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ABSTRACT

The aim of this study is to analyze the spatial dependence of municipalities in the Submédio São Francisco Region concerning rural development, seeking to identify the determining variables of the Rural Development Index (RDI) for these municipalities. Thus, Exploratory Spatial Data Analysis (ESDA) techniques and spatial econometrics models are applied and observes that the region being studied exhibits a very heterogeneous distribution in terms of rural development with clusters of the High-High (HH) type, concentrated around the Petrolina-Juazeiro pole, and the Low-Low (LL) type that indicates the existence of municipalities with low RDI's, which are surrounded by municipalities with similar characteristics. The analysis of the spatial econometric model SAR (Spatial Autoregressive Model) showed that the RDI is positively affected by the variables GDP per capita, Municipal Human Development Index (MHDI), Employment in agricultural & animal farming establishments and Proportion of agricultural & animal farming establishments that obtained funding, with emphasis on the MHDI. These results provide support for of the dynamics of rural development in the São Francisco River Sub-Middle Region, offering a comprehensive view of the complexities, challenges and opportunities to improve the living conditions of the populations in this region. These discoveries are fundamental to guide decision-making and the implementation of policies that seek leverage rural development in the municipalities under study.

Keywords: Rural development. São Francisco River Sub-Middle Region. Space dependence. Spatial Econometrics.

RESUMO

O objetivo deste estudo é analisar a dependência espacial dos municípios na Região do Submédio São Francisco em relação ao desenvolvimento rural, buscando identificar as variáveis determinantes do Índice de Desenvolvimento Rural (IDR) desses municípios. Utilizando técnicas de Análise Exploratória de Dados Espaciais (AEDE) e modelos de econometria espacial, identifica-se uma distribuição heterogênea do desenvolvimento rural na região, com *clusters* Alto-Alto (AA) concentrados em torno de Petrolina-Juazeiro e clusters Baixo-Baixo (BB), indicando municípios com baixos IDR's cercados por características semelhantes. O modelo econométrico espacial SAR (*Spatial Autoregressive Model*) mostrou que o IDR é positivamente influenciado por variáveis como PIB per capita, IDHM, Emprego nos estabelecimentos agropecuários e Proporção dos estabelecimentos agropecuários com financiamento, destacando o IDHM. Esses resultados oferecem subsídios às dinâmicas de desenvolvimento rural na Região do Submédio São Francisco, proporcionando uma visão abrangente das complexidades, desafios e oportunidades para melhorar as condições de vida na região. Essas descobertas são fundamentais para orientar políticas e decisões visando ao aprimoramento do desenvolvimento rural nos municípios estudados.

Palavras-chave: Desenvolvimento rural. Região do Submédio São Francisco. Dependência espacial. Econometria espacial.

INTRODUCTION

Development, a broad and multifaceted concept, encompasses diverse perspectives and factors, beyond strictly economic aspects. In this context, rural development gains prominence, as rural areas are fundamental to the Brazilian economy. For a long time, rural development in Brazil was linked to government interventions and the actions of international organizations, especially in regions less integrated into agricultural modernization (Navarro, 2001), such as the Northeast, where institutions such as the Superintendence for the Development of the Northeast (SUDENE), the Development Company for the São Francisco and Parnaíba Valleys (CODEVASF), and the Banco do Nordeste (BNB) were created to drive regional development. Beginning in the 1990s, discussions on the topic deepened, recognizing the importance of family farming and the need for public policies such as the National Program for Strengthening Family Farming (PRONAF), combined with greater government attention to agrarian reform, food security, and sustainability (Schneider, 2010).

This new vision of rural development transcends mere agricultural production, incorporating the value of social capital, the diversification of activities, and sustainability as essential factors. Furthermore, the interdependence between the rural and urban spheres has strengthened, highlighting that growth in one cannot be dissociated from advancement in the other. Rural development is, therefore, a multidimensional process, involving a complex interaction of physical, technological, economic, sociocultural, and institutional factors, resulting in territorial transformations. Rural restructuring aims to optimize these internal and external factors to reshape social and economic structures, improving regional spatial patterns.

Within the sub-middle São Francisco, a region of singular importance, irrigated fruit farming stands out as a driver of development. The region has significant potential to drive local and regional growth, encompassing 93 municipalities in two states, Bahia and Pernambuco, and is characterized by significant investments in irrigated areas, technological advances in agriculture, and energy generation, notably the Petrolina-Juazeiro irrigated fruit farming hub (Paes, 2009).

In the light of the above considerations, it is clear that the region in question holds significant potential to further boost local development through irrigated fruit farming. Fruit farming emerges as a viable option for farmers as an additional source of income, as the region benefits from favorable conditions, both in terms of infrastructure, economics, and social aspects, as well as ideal soil and climate characteristics for fruit cultivation (Oliveira; Lima, 2021; Ferreira, 2022).

Analyzing rural development requires approaches that consider heterogeneity and spatial interactions. The literature, although extensive, still lacks studies that apply a detailed spatial approach to the sub-middle São Francisco region. Therefore, the central objective of this paper is to analyze the spatial dependence of municipalities in the sub-middle São Francisco region on rural development, seeking to identify the variables that determine the Rural Development Index (RDI) of these municipalities.

Specifically, it is proposed to verify the spatial dependence of municipalities in relation to the RDI; ii) examine the spatial distribution of rural development in the sub-middle São Francisco; iii) investigate the effects of the determining factors of this rural development through a spatial econometrics model.

In addition to this introduction, the work is structured into five additional sections. The second presents the theoretical and conceptual foundation of rural development. The third introduces some empirical applications. The fourth describes the methodology used, including the data sources, the variables considered, and the spatial econometric techniques. The fifth shows, analyzes, and discusses the results obtained. Finally, the final section contains the concluding remarks of the study.

THEORETICAL AND CONCEPTUAL ASPECTS OF RURAL DEVELOPMENT

Locatel and Hespanhol (2006) emphasize that the current conception of rural development focuses on the process and territorial reference. They argue that rural development should seek territorial transformations based on the specific characteristics of each region. Implementing this development requires the creation of new organizations and social structures, as well as the involvement of social actors motivated within the political, economic, environmental, and social context of the territory.

To boost rural development, it is crucial to consider elements such as: i) commercial integration with local cities benefits rural communities; ii) promotion of family farming generates a local market, providing inputs for local industries; iii) pluriactivity reduces rural exodus; iv) diversification of income sources; v) employment and life improvement programs; vi) presence of territorial resources for specialized production (Veiga, 2000; Kageyama, 2008).

In the European Union, rural development policy aims to preserve 'positive externalities' linked to agriculture, while in China, the integration of peasants into modern dynamics is highlighted. In Brazil, the challenges include mitigating social imbalances and strengthening family farming, which are central to rural development (Ploeg, 2011).

The new vision of rural development goes beyond agriculture, prioritizing the valorization of social capital, the diversification of activities, and sustainability. The interconnection between rural and urban environments has strengthened, highlighting the interdependence of growth in both spheres. Rural development is a multidimensional process involving diverse actors, institutions, and sectors, from communities and farmers to policymakers, science and technology institutions, and representative organizations (Stumpf Júnior; Balsadi, 2015).

Banakar and Patil (2018) broaden the concept of rural development to encompass agriculture, rural industries, handcrafts, infrastructure, community services, and human resource development. Rural development results from complex interactions among physical, technological, economic, sociocultural, and institutional factors.

Mazzocchi *et al*. (2019) emphasize that multifunctionality depends on internal and external factors and can be directed by administrative agencies and local communities to promote sustainable improvements. Wu *et al*. (2023) emphasize the analysis of internal interactions in the social, industrial, and land components of the rural system. Yu, Yang, and Zheng (2023) argue that rural restructuring aims to optimize internal and external factors, reshaping social and economic structures in rural areas to optimize the regional spatial pattern.

EMPIRICAL APPLICATIONS OF RURAL DEVELOPMENT IN A SPATIAL APPROACH

Regarding rural development, some international and national empirical studies have applied the analytical tool of spatial econometrics. Below are some studies that are similar to the proposal of this paper.

Cui and Lui (2021) analyzed the efficiency of green development in 13 cities in the Jing-Jin-Ji region of China (2003 to 2017) using spatial methods. Green development efficiency decreased by 2%, from 0.965 (2003) to 0.948 (2017), with greater spatial differentiation in northern cities. Industrial structure and degree of openness were positively associated with efficiency, while urbanization had a negative impact.

Maier *et al*. (2022) identified determinants of the implementation of rural development projects based on the Common Agricultural Policy of European Union (CAP) in 40 Romanian municipalities, using cross-sectional regressions and spatial econometric techniques. The analysis indicated spillover and diffusion processes for the uptake of funds through projects. Agricultural land availability and land concentration had a positive influence, while the level of local human development was a negative determinant. Average wage and population density showed no significant effects.

Batistella *et al.* (2022) assessed the spatial relationship between RDI and greenhouse gas (GHG) emissions in agricultural production in Brazilian states in 2010, using the ESDA. The results indicated that states with high RDI have similar patterns, as do states with low RDI. Local bivariate analyses highlighted different patterns of association, especially in the states of Rio Grande do Sul, Mato Grosso do Sul, and Mato Grosso, which have high GHG emissions and RDI.

Mattei, Cattelan, and Alves (2022) measured the degree of agricultural diversification and rural development of municipalities in the southern region of Brazil using factor analysis and linked these indices to economic growth and spatial influence through the ESDA . The main results showed that only 0.3% of municipalities reached the highest level of development, all in the state of Paraná. Overall, most municipalities achieved low rural development. The findings from the ESDA technique revealed that municipalities with a high RDI have, on average, neighbors also with a high RDI, while municipalities with a low RDI are surrounded by municipalities with, on average, also low RDI.

Rego (2022) in his study addressed rural development in municipalities in the Brazilian Legal Amazon, exploring various dimensions. Using Factor Analysis, ESDA, and spatial regressions, he found that most municipalities have below-average rural development, with consistent spatial patterns over time. Variables such as education, family farming, employment, GDP per capita, and gross value per capita in agriculture have positive impacts on rural development in the region.

In his study, Lobão (2018) investigated the determinants, levels, and regional distribution of rural development in municipalities in the Brazilian Amazon in the 2000s. Using factor analysis, he created the Rural Development Index (RDI) and identified five main rural development hubs, as well as spatial clusters revealing six distinct patterns. This highlights a heterogeneous pattern of rural development in the region.

METHODOLOGY

The methodological approach of this study was designed in line with the theoretical framework that advocates rural development as a multidimensional process intrinsically linked to spatial dynamics. The reviewed literature suggests that the development of a rural municipality is not an isolated phenomenon but rather influenced by its characteristics and those of its neighbors, forming spatial patterns. Therefore, the choice of analytical tools was not arbitrary, but rather selected to respond to the need to capture and quantify the effects of spatial dependence and heterogeneity, which are inherent to the phenomenon under study.

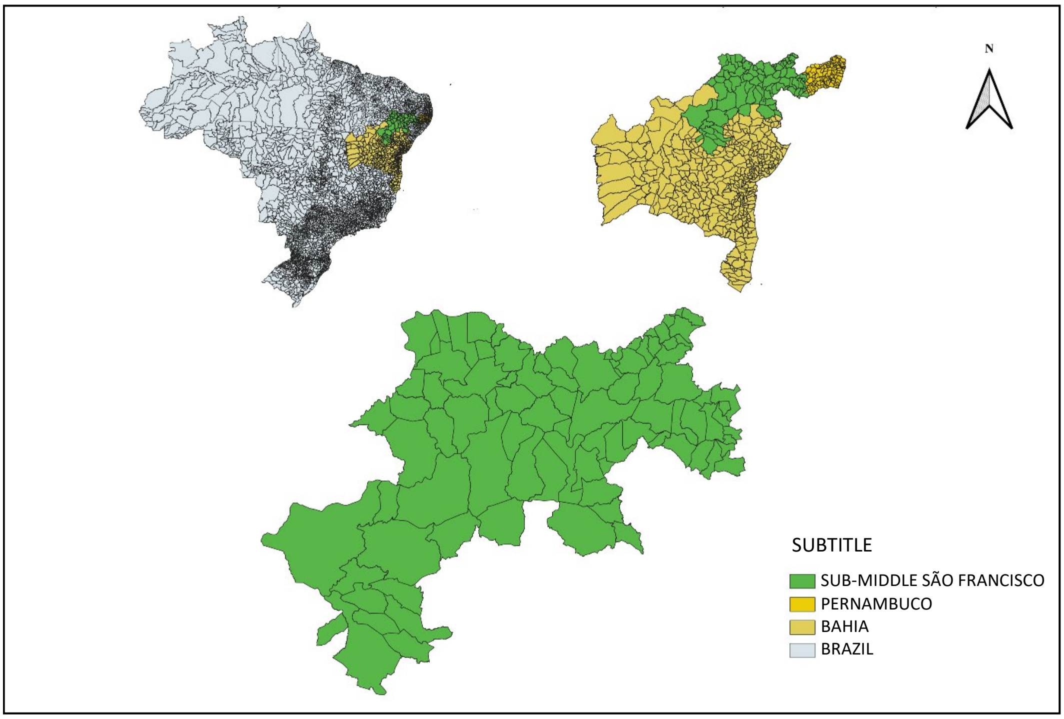
In the first phase, Exploratory Spatial Data Analysis (ESDA) was used to diagnose and visualize the presence of spatial autocorrelation. This initial approach is crucial because, if spatial dependence is ignored, the results of conventional Ordinary Least Squares (OLS) econometric models would be biased and inconsistent.

In the second stage, the selection of the spatial autoregressive (SAR) model was justified by its ability to incorporate the spatial autocorrelation present in the dependent variable. Unlike an Ordinary Least Squares (OLS) linear regression model, SAR allows the RDI of a municipality to be influenced not only by its own explanatory variables but also by the values of the dependent variable of its neighbors. The inclusion of variables such as GDP per capita, MHDI, agricultural employment, and access to financing was theoretically based, reflecting the multidimensional view of rural development discussed in the literature. Thus, the methodological approach is robust and aligned with best practices in regional economics research.

STUDY AREA

The study area was the sub-middle São Francisco region, located on the banks of the São Francisco River and comprising 93 municipalities spanning the states of Bahia and Pernambuco. Figure 1 shows the location of the region, allowing its identification both on the Brazilian map and between the states of Bahia and Pernambuco.

Figure 01 | Location of the sub-middle São Francisco region, Bahia-Pernambuco, Brazil



Source: Prepared by the authors using QGIS Software version 3.30.1 (2023).

EXPLORATORY SPATIAL DATA ANALYSIS (ESDA)

Exploratory Spatial Data Analysis (ESDA), according to Anselin (1995) and Almeida (2012), uses techniques to address the effects of spatial dependence and heterogeneity. These techniques allow us to describe spatial distribution, identify patterns (clusters), and recognize spatial regimes or instabilities. Before applying EDA or other spatial econometric techniques, it is crucial to define a spatial weight matrix (*W)*, indicating the connection between areas based on criteria such as contiguity, geographic distance, or *k* nearest neighbors.

GLOBAL SPATIAL AUTOCORRELATION

Global spatial autocorrelation detects whether a spatial distribution is random or not. Key measures include Moran's I statistic, Geary's C statistic, and Getis-Ord's G statistic. Moran's I is commonly used, ranging from -1 to 1. Values higher (or lower) than expected indicate positive (or negative) autocorrelation (Almeida, 2012).

Moran's I statistic can be defined as:

$$I = \frac{n\, Z'Wz}{S_0\, Z'Z} \tag{1}$$

Where: n is the number of municipalities; Z denotes the values of the standardized variable of interest (RDI); W_z represents the average values of the standardized variable of interest in neighboring municipalities, defined by a spatial weighting matrix W; S_0 indicates the sum of all elements of the weighting matrix W (Almeida, 2012; Cima *et al.*, 2021).

LOCAL SPATIAL AUTOCORRELATION

The global Moran's I does not detect significant local autocorrelations. For this purpose, it is relevant to use the local Moran's I or Local Indicator of Spatial Association (LISA), which identifies statistically significant local autocorrelation patterns (Anselin, 1995; Cima *et al.*, 2021). The local Moran's I statistic is given by:

$$I_i = z_i \sum_{j=1}^{i} w_{ij}\, z_j \tag{2}$$

Where: I_i covers only the neighbors of observation i, defined according to the weighting matrix W employed, z_i corresponds to the standardized RDI value of municipality i; z_j is the standardized RDI value of municipality j and w_{ij} corresponds to the element of the weighting matrix. The expected value of the statistic I_i is given by: E(Ii)= $-w_i/((n-1))$.

ECONOMETRIC MODEL

Spatial autocorrelation can affect the dependent variable, the explanatory variables, or the error term. To capture this effect, the model includes spatial lags in the dependent variable (*Wy)*, the explanatory variables (*Wx)*, and the error term (*Wμ* and *Wε)* (Pavan, 2013).

NON-SPATIAL MODEL – CLASSICAL LINEAR REGRESSION MODEL

The classic linear regression model represents a linear relationship between the dependent variable and the explanatory variables. In matrix form, this model is given by:

$$y = X\beta + \varepsilon \qquad \varepsilon \sim N\,(0,\sigma^2) \tag{3}$$

Where: *y is* a vector of N by 1 observations of the dependent variable and X is a matrix *n* by *k* observations, the exogenous explanatory variables (plus the constant), with an associated vector *k* by 1 regression coefficients *β* and *ε* is the *n* by 1 vector of random error terms, which follows a normal distribution, with zero mean and constant variance (Almeida, 2012). The estimation is done using the Ordinary Least Squares (OLS) method.

SPATIAL MODELS

SPATIAL AUTOREGRESSIVE MODEL (SAR)

The spatial autoregressive (SAR) model is commonly used in spatial econometrics, incorporating a lag term in the regressors to capture the 'neighborhood' effect of the phenomenon, reflecting how past behavior in nearby regions influences current decisions (Lesage; Pace, 2009).

According to Almeida (2012), the SAR model in its pure version is expressed by:

$$y = \rho W y + \varepsilon \tag{4}$$

Where: Wy is an n by 1 vector of spatial lags for the dependent variable, ρ is the spatial autoregressive coefficient.

The mixed SAR model used to include a set of exogenous explanatory variables, denoted by X, presents the following expression:

$$y = \rho Wy + X\beta + \varepsilon \tag{5}$$

Where: X is a matrix of exogenous explanatory variables and the rest of the notation remains as per the pure SAR model.

The spatial autoregressive coefficient (ρ) must be between -1 and 1 (|ρ| < 1), indicating positive global spatial autocorrelation if positive, and negative global spatial autocorrelation if negative (Lesage; Pace, 2009; Almeida, 2012). To avoid biases and inconsistencies when using Ordinary Least Squares (OLS), it is recommended to estimate ρ with Maximum Likelihood (MV) or the Instrumental Variables Method (IV).

SPATIAL ERROR MODEL (SEM)

The Spatial Error Model (SEM) incorporates lags in the error term, where spatial effects are reflected only in that term. These unmodeled effects exhibit spatial autocorrelation, and it is essential to note that they cannot be correlated with any explanatory variable (Almeida, 2012).

The SEM model can be specified as:

$$\begin{aligned} y &= X\beta + \xi \\ \xi &= \lambda W\xi + \varepsilon \end{aligned} \tag{6}$$

Where: λ is the spatial autoregressive error parameter that accompanies the lag $W\xi$. ξ is the error with unmodeled effects. The random error vector ε has a multivariate normal distribution and zero meaning. The scalar coefficient λ indicates the intensity of spatial autocorrelation between the residuals of the observed equation (Anselin, 1995; Albuquerque, 2020).

In order for the estimate to obtain consistent parameters for the SEM model, the maximum likelihood method must be used when the errors follow a normal distribution, otherwise, the generalized method of moments must be used.

STATISTICAL TESTS

After estimating the spatial econometric models, Lagrange multiplier (LM) tests such as LM lag, LM error, and their robust versions (LM_{ρ}^{*} and LM_{λ}^{*}) are performed to select the most appropriate model (Albuquerque, 2020). The process involves: (a) OLS, classical linear regression; (b) LM tests; (c) If not significant, OLS is appropriate; (d) If significant, choose between robust tests. If $LM_{\rho}^{*} > LM_{\lambda}^{*}$, uses the model with spatial lag; otherwise $LM_{\rho}^{*} < LM_{\lambda}^{*}$, the autoregressive error model is the most appropriate (Anselin *et al*., 1996; Anselin; Bera, 1998; Florax; Folmer; Rey, 2003; Almeida, 2012).

To verify the consistency of parameters in models, it is crucial to evaluate the assumptions of normality, homoscedasticity, and uncorrelated errors. According to Anselin (2005), three essential tests are indicated: multicollinearity, normality of residuals (Jaque-Bera), and heteroscedasticity (Breusch-Pagan, Koenker-Bassett, and White).

If normality and homoscedastic variance are violated, robust methods such as instrumental variables and GMM can be applied. Including only the spatial lag of endogenous variables requires the IV estimation method, while GMM is preferable when the spatial lag is incorporated into the error structure (Cienfuegos; Sánchez, 2022).

DATABASE AND DESCRIPTION OF VARIABLES

A spatial econometrics model was estimated to analyze the effects of several variables on the RDI. Table 1 shows the variables used in the model, as well as their databases and the studies supporting each variable.

Table 01 | Variables, data source and empirical basis of the spatial econometric model.

	Variable	Nomenclature	Database	Empirical basis
Dependent variable	RDI	RDI	Created through factor analysis	Parré (2013); Rego (2022)
Explanatory variables	GDP per capita (in thousands of BLR)	GDPCAPITA	SEI-BA (2017) CONDEPE-FIDEM (2017)	Souza (2019); Cui and Lui (2021)
	Value of production of permanent and temporary crops (in ten thousands of BLR)	VALUEPRODU	Agricultural Census (2017)	Parré (2013); Stege (2015); Cienfuegos and Sánchez (2022)
	MHDI	MHDI	Atlas of Human Development (2010)	Souza (2019); Maier *et al*. (2022); Rego (2022).
	Jobs generated in agricultural establishments (in thousands of units)	JOB	Agricultural Census (2017)	Cienfuegos and Sánchez (2022); Rego (2022).
	Proportion of family farming establishments that received technical assistance	ASSISTANCE	Agricultural Census (2017)	Santos, Ferreira and Campos (2018)
	Percentage of family farming establishments that took out rural credit	CREDIT	Agricultural Census (2017)	Santos, Ferreira and Campos (2018)
	Average values of PRONAF contracts (in thousands of BLR)	PRONAF	BCB (2017)	Rodrigues (2019)

Source: Prepared by the authors (2023).

GDP per capita indicates greater development, according to Souza (2019), Zekić, Kleut, and Matkovski (2017), Lima and Sousa (2017), and Kageyama (2008). The positive relationship between the value of crop production and the Rural Development Index (RDI) is expected, as it contributes to increased income and improved living conditions (STEGE, 2015). Job creation in rural establishments is crucial for development, associated with higher incomes and a better quality of life (Rego, 2022). Aspects such as rural credit and technical assistance are favorable to rural development (Buainain; Souza Filho, 2006).

RESULTS AND DISCUSSION

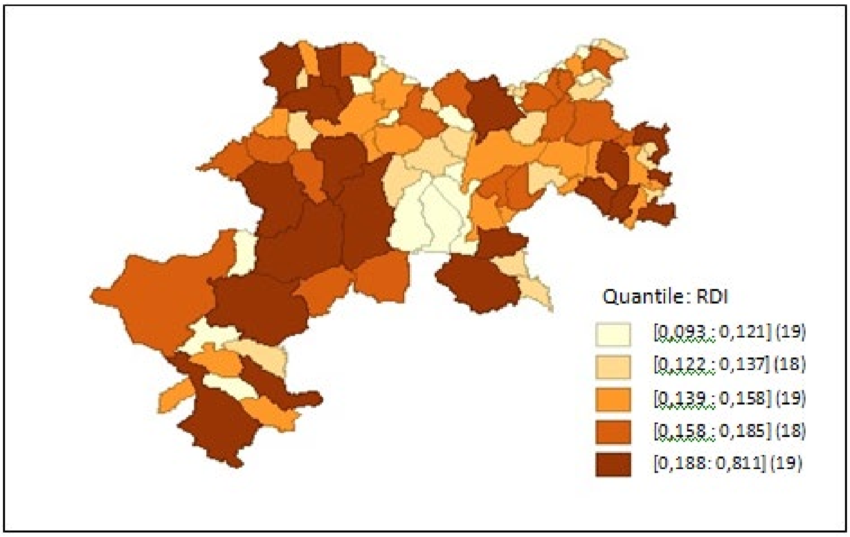
The first part addresses the spatial distribution of the Rural Development Index (RDI) in the sub-middle São Francisco region, calculated using factor analysis. Next, the ESDA identifies patterns of spatial association between municipalities in relation to the RDI. Finally, the determinants of the RDI are examined using a spatial econometric model.

SPATIAL DISTRIBUTION OF THE RDI IN THE MUNICIPALITIES OF THE SUB-MIDDLE SÃO FRANCISCO REGION

In Figure 02, the levels of rural development in the municipalities of the sub-middle São Francisco were distributed into five quantiles, revealing diversity and heterogeneity. The first quantile includes 19 municipalities with the lowest RDIs, 13 in Pernambuco (Brejinho, Calumbi, Cedro, Granito, Ingazeira, Itacuruba, Mirandiba, Moreilândia, Quixaba, Santa Terezinha, Solidão, Terra Nova, and Tuparetama) and 6 in Bahia (Chorrochó, Macururé, Rodelas, Sobradinho, Umburanas, and Várzea Nova). Moura and Campos (2022) also identified low levels of development in Bahian municipalities in MATOPIBA region.

In quantile 2, there are 18 municipalities (14 in Pernambuco and 4 in Bahia), such as Alagoinha, Belém do São Francisco, among others. Quantile 3 includes 19 municipalities (15 in Pernambuco and 4 in Bahia) with RDI between 0.139 and 0.158, such as Cabrobó, Floresta, Iati, among others.

Figure 02 | Spatial distribution of the RDI in the municipalities of the sub-middle São Francisco region

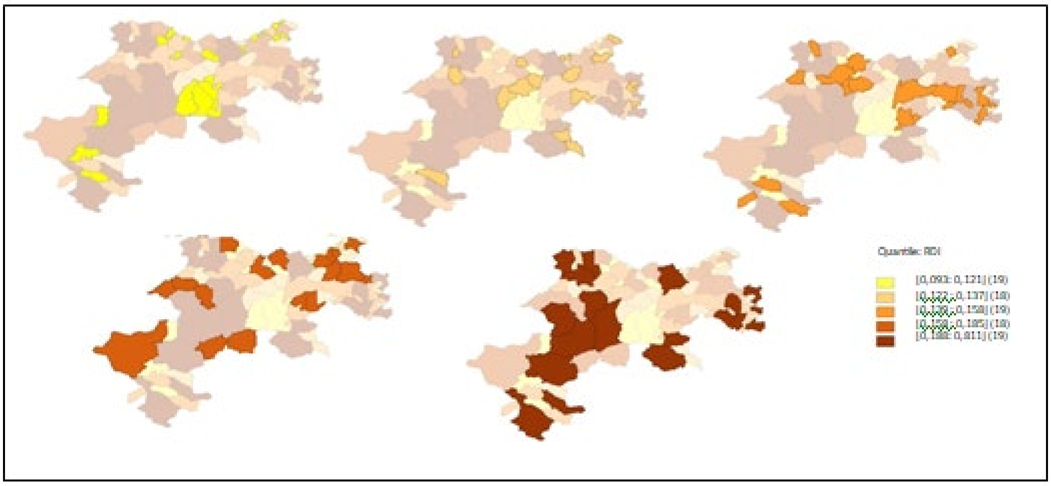


Prepared by the authors (2023) using Geoda software version 1.20.

In quantile 4, there are 18 municipalities (15 in Pernambuco and 3 in Bahia), such as Afogados da Ingazeira, Arcoverde, and Jaguarari. In the fifth quantile, the 19 municipalities with the best RDI levels include 12 in Pernambuco (Águas Belas, Bodocó, Petrolina, among others) and 7 in Bahia (Campo Formoso, Jacobina, Juazeiro, among others). Similar results were found by Moura and Sousa (2020), highlighting Petrolina and Araripina as the best ranked.

Figure 3 highlights the distribution of quantiles, highlighting the proximity between municipalities in the same quantile, suggesting spatial autocorrelation. Bahian municipalities have 29.17% in the highest quantile. For municipalities of Pernambuco, the average is 0.1612, 7.4% lower than the Bahia average. The majority (43.48%) of municipalities of Pernambuco are in quantiles 3 and 4, with 21.74% in each quantile.

Figure 03 | Distribution of the RDI in the municipalities of the sub-middle São Francisco region with emphasis on the quantiles



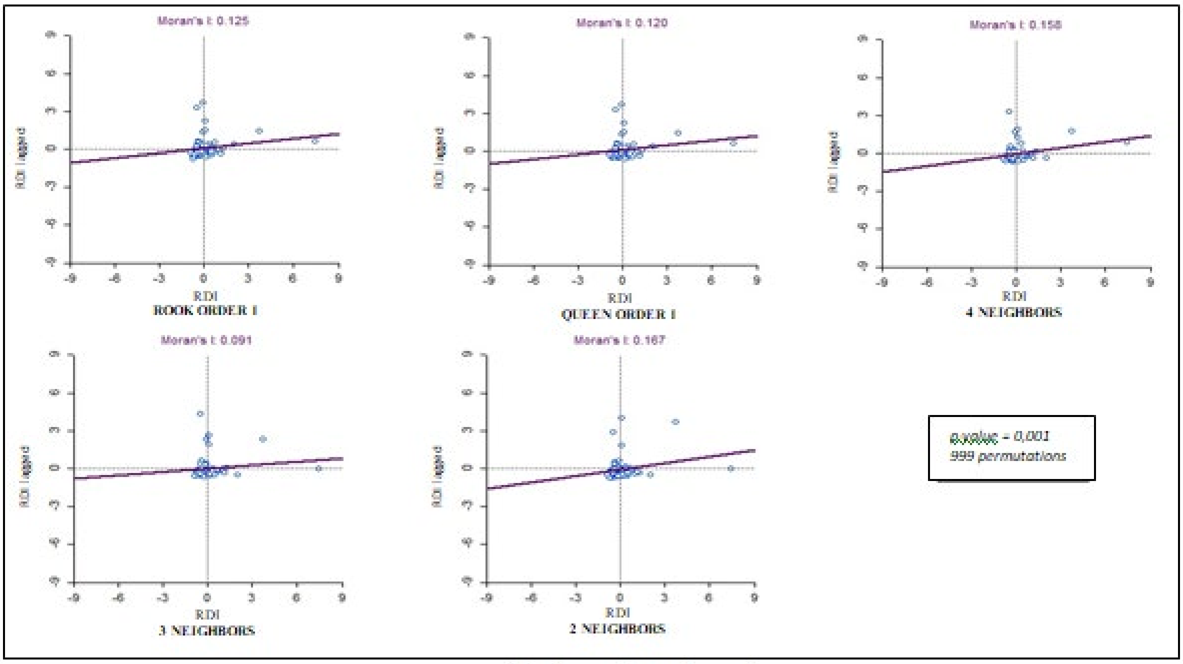
Prepared by the authors using Geoda software version 1.20 (2023).

EXPLORATORY SPATIAL DATA ANALYSIS (ESDA)

GLOBAL SPATIAL AUTOCORRELATION

The Global Moran's I was calculated to identify spatial dependence in rural development using different spatial weight matrices (queen contiguity, rook contiguity, and k-neighbors for 2, 3, and 4 neighbors). The results are shown in Figure 4.

Figure 04 | Univariate Global Moran's I of the RDI of the municipalities of the sub-middle São Francisco region



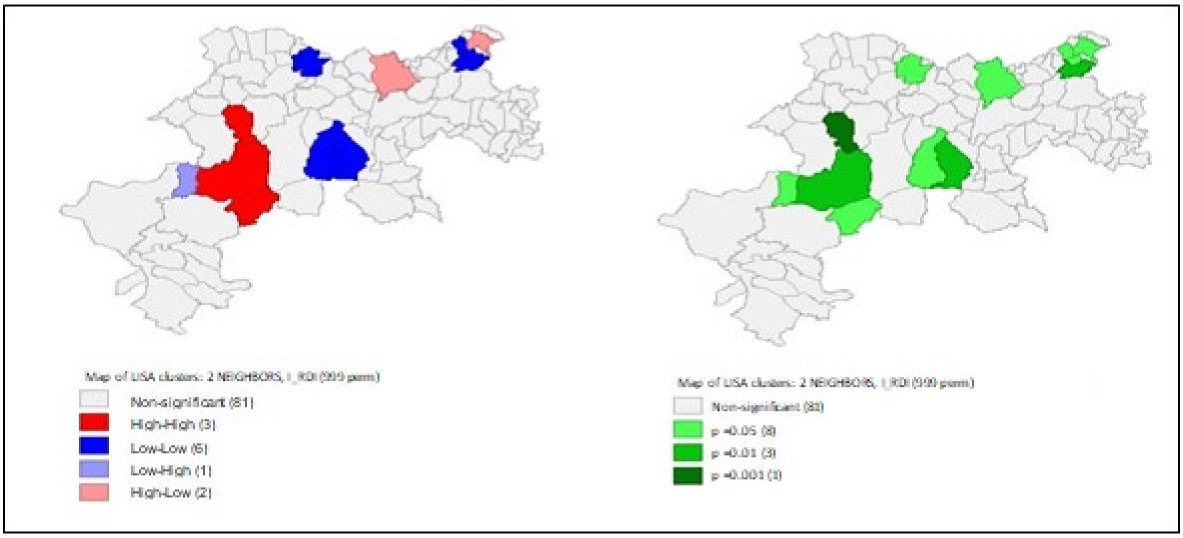
Prepared by the authors (2023).

Figure 4 reveals that all contiguity orders used exhibit positive indices, indicating positive spatial autocorrelation in the RDI of municipalities in the lower-middle São Francisco River. This means that municipalities with a high RDI tend to be surrounded by others with a high RDI, and the same pattern applies to municipalities with low rural development. The two-nearest-neighbor (K-2) matrix obtained the best result, with a Moran's I of 0.167.

LOCAL SPATIAL AUTOCORRELATION

Once global spatial autocorrelation has been detected, the next step is to create a LISA Cluster Map to analyze possible spatial clusters within the RDI. Figure 5 shows this map, highlighting only municipalities with statistical significance of at least 5%.

Figure 05 | Map of LISA clusters and significance for the RDI of the municipalities of the sub-middle São Francisco region



Prepared by the authors (2023).

In the local analysis, High-High (HH) and Low-Low (LL) clusters are visible, as well as High-Low (HL) and Low-High (LH) outliers, with statistical significance. The HH clusters are centered in Petrolina-Juazeiro, including Lagoa Grande (PE), Juazeiro, and Jaguarari (BA). This concentration reflects a development hub, especially due to irrigated fruit cultivation for export. Five LL clusters were identified, with low RDI municipalities such as Iguaracy and Ingazeira (PE) and Chorrochó and Macururé (BA). Sobradinho (BA) is a BA outlier, while Serra Talhada and São José do Egito (PE) are HL outliers. These results highlight the socioeconomic inequalities in the sub-middle São Francisco region.

ANALYSIS OF THE DETERMINANTS OF RURAL DEVELOPMENT

According to the proposed econometric model, the effect of some representative variables on the RDI of the municipalities of the sub-middle São Francisco River was verified. Thus, the Bivariate Moran's I was calculated to determine whether the values of a variable observed in one municipality are related to the values of another variable observed in neighboring municipalities. Table 1 shows positive spatial autocorrelation between the RDI and most exogenous variables, except for credit, which has negative autocorrelation. Municipalities with high (or low) RDI are associated with high (or low) values of these variables. The results are significant at the 1% level, indicating a significant spatial relationship between the variables in the model.

Table 01 | Bivariate Moran's I Coefficient of the RDI of the municipalities of the sub-middle São Francisco region and the explanatory variables

Variable	Moran's I	*P-value*
GDPCAPITA	0.129	0.001
VALUEPRODU	0.240	0.001
MHDI	0.066	0.001
JOB	0.176	0.001
ASSISTANCE	0.247	0.001
CREDIT	-0.229	0.001
PRONAF	0.104	0.001

Prepared by the authors (2023).

An initial OLS model was estimated. However, when using a spatial weights matrix, spatial effects were identified in the data. Tests for estimation problems, including multicollinearity, normality of residuals, and homoscedastic variance, were performed. The multicollinearity test, with values for all explanatory variables in Table 2 below the threshold of 30, indicates the absence of multicollinearity.

Table 02 | Variance Inflation Factor (VIF) of the explanatory variables of the RDI of the municipalities of the sub-middle São Francisco region

Variable	IVF
GDPCAPITA	1,3922
VALUEPRODU	3,9230
MHDI	1,5034
JOB	2.7420
ASSISTANCE	1,4849
CREDIT	1,2801
PRONAF	1,2217

Prepared by the authors (2023).

After the OLS model, the SAR and SEM models were estimated. Tests indicated that the errors do not follow a normal distribution and that there is heteroscedasticity. Therefore, the Instrumental Variables (IV) method was used for the SAR model, and the GMM was used for the SEM model. Lagrange Multiplier, spatial lag (LMρ), and error (LMλ) tests, as well as their robust versions (LMρ*, LMλ*), were performed. According to the tests, the SAR model was indicated as the most appropriate. The results are shown in Table 3.

Table 03 | Results of the a-spatial (OLS), spatial lag (SAR) and spatial error (SEM) models for the determinants of the RDI.

Variables	Model		
	OQL (1)	SAR (2)	WITHOUT (3)
CONSTANT	-0.06902	-0.039255	-0.072259
	(0.04679)	(0.049523)	(0.045344)
GDPCAPITA	0.002171***	0.0024767***	0.0021736***
	(0.0006)	(0.00065092)	(0.00062448)
VALUEPRODU	0.00003387***	0.00003433***	0.000033934***
	(0.000003805)	(0.0000036578)	(0.0000036131)
MHDI	0.1530**	0.14446**	0.15947**
	(0.06635)	(0.068483)	(0.064908)
JOB	0.008266***	0.0081456***	0.0082676***
	(0.0006265)	(0.00059575)	(0.00059085)
ASSISTANCE	-0.1086**	-0.081959*	-0.1055***
	(0.04268)	(0.042017)	(0.040564)
CREDIT	0.000802**	0.0006253*	0.00079513**
	(0.0003417)	(0.00034395)	(0.00032871)
PRONAF	-1.004e-07	-8.3885e-08	-1.1957e-07
	(3.053E-07)	(2.9387E-07)	(2.8980E-07)
λ	-	-	0.0671
			(0.2255)
ρ	-	-0.088248**	-
		(0.038632)	
R^2	0.9414	-	-
Adjusted R^2	0.9366	-	-
AIC	-436.4141	-	-
SC	-413.6207	-	-
LM_{ρ} (phase shift)	3.9569**	-	-
	(0.0467)		
LM_{ρ}* (robust lag)	5.4458**	-	-
	(0.0196)		
LM_{λ} (error)	0.4966	-	-
	(0.4810)		
LM_{λ}* (robust error)	1.9855	-	-
	(0.1588)		
SARMA	5.9424*		
	0.0512		
Breusch-Pagan test	19,844	-	-
	(0.0059)		
Jarque – Bera Test	25,997	-	-
	(0.0000)		

Note: *p<0.1; **p<0.05; ***p<0.01

Prepared by the authors (2023).

Note: In parentheses refers to the error. Λ is the spatial autoregressive error parameter; ρ is the spatial autoregressive coefficient; LM refers to the Lagrange multiplier.

The SAR model was chosen based on statistical tests. The explanatory variables are considered elasticities that affect the dependent variable. The effect on neighbors occurs when the explanatory variables locally affect the dependent variable and vice versa. The spatial coefficient ρ is -0.088248, significant at the 5% level, indicating inverse autocorrelation between municipalities. The direct and indirect effects are broken down in Table 4.

Table 04 | Direct and indirect effect based on the estimated coefficients for the SAR model for determining the RDI

Variables	Effects		
	Direct	**Indirect**	**Total**
GDPCAPITA	0.002483275***	-0.0002074066***	0.002275869***
VALUEPRODU	0.000034421***	-0.0000028749***	0.0000315461***
MHDI	0.1448456**	-0.01209771**	0.1327479**
JOB	0.008167201***	-0.0006821359***	0.007485065***
ASSISTANCE	-0.08217605*	0.006863456*	-0.07531259*
CREDIT	0.0006269586*	-0.0000523645*	0.0005745942*
PRONAF	-8.410739E-08	7.02477E-09	-7.70826E-08
Note: *p<0.1; **p<0.05; ***p<0.01			

Source: Prepared by the authors (2023).

Different factors influence rural development in the sub-middle São Francisco region, as revealed by the effects of the explanatory variables on the RDI.

GDP per capita and Value of Agricultural Production: Increases in average per capita income are associated with greater rural development. When this value increases, it suggests that, on average, people have access to more financial resources. In the rural context, this increase not only translates into greater purchasing power for individuals; it reflects and drives a series of factors that lead to development. It enables greater investment in technology and infrastructure (such as agricultural mechanization, irrigation, or transportation improvements), which, in turn, increase the productivity of rural activities. Increased income also allows rural families to invest in their own quality of life. This includes housing improvements, access to better health and education services, and a greater capacity to weather crises (such as crop failures). Similarly, a stronger economy can lead to the diversification of rural activities beyond primary production. Increased income can drive the development of food processing industries, ecotourism, or other service activities in the countryside, generating more jobs and opportunities. Rego (2022) provides specific data for municipalities in the Legal Amazon. The findings infer that a 1% increase in GDP per capita generates a 0.010% increase in the Rural Development Index (RDI). It is noteworthy that GDP per capita is a relevant economic variable and a good indicator for measuring rural development progress. Another relevant finding is that increases in production value have a direct positive effect on the RDI, but the indirect effect suggests an inverse relationship between neighboring municipalities and the RDI, possibly indicating that a municipality with very high production attracts resources and labor from neighboring areas, negatively impacting their rural development. Rego (2022) also indicates that the Gross Production Value (GPV) has a positive, albeit slightly smaller, effect (a 1% increase generates a 0.0065% increase in the RDI). This suggests that, while agricultural production is paramount, the average income of the population is an even more powerful force in driving rural development in the Amazon.

In short, the discussion goes beyond simple correlation. GDP per capita is not just a symptom of development, but a catalyst that, by indicating greater wealth and productivity, creates a virtuous cycle of improvements that translate into more robust and sustainable rural development.

MHDI: An increase in the Municipal Human Development Index (MHDI) has a positive effect (0.1448) on the rural development of municipalities in the sub-middle São Francisco region, implying that better human development is associated with a higher RDI. The value of 0.1448 means that for each percentage point improvement in a municipality's MHDI, a 0.1448% increase in its RDI is expected. This statistical result corroborates the thesis that human development, in its dimensions of longevity, education, and income, is a precursor to and driver of rural development.

Employment on Agricultural Establishments: The relationship between employment on agricultural establishments and rural development is complex, manifesting both positive direct effects and indirect effects that can be negative. In this study, increased employment has a positive direct effect, but the indirect effect, influenced by neighboring municipalities, is negative. Increased employment in the agricultural sector has a direct and beneficial effect on the Rural Development Index (RDI) of the municipality where the jobs are created. This means that, with more jobs, there are more people with fixed incomes, which increases the purchasing power of the local population and stimulates the economy. The availability of jobs in the countryside helps retain the rural population, combating rural exodus and maintaining the vitality of communities. Thus, it strengthens productive activities, allows for the expansion of agricultural activities, increasing production and, consequently, the development of the municipality. This positive relationship is evidenced by studies such as that of Rego (2022), who, when analyzing rural development in the Legal Amazon, found that job growth is one of the main factors driving RDI growth. The research suggests a strong correlation, showing that doubling the number of jobs results in a significant 1% increase in rural development in municipalities, reinforcing the importance of job creation for territorial progress.

Technical assistance: The finding that technical assistance has a negative overall effect on rural development in municipalities in the sub-middle São Francisco region is a counterintuitive result that deserves in-depth analysis. Technical assistance is commonly seen as a fundamental pillar for the advancement of family farming and the improvement of living conditions in rural areas. However, this conclusion suggests that the mere existence of technical assistance programs does not guarantee positive results; the effectiveness and quality of these programs are crucial. This negative effect can be explained by a series of inefficiencies and systemic failures in the implementation of technical assistance programs. Technical assistance may not be reaching the most vulnerable farmers or those in greatest need. Rural development goes beyond agricultural productivity. It encompasses improving quality of life, environmental sustainability, and social organization. If technical assistance focuses solely on increasing production without considering market access, risk management, or community organization, its overall impact on development may be limited or even negative. The consistency of this result with other studies, such as that of Santos, Ferreira, and Campos (2018), reinforces the need for a critical reassessment of current technical assistance models. The study suggests that, to boost rural development, programs need to undergo a profound restructuring, focusing on a participatory approach, adapting to local realities, and addressing development more comprehensively.

Proportion of establishments with financing: Access to credit is a factor that affects rural development, and its importance is clearly evidenced by the positive impact that the proportion of establishments with financing has on the RDI. This relationship is especially relevant in regions such as the sub-middle São Francisco, where well-targeted credit policies can be a differentiator for growth. Financing acts as a dynamic element, allowing rural producers to invest in their activities and, consequently, boost the entire local economy. By obtaining credit, they can increase productivity, purchase better-quality inputs such as seeds and fertilizers, invest in new technologies, acquire more efficient machinery, and improve the infrastructure of their properties. Although both private and public credit contribute to development, public financing plays a particularly crucial role. As the study by Cienfuegos and Sánchez (2022) points out, the use of public credit generates even more significant results in terms of entrepreneurship, economic development, and population growth in rural areas. This is because, in general, public financing programs are designed to serve a wide range of producers, including those with lower investment capacity. These programs offer lower interest rates, longer terms, and more accessible conditions, making them essential tools for productive inclusion, combating inequality, and strengthening family farming.

Average value of PRONAF contracts: Although rural financing has an overall positive effect, an analysis of the average value of PRONAF contracts in the sub-middle São Francisco region reveals a critical point: the average value of contracts alone does not have a significant impact on rural development. This finding suggests that the mere existence of a certain volume of credit does not guarantee that it will boost a region's development. This result may indicate a problem of resource concentration. Instead of credit being distributed more broadly, it may be being directed to a small number of beneficiaries, who receive higher-value contracts. The effectiveness of a public policy like PRONAF should not be measured solely by the total amount injected into the economy, but rather by its ability to reach the largest possible number of families, ensuring that credit reaches those who need it most.

FINAL CONSIDERATIONS

This study achieved its objective of analyzing the spatial dependence of rural development and identifying the determinants of the Rural Development Index (RDI) in the municipalities of the sub-middle São Francisco region. Using Exploratory Spatial Data Analysis (ESDA) and spatial autoregressive econometric models, the study highlighted the heterogeneity of rural development distribution in the region.

The results demonstrate the existence of patterns of positive spatial autocorrelation, with the formation of 'High-High' clusters around the Petrolina-Juazeiro region and 'Low-Low' clusters in other areas, indicating that municipalities with high (or low) development tend to be surrounded by municipalities with similar characteristics. This concentration of wealth and development, driven largely by irrigated fruit farming, highlights the importance of a specific development hub for boosting the regional economy. On the other hand, the persistence of clusters with low rural development highlights the need for public policies focused on mitigating existing socioeconomic inequalities.

The econometric analysis confirmed that the RDI is significantly positively influenced by variables such as GDP per capita, the MHDI, employment in agricultural establishments, and the proportion of establishments with financing. The most notable contribution came from the MHDI, reinforcing the importance of social factors in the rural development process. Thus, the spatial model of determinants of rural development highlights the influence of socioeconomic and environmental factors, with the exception of technical assistance, which has an inverse relationship with the RDI.

In terms of contribution, this study advances the understanding of development dynamics in the sub-middle São Francisco region by applying a spatial approach that goes beyond descriptive analysis and quantifies the influence of several variables. The findings are crucial for informing public policy planning and strategic decision-making aimed at improving living conditions in rural areas.

For future research, we suggest conducting a longitudinal analysis to observe the evolution of spatial clusters over time. Other variables that have not been explored, such as transportation infrastructure, internet access, or specific rural development policies, could be included in future models for an even more comprehensive understanding of the topic. We also suggest that future studies evaluate the impact of existing public policies and monitor progress over time. Such tailored approaches are essential for guiding future rural development research and policies in the region and beyond.

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