can be implemented. First, it is essential to increase investments in infrastructure, including the improvement of transportation, storage, and distribution networks, thereby facilitating access to markets and reducing logistical costs for producers. Additionally, fostering technological innovation through support for agricultural research and the dissemination of advanced technologies, such as precision agriculture and biotechnology, can enhance productivity and sustainability of agricultural practices. Strengthening farmers' cooperatives is also vital, as these organizations facilitate access to resources, knowledge, and markets, while improving producers' bargaining power.

Concurrently, the implementation of public policies that encourage sustainable agricultural practices, such as efficient water resource use, soil conservation, and reduction of environmental impact, should be prioritized. Training and education programs for farmers on sustainable techniques and environmental management will contribute to the adoption of more responsible and efficient practices. Furthermore, expanding access to rural credit and fiscal incentives can stimulate investments in green technologies and the modernization of agricultural activities. Finally, collaboration among governments, the private sector, and civil society is crucial to develop integrated strategies that address the various dimensions of sustainable development, thereby promoting balanced and inclusive growth in the analyzed regions.

Given the complexity and breadth of the subject, combined with the lack of consensus on the conceptual framework and dimensions of sustainable development, as well as the difficulty in defining variables that capture the interaction between agricultural and sustainable development, and the limitations in obtaining consistent data, particularly data from the same year for the analysis, further research is recommended. Subsequent studies should consider expanding the number of variables analyzed or conducting analyses at regional, state, and national levels to deepen the understanding of sustainable and agricultural development dynamics.

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