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CLIMATE CHANGE AND URBANIZATION: EVIDENCE FROM THE SEMI-ARID REGION OF BRAZIL*

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ABSTRACT: To better understand urbanization in the semi-arid region of Brazil and the related intra-municipality rural-urban migration, this study aimed to examine whether climatic factors have contributed to the urbanization process in the last two decades and how future scenarios of climate change would affect it. Using fixed-effects panel data considering spatial dependence, the results confirmed that climate drivers (mainly temperature) were decisive for the intensification of the urbanization process in the municipalities of the semi-arid region. The effect of climate on the urbanization process was even more intense in municipalities that relied widely on the agricultural sector. Simulations of future climate change indicated that the urbanization process tends to accelerate over time for severe climate change scenarios.

Keywords: Intra-municipality migration flows; Urbanization rate; Climate change.

JEL Codes: Q15; Q54; R11.

MUDANÇAS CLIMÁTICAS E URBANIZAÇÃO: EVIDÊNCIAS PARA O SEMIÁRIDO BRASILEIRO

RESUMO: O presente artigo procurou compreender o processo de urbanização – e de migração rural-urbana intramunicipal relacionada – na região semiárida brasileira. A principal questão analisada foi se fatores climáticos contribuíram para a intensificação da urbanização nas duas últimas décadas e se cenários futuros de mudanças climáticas poderiam alterar a dinâmica atual. Usando modelos de dados em painel com efeitos fixos e dependência espacial, os resultados confirmaram que os condutores climáticos – principalmente as variações de temperatura – foram decisivos para a intensificação da urbanização no Semiárido. O efeito do clima sobre a urbanização foi ainda mais intenso em municípios com maior dependência do setor agrícola. As simulações de cenários futuros de alteração climática indicaram que o processo de urbanização tende a se acelerar ao longo do tempo caso sejam confirmadas mudanças climáticas mais severas.

Palavras-Chave: Migração rural-urbana intramunicipal; Urbanização; Mudança climática.

Classificação JEL: Q15; Q54; R11.

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1. Introduction

Over the past few years, the discussion of the impacts of human activities on climate change by increased greenhouse gas (GHG) emissions has intensified (IPCC, 2013), and has highlighted the impact of economic activity on the environment. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) projects increases in global temperatures by 2100 in different scenarios of future GHG emissions based on socioeconomic and technological characteristics. Among many other potential impacts on human societies, this report also predicts that climate change is likely to increase the displacement of people, especially in developing countries with low income.

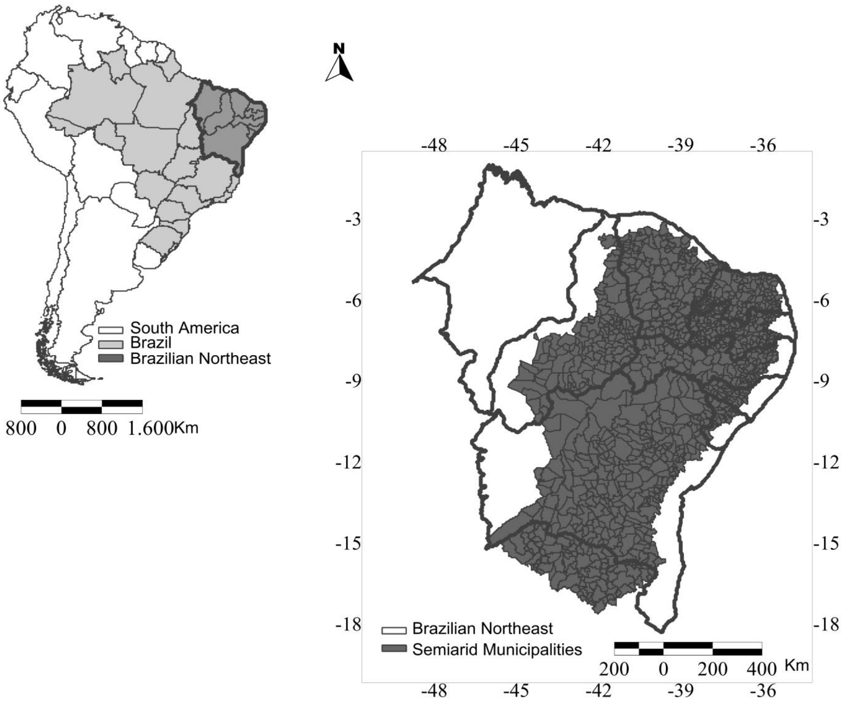
The effects of climate change have been noticeable in different ways, and their associated risks, though uncertain, have the potential to increase social vulnerability, thereby affecting the livelihood of the most vulnerable populations and exacerbating socioeconomic challenges. Environmental factors influence individuals' decisions to leave a location and shape migration flows through a complex web of causal links. They may also interact in non-trivial ways with economic activity and indirectly affect individuals' migration decisions (MASTRORILLO et al., 2016). As the most important income source in rural areas, agriculture is one of the sectors in which the main negative impacts are expected to occur (DESCHÊNES; GREENSTONE, 2007; IPCC, 2013). Since climate change affects crop yields, Brazilian agriculture is expected to face higher risks of crop failure and agriculture losses due to climate change (HADDAD; PORSSE; PEREDA, 2013; NELSON et al., 2014). The reduction in precipitation levels and the increasing temperature may negatively affect income and employment opportunities for people working in the agricultural sector or in industries that are strongly dependent on it. As a result, it could have implications on food production, which could lead to food insecurity due to a decrease in subsistence agriculture production (WHEELER; VON BRAUN, 2013), and possibly boost urbanization via rural-urban migration (MASTRORILLO et al., 2016). According to Henderson, Storeygard, and Deichmann (2017), adverse climatic shocks can trigger rural-urban migration of farmers. The "local mobility may therefore be relatively more available as a coping mechanism to the poor" (THIEDE; GRAY; MUELLER, 2016).

The analyses regarding urbanization and rural-urban migration induced by climate change in the literature are divergent and controversial, which reflects the methodological challenges in establishing causal links between climate change and urbanization and/or migration (JOHNSON; KRISHNAMURTHY, 2010). Although several studies have documented climate change impacts on rural-urban migration and consequent urbanization levels in other countries (BARRIOS; BERTINELLI; STROBL, 2006; BEINE; PARSONS, 2015; GRAY, 2009; MARCHIORI; MAYSTADT; SCHUMACHER, 2012; MASTRORILLO et al., 2016; MUELLER; GRAY; KOSEC, 2014; MUNSHI, 2003; VISWANATHAN; KAVI KUMAR, 2015), the Brazilian literature on this topic is still incipient (ASSUNÇÃO; FERES, 2008). Initial understandings of the vulnerability of the northeast region of Brazil to the projected impacts of climatic change have been published (BARBIERI et al., 2010; CONFALONIERI et al., 2014); however, an econometric analysis specifically for urbanization caused by intra-municipality rural migration from the semi-arid region requires attention.

Motivated by these lines of evidence, we explored whether and how climate change has affected urbanization levels across the semi-arid region of Brazil in the period of 1991-2010. Since climatic impacts on migration and urbanization patterns have shown more accurate results at regional and sub-regional levels (MCLEMAN, 2013), investigations on regional Brazilian cases have required special attention (BARBIERI et al., 2010, 2015).

The semi-arid region of Brazil is a relevant case study for many reasons. First, the northeast region of Brazil, which is composed by 58.5% of the semi-arid region municipalities (Figure 1), is historically characterized by high internal migration rates due to the occurrence of droughts. Between 1995 and 2000, approximately 805,855 people moved from rural to urban areas, which represented 39.7% of this type of migration flow in Brazil. Second, the semi-arid region of Brazil is already experiencing significant changes in climate. The average annual temperature exhibited positive trends between 1980 and 2010, with an increase of about 1.4°C over this period. Average annual rainfall trends are weak, but there is a tendency toward significant variability in precipitation. The Brazilian Panel on Climate Change (PBMC, 2014) projects intensification of these trends by the end of this century. According to the PBMC (2014), the temperature might increase from 3.5 to 4.5°C and precipitation levels might be reduced by 40 to 50% by the end of the century, which may hinder future agricultural production in the region and result in the intensification of rural migration. Third, the semi-arid region of Brazil is characterized by persistent poverty and inequality. According to the Institute of Applied Economic Research (IPEADATA, 2014), in 2011, the share of the population below the national poverty line was 35.16%, while the income Gini coefficient was estimated to be 0.54, which makes the semi-arid region of Brazil one of the most unequal regions in the country. Fourth, although the economy of the semi-arid region of Brazil is increasingly dominated by the tertiary sector, which makes up approximately 90% of the gross domestic product (GDP), agriculture is still relevant for subsistence and rain-fed, small-holder farming. Therefore, if climate variability influences people's decision to leave the rural area of a municipality, this may occur through its impact on people directly or indirectly through the agricultural channel (MASTRORILLO et al., 2016).

Figure 1 – Geographical boundaries of the semi-arid region of Brazil highlighted inside the northeast region



Source: Elaborated by the authors using data from the IBGE.

Attempting to better understand the rural-urban intra-municipality migratory process and the consequent increase in urbanization levels in the semi-arid Brazilian municipalities, this study aimed to examine whether climatic factors associated with economic, social, and demographic factors have contributed to intra-municipality rural-urban migration, proxied by the urbanization rate, between 1991 and 2010. It is widely recognized that geographically close entities are not independent, but are spatially correlated, which means that closer municipalities tend to be more similar than further ones (BELOTTI; HUGHES; MORTARI, 2016). Since ignoring this spatial dependence may lead to model misspecification (ALMEIDA, 2012), this study used spatial econometric techniques to properly test the relationship between climate change and urbanization levels. As far as we know, it is the first study to analyze the effects of climate change on the level of urbanization using econometric techniques to take into account spatial dependence. Furthermore, this study investigated if the relationship between climate change and urbanization levels was more evident in highly agricultural-dependent municipalities. Last, it was assessed how the rural-urban migration flows would be affected by two different climate change scenarios in the future, specifically in the periods of 2016-2035 and 2046-2065, as defined by the IPCC (2013).

It is important to emphasize that the variation in the urbanization rate between the years considered in the analysis was not exclusively due to rural migration. Other factors, such as the rate of growth of rural and urban population, influence this rate. However, according to Ojima (2013), the contribution of rural-urban migration to the growth in the urbanization rate in the northeast region between 1970 and 2000 was approximately 46%, which indicates the importance of this migratory flow in the composition of the urban population of the semi-arid region of Brazil. A better understanding of the causes that influence the decision to leave the rural area for the urban area of a municipality can enable the investment in specific policies that prevent small farmers from being forced to leave rural areas. Furthermore, these policies should be able to indirectly control the adverse factors associated with the rural-urban intra-municipality flow, such as underemployment and lack of access to public services (BLACK et al., 2011). Thus, this study is an important tool in the development of public policies to mitigate the economic and social imbalances caused by intra-municipality rural-urban migration.

The remainder of the paper proceeds as follows. In the next section, we present our estimates of the urbanization levels in the semi-arid region of Brazil, and discuss our test for spatial dependence and heterogeneity across demographic groups. Then, from a final set of analyses, we discuss whether the effects of climate variability on urbanization levels will increase over time. We conclude by discussing our results and identifying implications for future research on this topic.

2. Methodological framework

The role of intra-municipality rural-urban migratory movements in the urbanization process in developing countries is recognized in the literature (BRUECKNER, 1990, BARRIOS; BERTINELLI; STROBL, 2006; HENDERSON; STOREYGARD; DEICHMANN, 2017). Thiede, Gray, and Mueller (2016) argued that there is concrete evidence in the literature linking climate-induced population movements to urban growth and urbanization. At the same time, Henderson, Storeygard, and Deichmann (2017) argued that rural-urban migration provides a kind of "escape" from adverse climate shocks. According to Barrios, Bertinelli, and Strobl (2006), rural-urban migration is one of the most important supply-push determinants of the urbanization process in developing countries, especially in poor regions affected by climate change. In addition, Jedwab, Christiaensen, and Gindelsky (2017) postulated that in the standard models of urbanization, rural-urban migration plays a very important role. Based on these assumptions, the theoretical framework of this study was derived from the microeconomic utility maximization theory used by Beine, Doquier, and Ozden (2011) and Beine and Parsons (2015) to analyze the link between climate change and migration.

This model postulates that rural population i in municipality k at time t chooses to leave or not to leave the rural area of municipality k based on the utility maximization process. N_{it} is rural population i of municipality k that chooses to leave the rural area for urban area j of the same municipality k at time t.[1] The utility of the individual to leave the rural area is log-linear on income to capture the variation in utility on each percentage change in the product, and it depends on the characteristics of the origin and destination areas and on the costs of leaving rural area i. Thus, the utility of an individual living in rural area i to remain in rural area i of municipality k at time t (U_{iit}) is described as follows:

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[1] Since this study considered intra-municipality rural-urban migration, $i, j \in k$.

$$U_{iit} = \ln(W_{it}) + A_{it} + \varepsilon_{it} \tag{1}$$

where W_{it} is the wage in rural area *i* of municipality *k* at time *t*; A_{it} are the characteristics of rural area *i* at time *t*, considering the multiple factors that influence the decision to leave; and ε_{it} is an iid (independent and identically distributed) term of random distribution.

Alternatively, the utility of an individual living in rural area *i* to leave the rural area for urban area *j* of municipality *k* at time *t* (U_{ijt}) is described as follows:

$$U_{ijt} = \ln(W_{jt}) + A_{jt} - C_{it} + \varepsilon_{it} \tag{2}$$

where W_{jt} is the wage in urban area *j* of municipality *k* at time *t* and C_{it} is the cost of leaving rural area *i* at time *t*.

When the random term follows an iid extreme value distribution, the probability of an individual leaving rural area *i* for urban area *j* of municipality *k* at time *t* is described as follows:

$$\left(\frac{N_{ijt}}{N_{iit}}\right) = \frac{\exp\left[\ln\left(W_{jt}\right) + A_{jt} - C_{it}\right]}{\exp\left[\ln\left(W_{it}\right) + A_{it}\right]} \tag{3}$$

where N_{ijt} is the number of individuals that decided to move from *i* to *j* and N_{iit} is the number of individuals that decided to stay in *i*, both at time *t*. Since this study dealt with intra-municipality rural-urban migration, we considered the urbanization rate as a proxy for this type of migratory flow:

$$\frac{N_{ijt}}{N_{iit}} \cong \frac{N_{jt}}{N_{kt}}$$

where N_{jt} is the urban population and N_{kt} is the total population of municipality *k* at time *t*.

Taking logarithms of the differential utility between staying in *i* or leaving *i* for *j*, we obtain the following specification model:

$$\ln\left(\frac{N_{jt}}{N_{kt}}\right) = \ln\left(\frac{W_{jt}}{W_{it}}\right) + A_{jt} + A_{it} - C_{it} \tag{4}$$

where W_{jt}/W_{it} is the ratio between the wage in urban area *j* and the wage in rural area *i* at time *t*. Therefore, Equation 4 states that intra-municipality rural-urban migration, proxied by the urbanization rate, is a function of the wage gap between areas *i* and *j*, the characteristics of the origin and destination, and the rural migration costs.

Regarding migration costs, there is no consensus in the literature. Generally, according to Alves (2006), the greater the distance between the origin and destination, the higher the costs associated with migration. A similar idea was defended by Timmins (2007), which related the fixed costs of migration to the distance between the origin and destination and to the migrant's attributes (especially schooling). Specifically, considering the integration of labor markets, Morten and Oliveira (2017) demonstrated the importance of the costs involved in inter-municipality migration processes; the authors showed that improving roads considerably reduces the migration cost. At the same time, other authors considered the possibility of very low or zero costs depending on the type of migratory flow considered. As stated by Alves (2006) and Assunção and Feres (2008), the costs of leaving a rural area for an urban area of the same municipality are very low or zero. The methodological presupposition of Barrios, Bertinelli, and Strobl (2006) indicated that migration cost is very important when dealing with displacement over larger distances; these authors argued that when considering urbanization resulting from intra-municipality rural-urban migration, the costs are irrelevant. Finally, Thiede, Gray, and Mueller (2016) argued that the intra-municipality or local rural-urban migration, mediated by the agricultural channel (an important urbanization component), is so low that it can be disregarded.

From this brief literature review, we concluded that consideration of migration costs depend on the specificities of the research problem addressed. Therefore, in the case of this study that dealt with urbanization resulting from intra-municipality rural-urban migration, it was reasonable to follow the propositions of Barrios, Bertinelli, and Strobl (2006); Assunção and Feres (2008); and Thiede, Gray, and Mueller (2016).[2]

In the present study, the focus was on the characteristics of origin areas *i*, which were a function of economic (Eco_{it}), social (Soc_{it}), demographic (Dem_{it}), and environmental factors (Env_{it}). Since adaptive measures (Adp_{it}) could mediate the effects of climate change on the decision to leave a rural area for an urban area, responses to climate change should include the adaptation to potential impacts of GHG emissions and consequent variations in temperature and rainfall. Thus, the characteristics of the origin areas are a function of the following:

$$A_{it} = A\left(Eco_{it}, Soc_{it}, Dem_{it}, Env_{it}, Adp_{it}\right) \tag{5}$$

2.1. Econometric specification

2.1.1. Baseline specification – non-spatial model

In order to test the hypothesis introduced by this study properly, the starting point was Equations 4 and 5 from the theoretical framework, which led to the following empirical specification whose explanatory variables were based on Barrios, Bertinelli, and Strobl (2006); Beine, Doquier, and Ozden (2011); Marchiori, Maystadt, and Schumacher (2012); Dallmann and Millock (2013); and Beine and Parsons (2015):

$$\ln\left(\frac{N_{jt}}{N_{kt}}\right) = \beta_0 + \beta_1 \ln\left(\frac{W_{it}}{W_{jt}}\right) + \beta_2 SCH_{kt} + \beta_3 AGE_{kt} + \beta_4 IRR_{kt} + \beta_5 T_{kt} + \beta_6 P_{kt} + \alpha_i + \alpha_{jt} + \varepsilon_{kt} \tag{6}$$

where N_{jt}/N_{kt} is the urbanization rate, namely the ratio between urban population *j* and the total population of municipality *k* at time *t*; W_{it}/W_{jt}, is the ratio of the agricultural GDP per capita and the non-agricultural GDP per capita in municipality *k* at time *t*, which is used as a proxy for the wage gap between rural and urban areas; SCH_{kt} is the ratio between the number of schools in rural area *i* and the total number of schools in municipality *k*; AGE_{kt} is the percentage of the age group population more prone to leave the rural area due to adverse climate change effects[3]; IRR_{kt} is the share of agricultural establishments that use some kind of irrigation in the rural area of municipality *k* at time *t*; T_{kt} and P_{kt}, are average annual temperature and rainfall anomalies, respectively, in municipality *k*; α_i is the fixed effect, which is invariant over time and captures the vulnerability of rural area *i* of municipality *k*; α_{jt} is the fixed effect of *j* that varies over time; and ε_{it} is the idiosyncratic error, which

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[2] Since we dealt with data on municipality urbanization rates as a proxy to intra-municipality rural-urban migration, distance was not liable to be measured (even if it were possible to measure the distance between rural and urban areas of the same municipality, the variability in this measurement between municipalities would probably be minimal). Moreover, as opposed to the assumptions of Morten and Oliveira (2017), it is improbable that road infrastructure would be significant in the decision to leave a rural area for an urban area of the same municipality. Even recognizing the importance of Morten and Oliveira’s results, data on infrastructure of the roads connecting the rural area and the urban area of the studied municipalities were not available. Finally, in order to indirectly control the cost related to migrant schooling, similar to Timmins (2007), we used the variable school in our model, which sought to capture the influence of some level of schooling on the decision to migrate.

[3] Individuals between 35 and 64 years old. The age gap selected as the group most prone to migrate was due to the fact that 65.63% of the agricultural establishment owners were in this age group, according to the 2006 Agricultural Census (IBGE, 2006).

represents the non-observed factors that change over time and affect the dependent variable.

From the analytical model proposed in this study (Equation 6), the panel data model was used to evaluate the role of climatic factors and socioeconomic conditions in the urbanization level of the municipalities of the semi-arid region in the recent past. After testing for model specification, heteroscedasticity, and autocorrelation using Hausman, White, and Wooldridge tests, respectively, the fixed effects model proved to be the best fit (Table A1).

To confirm the robustness of parameter signs and significances, multiple alternative specifications of Equation 6 were tested. The first version of the model included climatic, economic, social, and demographic drivers, as well as the variable that captures adaptation. In this equation, wages, school, age group, and irrigation variables were used as explanatory variables. The second version included interaction variables, namely T*Agri and P*Agri, which were created to verify if the effects of climate variability on urbanization levels were most evident in the municipalities that depend more heavily on the agricultural sector, as proposed by Dell, Jones, and Olken (2012) and Marchiori, Maystadt, and Schumacher (2012). The created dummy variable took a value of 1 for all municipalities with agricultural GDP participation in the total GDP higher than the average value determined for Brazil, and took a value of 0 otherwise[4]. Then, these dummy variables were interacted with the climatic variables of temperature and precipitation.

To verify if the urbanization levels were randomly distributed or if they were spatially autocorrelated and to infer about the need to estimate spatial models, Moran's I and Pesaran's CD statistics were used. Thus, residuals from the ordinary least squares (OLS) fixed-effects models, which do not incorporate any spatial components, were spatially lagged using a spatial weights matrix. If spatial autocorrelation is detected, the proposed models to relate the level of urbanization to climate change should incorporate the spatial components.

2.1.2. Spatial model specification and estimation

To evaluate the possibility of spillovers of the urbanization levels among municipalities so that attributes in some municipalities could have effects on the others through a spatial mechanism, we estimated models that considered the spatial dependence among municipalities. The spatial panel data model with fixed effects that was used is as follows:

$$\ln\left(\frac{N_{jt}}{N_{kt}}\right) = \rho W\left(\frac{N_{jt}}{N_{kt}}\right) + \beta X_{it} + \theta W X_{it} + \alpha_i + \varepsilon_{it} \tag{7a}$$

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \upsilon_{it} \tag{7b}$$

where W is the spatial weight matrix, X is a vector of explanatory variables (W_i/W_j, SCH, AGE, IRR, T, and P), ρ is the coefficient that captures the spillover effects of urbanization levels of contiguous municipalities on the urbanization level of municipality k; θ expresses the spillover effects of explanatory variables of contiguous municipalities on the urbanization level of municipality k; and λ represents the spatial autocorrelation error coefficient.

Based on Baumont, Ertur, and Le Galo (2004), contiguity was the criterion used to create the spatial weight matrix[5] because it was reasonable to suppose that neighboring municipalities had stronger interactions with one another than noncontiguous municipalities. The queen contiguity

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[4] We found that 51% of the municipalities used in the analysis had a share of agricultural GDP in the total GDP that was above the average value for Brazil, which is 0.3644. Thus, we considered these municipalities as the most dependent on the agricultural sector.

[5] The Baumont, Ertur, and Le Galo procedure (2004) involves choosing the spatial weight matrix that is able to capture the maximum of the spatial autocorrelation given by the highest value of Moran's I. The matrices of spatial weights used in the test were the queen contiguity matrix and K nearest neighbors (K = 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, and 20). In the queen contiguity convention, in addition to the boundaries with non-zero extension, the vertices are considered contiguous.

matrix takes a value of 1 if two municipalities share a border, and takes a value of 0 otherwise. As a standard, we row normalized the matrix, which involved dividing each value in a row by the sum of the values in that row, thereby ensuring that each row added up to 1.

We considered four different fixed effects models that were able to include spatial dependence, namely the spatial autoregressive model (SAR) ($\lambda = 0$, $\theta = 0$, $\rho \neq 0$), spatial error model (SEM) ($\lambda \neq 0$, $\theta = 0$, $\rho = 0$), spatial autocorrelation model (SAC) ($\lambda \neq 0$, $\theta = 0$, $\rho \neq 0$), and spatial Durbin model (SDM) ($\lambda = 0$, $\theta \neq 0$, $\rho \neq 0$). In the presence of spatial dependence, estimates by OLS become inappropriate; therefore, the estimation method used to estimate the SAR, SEM, SAC, and SDM was the quasi-maximum likelihood model, as proposed by Belotti, Hughes, and Mortari (2016).

A common problem in spatial econometric models is selecting the correct type of spatial model. Beginning from the SDM, which includes the spatially lagged values of both dependent and independent variables, we followed the procedures described by LeSage and Pace (2009) and Elhorst (2010) and performed Wald and likelihood-ratio (LR) tests. The authors highlighted that the SDM can be used as a general specification and then tested against alternative specifications, such as the SAR, SEM, and SAC. Following the estimation of the SDM, it was possible to test if it could be simplified to a SAR if $\theta = 0$ and $\rho \neq 0$, while if $\theta = -\beta\rho$ then the model could be simplified to a SEM. Finally, since the SAC and SDM are non-nested models, Akaike information criteria (AIC) could be used to determine which is the most appropriate model (BELOTTI; HUGHES; MORTARI, 2016).

Since spatial regression models exploit the complicated dependence structure between units, the effect of an explanatory variables' change on a specific municipality will affect the municipality itself, and potentially affect all other municipalities indirectly. This implies the existence of direct, indirect, and total effects (BELOTTI; HUGHES; MORTARI, 2016). These are calculated as the partial derivatives of the dependent variable with respect to each independent variable. The direct effect measures the impact of a particular explanatory variable in municipality *i* on the dependent variable in municipality *i*, while the indirect effect measures the impact of changes of a particular explanatory variable in municipality *j* ($i \neq j$) on the dependent variable in municipality *i*. The total effect is the sum of the direct and indirect effects.

Everything else held constant, the greater the difference in per capita GDP between rural and urban areas, the population in the age group more prone to leave rural area *i*, and the deviation from the average temperature, the greater the incentive to leave rural areas for urban areas (BEINE; PARSONS, 2015; CONIGLIO; PESCE, 2015; MARCHIORI; MAYSTADT; SCHUMACHER, 2012; MUELLER; GRAY; KOSEC, 2014). On the other hand, the greater the number of people with some level of education, the volume of precipitation, and the number of establishments using irrigation, the higher the permanence rate (BEINE; DOCQUIER; ÖZDEN, 2011; GRAY; MUELLER, 2012; RAMÍREZ; KRONICK; MASON, 2012).

2.1.3. Simulations for future climate change impacts on urbanization levels

A comparative static analysis was performed in order to verify how urbanization levels will respond to the expected climate change. By using the estimated coefficients from Equations 7a and 7b, the semi-arid urbanization rate was estimated considering the average temperature and the average precipitation for the base year of 2010[6] in regard to the period between 1986 and 2005[7] according to Equation (8):

$$\left(\frac{\hat{N}_{jBASE}}{\hat{N}_{kBASE}}\right) = \hat{\beta}_0 + \exp\left[\hat{\beta}_1\right]\left(\frac{W_{it}}{W_{jt}}\right) + \hat{\beta}_2 SCH_{kt} + \hat{\beta}_3 AGE_{kt} + \hat{\beta}_4 IRR_{kt} + \hat{\beta}_5 T_{kBASE} + \hat{\beta}_6 P_{kBASE} \tag{8}$$

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[6] We used the year 2010 as a reference since this was the last year of the analysis period proposed by this study; thus, it eliminated the existing bias between the expected and observed values of the climate variables considered.

[7] The IPCC AR5 stipulated the base period.

Then, the urbanization rate was estimated taking into consideration the average temperature and average precipitation projected for future periods established by the IPCC (2013) for the periods of 2016-2035 and 2046-2065, according to Equation (9):

$$\left(\frac{\hat{N}_{jFUTURE}}{\hat{N}_{kFUTURE}}\right) = \hat{\beta}_0 + \exp\left[\hat{\beta}_1\right]\left(\frac{W_{it}}{W_{jt}}\right) + \hat{\beta}_2 SCH_{kt} + \hat{\beta}_3 AGE_{kt} + \hat{\beta}_4 IRR_{kt} + \hat{\beta}_5 T_{kFUTURE} + \hat{\beta}_6 P_{kFUTURE} \tag{9}$$

Last, the percentage of change in the urbanization rate in response to changes in the expected temperature and precipitation was calculated according to Equation (10):

$$\%\Delta\left(\frac{\hat{N}_j}{\hat{N}_k}\right) = \frac{\hat{N}_{jFUTURE}\big/\hat{N}_{kFUTURE} - \hat{N}_{jBASE}\big/\hat{N}_{kBASE}}{\hat{N}_{jBASE}\big/\hat{N}_{kBASE}}.100 \tag{10}$$

This study aimed to evaluate the change in the urbanization rate in response to changes in temperature and rainfall without taking into account the indirect effects of other variables, which is common in studies aimed at analyzing the effect of climate change on a given variable. In this way, following the procedure described by Seo (2011) and Cunha, Coelho, and Féres (2015), no assumption about the future values of other variables was made.

The climate change projections were provided by the IPCC (2013) based on several scenarios of socioeconomic and technological characteristics that determine future GHG emissions. The projections used in this study came from the Representative Concentration Pathways (RCPs) 8.5 and 4.5. The former describes a high GHG emission scenario with the absence of emissions reduction policies, and the latter describes an intermediate scenario of GHG emissions. The selection of these scenarios was due to the fact that they are closest to the scenarios that different forums on climate change currently propose. It is important to emphasize that the RCPs were presented by the IPCC AR5 (IPCC, 2013), which replaced the Special Report on Emissions Scenarios (SRES) (A2, A1B, B1, etc. - Fourth Assessment Report (AR4)). RCPs represent a step up from SRES because they include other factors related to climate change that are not accounted for by AR4 scenarios, such as emissions resulting from land-use change and more consistent short-lived gases. These two scenario categories (RCPs and SRES) are not exactly comparable because they are based on different technical formulations (IPCC, 2013). However, it can be stated that RCP 8.5 represents a pessimistic climate change scenario, as well as the SRES-A2, while RCP 4.5 maintains an intermediate scenario similar to SRES-B1. In addition, RCPs time windows (2016-2035, 2046-2065, and 2081-2100) are different from those of the SRES (2010-2040, 2041-2070, and 2071-2100), but maintain the idea of short, medium, and long term.[8]

For simulations of the urbanization rate, we adopted climate projections data for the average value of each month over two periods of time (2016-2035 and 2046-2065). Future climate variables were designed for three general circulation models (GCMs)[9] from Coupled Model Intercomparison

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[8] Further technical details on RCPs and SRES can be obtained from the IPCC (2013) in Chapter 1. Figure 1.15 of this chapter shows a comparison between the time trajectories of the two sets of scenarios, namely RCPs, and SRES.

[9] GCMs translate GHG emission levels into changes in temperature, precipitation, solar radiation, and sea level rise, among others (HANEMANN, 2008). GCMs consist of atmospheric processes and terrestrial and oceanic surface mathematical formulations based on the classical physical principles of hydrodynamics (MARGULIS; DUBEUX, 2010).

Project Phase 5, namely MIROC5, MRI-CGCM3, and NORESM1-M[10]. The main reason for choosing these models among several GCMs was the fact that they present the most realistic simulations of the Brazilian climatic conditions. However, despite consistency with the Brazilian climate behavior, the GCMs presented dissimilar results for magnitudes and expected mean values for the climate variables. Since they do not use the same methodology for the development of climate projections and thus were not directly comparable, it was not possible to assume which was the most appropriate model. For this reason, the temperature and precipitation average data were used for the future scenarios using the three models described above.

2.2. Data and variables construction

The main sources of data were Brazil's 1991, 2000, and 2010 demographic censuses and the 1996 and 2007 population counts provided by the Brazilian Institute of Geography and Statistics (IBGE) (2014). Economic, social, demographic, and adaptation data were collected from the Institute of Applied Economic Research (IPEADATA) (2014), school census from the National Institute for Educational Studies and Research Anísio Teixeira (INEP) (2014), Department of Informatics of the Unified Health System (Datasus) (2014), and 1996 and 2006 agricultural censuses, respectively. The climatic data (0.5×0.5 degree grid-cell aggregation level) were provided by the CL3.21 database of the Climate Research Unit (CRU) at the University of East Anglia (2014).

i. Urbanization rate (N_{jt}/N_{kt}) is the ratio between the urban population and the total population of municipality k at time t (BARRIOS; BERTINELLI; STROBL, 2006). The data were obtained from the 1991, 2000, and 2010 demographic censuses, and from the 1996 and 2007 population counts provided by the IBGE (2014).

ii. Wage (W_{it}/W_{jt}) is the ratio between the agricultural GDP per capita and the non-agricultural GDP per capita in municipality k at time t at base year 2000 constant prices for all years considered in the analysis (BARRIOS; BERTINELLI; STROBL, 2006; BEINE; PARSONS, 2015; MARCHIORI; MAYSTADT; SCHUMACHER, 2012). The data were obtained from the IPEADATA (2014). It represents the economic factor.

iii. School (SCH_{kt}) is the ratio between the number of schools located in rural areas and the total number of schools in municipality k at time t. The data were obtained through the school census from the INEP (2014). It represents the social factor.

iv. Age Group (AGE_{kt}) is the ratio between the number of people between 35 and 64 years old living in the rural area and the total number of people living in the rural area of municipality k at time t. The data were provided by Datasus (2014). It represents the demographic factor.

v. Irrigation (IRR_{kt}) is the ratio between the number of agricultural establishments that use irrigation and the total number of agricultural establishments in municipality k at time t. The data were obtained from the agricultural censuses provided by the IBGE (1996, 2006). To obtain these data for the years under analysis, we exponentially interpolated the number of agricultural establishments with irrigation and the number of total establishments of each municipality. It represents the adaptation measures factor.

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[10] Model for Interdisciplinary Research on Climate version 5 (MIROC5) of the Atmosphere and Ocean Research Institute (The University of Tokyo), the National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology; Meteorological Research Institute Coupled Atmosphere-Ocean General Circulation Model version 3 (MRI-CGCM3); Norwegian Earth System Model version 1 (NORESM1-M) of the Norwegian Climate Centre.

vi. Temperature (T_{kt}) and precipitation (P_{kt}) are climatic anomalies calculated as the ratio of the difference between the current and long-term averages and the long-term standard deviation of temperature and precipitation (BEINE; PARSONS, 2015; MARCHIORI; MAYSTADT; SCHUMACHER, 2012). As climate scientists consider climate change a long-term phenomenon, the period considered in the analysis for the determination of anomalies was a 30-year period between 1981 and 2010. The data were provided by the CL3.21 database of the CRU at the University of East Anglia (2014). They represent the environmental factor.

It is important to clarify that we initially considered 957 municipalities that comprised the semi-arid region of Brazil in 1991 as observation units for the construction of the database. However, we decided to exclude all the municipalities that resulted in new municipalities since 1991. We supported the exclusion by the fact that the territory and population losses of a given municipality to another newly created municipality would introduce outlier values not consistent with the increasing or decreasing trends. For this reason, we excluded 161 municipalities from the sample; thus, 796 municipalities comprised the sample, which corresponded to approximately 70% of the total number of semi-arid region municipalities in Brazil.

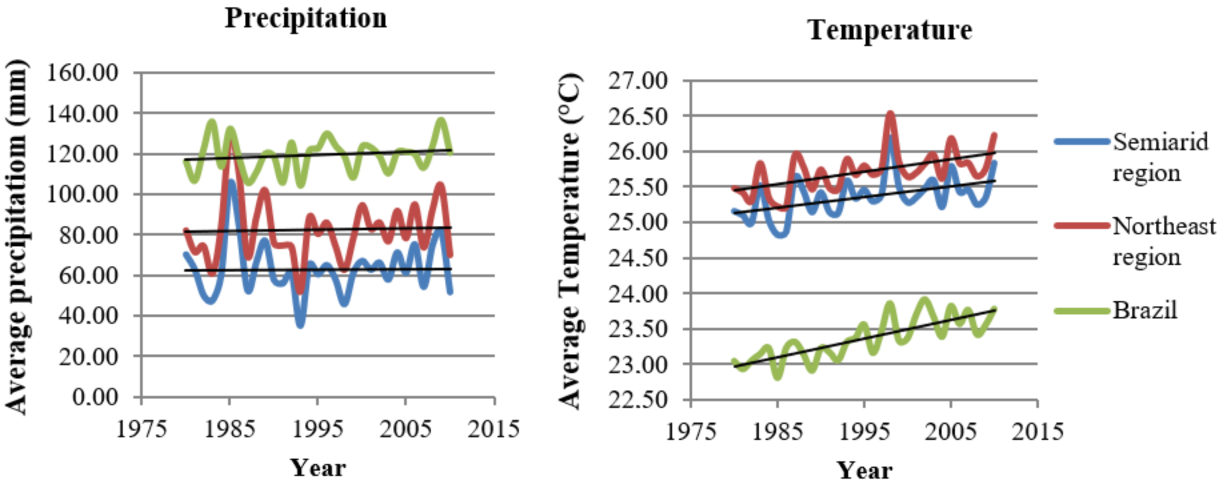
3. Results and discussion

3.1. Descriptive results

Toward an understanding of the regional differences and general characterization of the climatology of the studied area, we presented the behavior of the climate series variables (precipitation and temperature) over a 30-year period (1981-2010) distinctly for the municipalities in the semi-arid region, northeast region, and all of Brazil in Figure 2. Despite the noticeable interannual variability, the average annual rainfall of the three regions remained relatively stable over the period, with the semi-arid region showing the lowest volume of rainfall (Figure 2A). Unlike rainfall, the historical pattern of average temperature showed an increasing trend of about 1.4°C over a 30-year period for the semi-arid region, with values close to those of the northeast region (1.3°C) (Figure 2B). Figure A1 shows the relative variability in these climatic variables in the municipalities of the semi-arid region over the same period. The variability in the climate variables used in this study was consistent with the studied phenomenon type, namely slow-onset. Such climatic processes are characterized as long lasting and continuous, with slow trajectories (these include sea level rise, increasing temperatures, ocean acidification, glacial retreat and related impacts, salinization, land and forest degradation, loss of biodiversity, and desertification). Although the temperature variability was not very high when the coefficient of variation was considered as a measure, the semi-arid region maintained an increasing trend for this variable.

Droughts are part of the natural climate variability of the semi-arid region. Regional climate change projections suggest that drought conditions will be intensified mainly in the second half of the 21st century (MARENGO; BERNASCONI, 2015). During the most severe droughts of the last decade (2012-2013), about 38% of the semi-arid population was affected. This indicates that measures of reduction in GHG emissions should be applied in order to reduce the number of people affected by climate change in the future.

Figure 2 – (A) Annual average precipitation (mm) and (B) temperature (°C) from the semi-arid region, northeast region, and all Brazilian municipalities over a 30-year period (1981-2010)



Source: Elaborated by the authors using data from the CRU/CL3.21 database.

An overview of population movements showed that the semi-arid region presented the lowest urbanization rates and the highest growth rate of the urban population from 1991 to 2010, followed by the northeast region and all Brazilian municipalities, respectively (Table 1). Despite their lower urbanization rates, with an increased urbanization growth rate of about 28% and 21% in 20 years, respectively, the semi-arid and the northeast regions presented an accelerated transitional process from rural to urban areas. Remarkably, such urban growth is not a function of population growth, as according to the 2010 demographic census (IBGE, 2014), the rate of population growth is declining.

Table 1 – Evolution of the urbanization rate (%) and urbanization growth using 1991 as the calculation basis (%) for the semi-arid region, northeast region, and general Brazilian municipalities from 1991 to 2010

Region	Urbanization Rate (%)			Urbanization Growth Rate (%)
	1991	2000	2010	1991-2010
Semi-arid	48.69	56.42	62.15	27.64
Northeast	60.65	68.98	73.14	20.59
Brazil	75.59	81.19	84.37	11.62

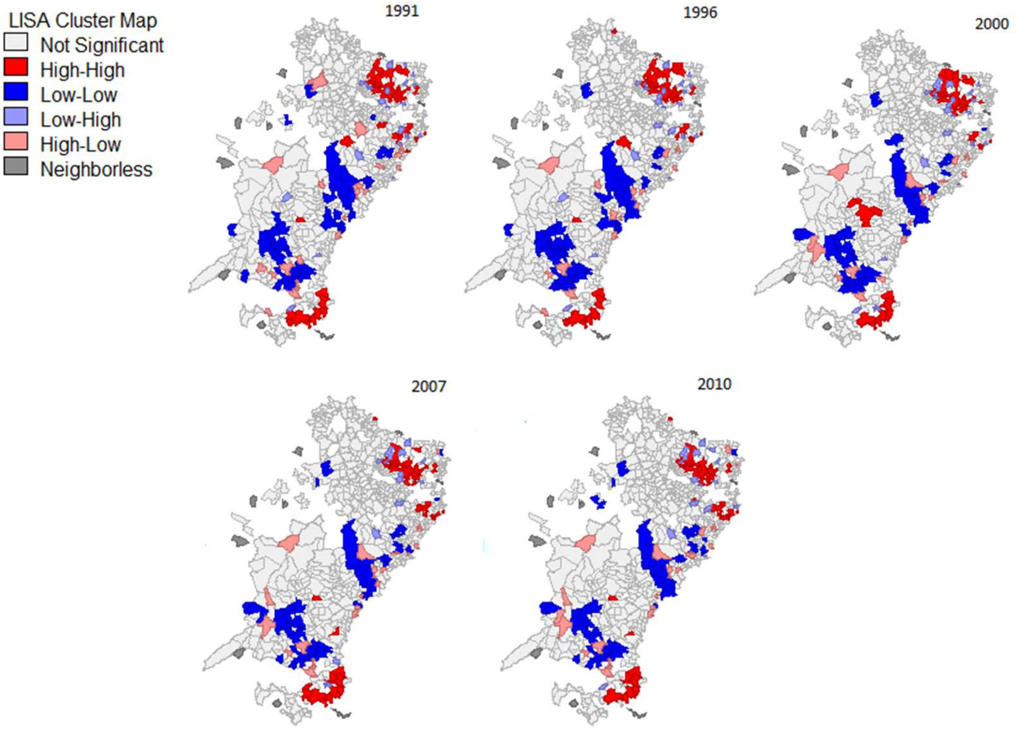
Source: Elaborated by the authors using data from the IBGE.

3.2. Spatial autocorrelation model results

As stated before, urbanization levels of municipalities may be under the influence of urbanization levels and other attributes that determine urbanization levels in neighboring municipalities. Aiming to analyze the existence of spatial dependence among the urbanization rates of the municipalities in the semi-arid region, we applied Moran's I spatial autocorrelation test for each year considered in the study using a queen contiguity matrix (Table A2). Moran's I statistics was highly significant in all analyzed years and revealed a positive spatial autocorrelation for the urbanization rate. It indicated that municipalities that presented a high (low) urbanization rate were contiguous of other municipalities that also presented a high (low) rate of urbanization.

Spatial autocorrelation is divided into spatial dependence and spatial heterogeneity. Through the global Moran's I statistic, which indicates the presence of spatial autocorrelation, it was not possible to infer whether it was derived from spatial dependence or from spatial heterogeneity. Thus, in order to verify which regions contributed to the existence of spatial autocorrelation, we implemented a local spatial correlation measure, namely the local indicators of spatial association (LISA), for each of the 5 cross-section units. According to Anselin (1995), the LISA statistic evaluates the null hypothesis of the absence of local spatial association. Cluster maps (Figure 3) revealed the existence of groups of municipalities with their own characteristics, thereby rejecting the hypothesis that the entire Brazilian semi-arid territory is spatially homogeneous.

Figure 3 – Local indicators of spatial association



Source: Elaborated by the authors using GeoDa Software.

The Hausman test (Table A1) identified the fixed effects model as the most adequate model for this study. It should be noted that although the fixed effects estimates eliminate the non-observed effect, they also eliminate any type of heterogeneity, so it is not possible to capture spatial heterogeneity through fixed effects estimates. As a robustness check, a spatial model with dummy variables was also estimated for the 9 Brazilian states belonging to the semi-arid region using random effects instead of fixed effects.

Initially, we estimated the model without considering spatial dependence. Non-spatial models with and without interaction dummies were estimated using OLS with fixed effects (FE-OLS), and its residuals were analyzed to determine the presence of spatial dependence and to verify the relevance of the spatial models' estimation. Moran's I test on the residuals of each analyzed year and Pesaran's CD test for longitudinal data indicated the presence of significant spatial autocorrelation for both non-spatial models (Table A3). To explicitly consider the detected spatial dependence, we verified whether spatial lags related to spatial processes took the form of a spatial lag in the dependent variable (SAR), in the error term (SEM), in the dependent variable and in the error term jointly (SAC), or in the explanatory variables and the dependent variable (SDM). With the presence of heteroscedasticity evident in the initial specification (Table A1), the spatial models were fitted with robust standard errors. Table 2 presents the results for both spatial and non-spatial estimations and for the specification without interaction dummies (Panel A) and with interaction dummies (Panel B).

Table 2 – Coefficients of estimated equations for the semi-arid region municipalities

continued on next page

Panel A

Variable	**FE-OLS**	**SDM**	**SAR**	**SEM**	**SAC**
Constant	-0.9987*** (0.0373)	-	-	-	-
Wage	-0.0370*** (0.0037)	0.0224*** (0.0072)	-0.0168*** (0.0039)	-0.0032 (0.0123)	-0.0085*** (0.0019)
School	-0.1782*** (0.0687)	-0.0396 (0.0598)	-0.1293* (0.0662)	-0.1099 (0.0721)	-0.0543 (0.0447)
Age group	0.9951*** (0.2109)	-0.8096*** 0.2384	0.4632** (0.2240)	0.1178 (0.4664)	0.2147* (0.1258)
Irrigation	-0.0193 (0.0570)	0.0028 (0.0551)	-0.0233 (0.0524)	-0.0371 (0.0538)	0.0037 (0.0407)
Temperature	0.0533*** (0.0051)	0.1099*** (0.0194)	0.0375*** (0.0047)	0.1032*** (0.0230)	0.0103*** (0.0018)
Precipitation	-0.0125*** (0.0045)	0.0003 (0.0122)	-0.0069 (0.0040)	-0.0106 (0.0066)	-0.0024 (0.0020)
W_Wage	-	-0.0643*** (0.0097)	-	-	-
W_School	-	-0.0648 (0.0978)	-	-	-
W_Age group	-	1.8298*** (0.2319)	-	-	-
W_Irrigation	-	0.1376 (0.1006)	-	-	-
W_Temperature	-	-0.0966*** (0.0194)	-	-	-
W_Precipitation	-	-0.0099 (0.0126)	-	-	-
ρ	-	0.3587*** (0.0548)	0.4261*** (0.0656)	-	0.7970*** (0.0236)
λ				0.4892*** (0.1246)	-0.7313*** (0.0627)

Panel B

Constant	-0.9866*** (0.0895)	-	-	-	-
Wage	-0.0369*** (0.0036)	0.0255*** (0.0071)	-0.0164*** (0.0039)	-0.0007 (0.0125)	-0.0086*** (0.0019)
School	-0.1925*** (0.0681)	-0.0567 (0.0587)	-0.1436** (0.0655)	-0.1239* (0.0707)	-0.0649 (0.0446)
Age group	0.9892*** (0.2094)	-0.8275*** (0.2423)	0.4573** (0.2218)	0.0567 (0.4731)	0.2187* (0.1259)
Irrigation	-0.0063 (0.0577)	0.0142 (0.0551)	-0.0104 (0.0530)	-0.0252 (0.0551)	0.0144 (0.0401)
Temperature	0.0291*** (0.0055)	0.0705*** (0.0203)	0.0134*** (0.0048)	0.0787*** (0.0228)	-0.0040 (0.0027)
Precipitation	-0.0167*** (0.0056)	-0.0009 (0.0123)	-0.0094* (0.0051)	-0.0117 (0.0073)	-0.0044 (0.0031)
Temp*Agri	0.0456*** (0.0072)	0.0513*** (0.0070)	0.0451*** (0.0067)	0.0495*** (0.0071)	0.0277*** (0.0046)
Rain*Agri	0.0075 (0.0082)	0.0032 (0.0073)	0.0047 (0.0074)	0.0026 (0.0081)	0.0035 (0.0048)
W_Wage	-	-0.0649*** (0.0096)	-	-	-
W_School	-	-0.0455 (0.0947)	-	-	-

Table 2 – Coefficients of estimated equations for the semi-arid region municipalities

Conclusion

Panel B					
Variable	**FE-OLS**	**SDM**	**SAR**	**SEM**	**SAC**
W_Age group	-	1.8427*** (0.2348)	-	-	-
W_Irrigation	-	0.1383 (0.0962)	-	-	-
W_Temperature	-	-0.0731*** (0.0206)	-	-	-
W_Precipitation	-	-0.0150 (0.0149)	-	-	-
W_Temp*Agri	-	-0.0226*** (0.0110)	-	-	-
W_Rain*Agri	-	0.0089 (0.0121)	-	-	-
ρ	-	0.3654*** (0.0525)	0.4287*** (0.0646)	-	0.7920*** (0.0243)
λ	-	-		0.5084*** (0.1222)	-0.0722*** (0.0641)
Number of observations: 3970					

Note: (***), (**), and (*) indicate significance levels of 1%, 5%, and 10%, respectively. Values in brackets refer to the standard errors.

Source: Elaborated by the authors using results from this research.

Starting from the SDM as a general specification, we performed the Wald and LR statistical tests for the variables exclusion for nested models (SAR and SEM), while for the SAC model we adopted the AIC criteria. Overall, the test results shown in Table 3 indicated that the SDM was the best fit for the specification without interaction dummies (Panel A) and with interaction dummies (Panel B). This meant that the urbanization level was not only a function of explanatory variables in municipality *i*, but also a function of urbanization levels and certain explanatory variables of neighboring municipalities.

Table 3 – Test for model selection

		Without interaction dummies			**With interaction dummies**		
		χ^2	***p*-value**	**AIC**	χ^2	***p*-value**	**AIC**
SAR vs. SDM	Wald test	615.28	0.0000	-	656.85	0.0000	-
	LR test	518.25	0.0000		617.27	0.0000	-
SEM vs. SDM	Wald test	616.30	0.0000	-	634.98	0.0000	-
	LR test	719.05	0.0000		745.12	0.0000	-
SAC		-	-	-5619.234	-	-	-5688.666
SDM		-	-	-5768.21	-	-	-5890.492

Source: Elaborated by the authors using results from this research.

The coefficient ρ for the SDM (Table 2) was positive and significant, which indicated that the level of urbanization of a municipality was positively related to the level of urbanization of the neighboring municipalities. The significance of the spatial lags of the explanatory variables showed that the characteristics of neighboring municipalities were important in determining urbanization in a given municipality. This result might have been associated with two main factors. First, the region as a whole had similar climatic characteristics, and the municipalities were undergoing a warming process and reduction/irregularity in precipitation patterns (Figure A1). In addition, the issue related to the agricultural channel emphasized in this study was the other factor that explained the importance of spatial lag of the dependent variable. The literature on the effects of climate change emphasizes the negative impacts on agricultural production, especially in semi-arid regions (NELSON et al., 2014). As the studied municipalities generally had similar agricultural patterns and were exposed to adverse climate effects, the spillover effect identified in this study was expected.

As previously mentioned, a peculiar feature of spatial regression models is the feedback process among spatially correlated municipalities, which leads to the distinction between direct, indirect, and total effects. The interpretation of the spatial model coefficients from Table 2 was not ideal, and instead, we obtained, based on these coefficients, the marginal effects as discussed in the methodology section. According to LeSage and Pace (2009), it is now standard in the spatial econometrics literature to discuss these effects instead of the actual coefficients of the model. Since the SDM proved to be the best specification, Table 4 presents the total marginal effects for this model and for specifications without and with the interaction dummies (Panels A and B, respectively). The direct and indirect effects are reported in Table A4.

Table 4 –Total marginal effects from the SDM

Variable	Panel A	Panel B
	Total	Total
Wage	-0.0606*** (0.0065)	-0.0614*** (0.0064)
School	-0.1632 (0.1645)	-0.1577 (0.1579)
Age group	1.5637*** (0.3350)	1.5679*** (0.3222)
Irrigation	0.2199 (0.1694)	0.2349 (0.1562)
Temperature	0.0216*** (0.0052)	-0.0032 (0.0098)
Precipitation	-0.0147** (0.0071)	-0.0246** (0.0112)
Temp*Agri	-	0.0449*** (0.0164)
Rain*Agri	-	0.0178 (0.0159)

Note: (***) and (**) indicate significance levels of 1% and 5%, respectively. Values in brackets refer to the standard errors.
Source: Elaborated by the authors using results from this research.

While including spatial dependence for all the considered municipalities of the semi-arid region (Panel A), the estimated total effect for temperature stated an increase of 0.0216 percentage point in the urbanization rate in response to one unit increase in the temperature anomaly. These results corroborated the results found by Marchiori, Maystadt, and Schumacher (2012), in which temperature increase induced rural-urban migration in Sub-Saharan Africa via reductions in agricultural wages. The results also corroborated those found by Mueller, Gray, and Kosec (2014), which indicated that the increased temperature in rural areas of Pakistan resulted in increased migration to urban areas due to the negative impact of climate on agricultural income.

Regarding the total effect of precipitation, reducing one unit of its anomaly resulted in an increase of 0.0147 percentage point in the urbanization rate. This significant negative influence of precipitation on urbanization levels described in the present study corroborated the results found by Barrios, Bertinelli, and Strobl (2006), which found that reductions in the amount of precipitation in Sub-Saharan Africa led to increased urbanization rate. Additionally, Gray (2009) concluded that a decrease in rainfall in rural communities in Ecuador resulted in internal migration in the country.

Besides climatic factors, while including the socioeconomic conditions in the model, the coefficients for wage and age group were relatively consistent, significant, and with expected signs. Regarding the age group variable, an increase of 1 percentage point in the ratio of the number of people between 35 and 64 years old living in rural areas and the total number of residents in the rural area resulted in an increase of 1.5637 percentage point in the urbanization rate. This result was also consistent with those of Beine and Parsons (2015), which found that the higher the number of people in the age group more likely to leave the origin areas, the greater the migration to urban areas.

As for the wage variable, a decrease of 1 percentage point in the ratio between the agricultural GDP per capita and the non-agricultural GDP per capita resulted in an increase of 0.0606 percentage point in the urbanization rate. A similar result was reported by Barrios, Bertinelli, and Strobl (2006) and Marchiori, Maystadt, and Schumacher (2012), who found that the higher the wage differentials between urban and rural areas, the greater the number of people who leave rural areas in Sub-Saharan Africa. The results found for the wage variable were especially important because the semi-arid municipalities are widely dependent on the agricultural sector as a source of income. People in this region are more sensitive to changes in agricultural income, thus, the lower the resulting income from agricultural production, the greater the number of people leaving rural areas for urban areas.

While the school variable showed significant negative impacts on urbanization rates in the FE-OLS estimation, which did not include spatial dependence, it was not significant in the SDM, which indicated that ignoring spatial dependence could lead to omitted variable bias. Furthermore, irrigation proved not to be significant in curbing the decision to leave the rural area for the urban area of the municipality. One possible reason for this non-significance was that, in this sample, most agricultural establishments in the semi-arid municipalities underutilized irrigation practices. An average of only 7.38% of establishments using irrigation was detected, even though this is a higher average when compared to the Brazilian agricultural establishments (6.3%), according to the 2006 agricultural census (CUNHA; COELHO; FÉRES, 2015).

Despite the significant benefits of irrigation, this practice has high implementation, operation, and maintenance costs (CUNHA; COELHO; FÉRES, 2015). Therefore, irrigated agriculture has limited benefits in terms of costs, which makes the condition of small producers even more significant because they usually have low investment capacity. Although we could not confirm irrigation effectiveness in the recent past, it is possible to infer that this practice is likely to be effective in the future, especially in the semi-arid region of Brazil where agricultural production is high-risk and low-yield without irrigation, especially considering the scenarios of future climate change. Therefore, further studies are necessary to investigate this climate change adaptation measure in future scenarios.

Scrutinizing whether the effects of climate variability on urbanization levels were most evident in municipalities that depend more heavily on the agricultural sector, the total effects in Panel B indicated that when the dummy variables interacted with the climate variables, temperature proved to be constant, significant, and with the expected sign. The increase of one unit in the temperature anomaly in the municipalities that depend more widely on the agricultural sector led to an increase of 0.0450 percentage point in the urbanization rate. On the other hand, the effect of precipitation on urbanization levels in these municipalities was not significantly different to the effect on the remaining municipalities.

Thus, the results suggested that the total effect of climate change, especially temperature, has an impact on urbanization levels, and the agricultural municipalities are the most affected by climate change. These results are consistent with existing literature and provide support for the growing body of work relating urbanization to climate change.

As previously mentioned, fixed effects models automatically exclude variables that do not vary over time, so spatial heterogeneity could not be captured by these models. Although the Hausman test indicated that the SDM with fixed effects was the most appropriate, the SDM with random effects (RE-SDM) and state dummy variables was estimated (Table A5). In general, the results obtained through the RE-SDM estimation presented the same signs and significance levels. An exception was the irrigation variable, which was not significant in the FE-SDM, but was significant and positive in the RE-SDM. This result for the irrigation variable may have been indicative of the non-adequacy of the random effects model, as indicated by the Hausman test.

We verified the residuals from both models (FE-SDM and RE-SDM) for the existence of spatial autocorrelation (Table A6) for specifications with and without climatic interaction dummies. The Moran's I test indicated the existence of spatial autocorrelation in the residuals of the FE-SDM without interaction dummies for all the years considered in the analysis, although in a lower magnitude than that verified in the OLS model without the inclusion of spatial components. However, for the FE-SDM with interaction dummies, the Moran's I test indicated the absence of spatial autocorrelation in the residuals for the years 1991, 1996, 2000, and 2007. On the other hand, spatial autocorrelation was present for both specifications estimated by the RE-SDM. This indicated that controlling for spatial heterogeneity using a model that is not the most suitable for the data, such as the random effects model, did not result in the elimination of spatial autocorrelation. The difficulty of controlling the spatial effect is not a peculiarity of this work. In some cases, as in our work, even when using spatial models, it is only possible to mitigate this effect.

To face rural poverty, rural exodus should be thought of as an adaptation process that may be the most effective way to allow people to diversify their income and build resilience where environmental change threatens livelihoods (BLACK et al., 2011). Nevertheless, policies should be implemented seeking organized and planned development of urban centers in order to receive the individuals that leave rural areas to escape the adverse effects of climate change and to seek employment.

The results found by the SDM may indicate that, among the climate variables, temperature is the most prominent variable in the individuals' decision to leave rural areas. In addition, for both Panel A and Panel B, the magnitude of the temperature coefficients was larger than that of the precipitation coefficients, which supported the premise that temperature has a greater influence on the decision to leave rural areas in the semi-arid region of Brazil. This output corroborated the results of Muller, Gray, and Kosec (2014), which found that heat stress rather than floods was the most related to migration in rural Pakistan over a 21-year period.

The increasing threat of high temperatures might lead to crop productivity losses and result in widespread famine around the world. In addition, the arguments presented by Angelotti, Sá, and Petrere (2009) indicated that temperature is the primary determinant of water stress in the semi-arid region. According to these authors, the increase in temperature leads to a greater amount of water vapor in the atmosphere, which in turn feeds back to the temperature increase. Furthermore, the increase in temperature decreases soil moisture by direct evaporation and increased plant evapotranspiration. As the soil in the semi-arid region is rich in salts, the intense evaporation caused by increasing temperatures may reduce, or even inhibit agricultural production and contribute to increased rural-urban migration.

The findings obtained so far confirmed the hypothesis that climate change, especially increased temperature, contributed to the decision of leaving the rural areas of municipalities in the semi-arid region and that this was more evident in municipalities that depend more heavily on the agricultural sector. Thus, the results of the present study indicated that it is imperative to develop specifically targeted policies for the semi-arid region of Brazil in order to eliminate, or at least control, the advancement of migration to urban areas driven by the negative impact of climate change on the population of semi-arid municipalities.

Since the FE-SDM presented greater adequacy for the estimation of the empirical model, it was from this model that we conducted the simulations for future urbanization. The assessment of the impact of two different future climate change scenarios on urbanization levels in the periods of 2016-2035 and 2046-2065 considering the average of the IPCC models indicated an increase in urbanization levels in the semi-arid region from -0.08% to 0.8% in the first period and from 4.02% to 6.98% in the second period under RCP 4.5 and RCP 8.5, respectively (Table 5).

Table 5 – Change in future urbanization rate (%) in response to climate change projected by the IPCC models under RCP 4.5 and RCP 8.5 from 2016-2035 and from 2046-2065

IPCC Models	**Change in urbanization rate (%)**			
	2016-2035		**2046-2065**	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
MIROC5	-4.11	4.43	0.78	11.21
NORESM1-M	3.23	-3.56	6.46	1.21
MRI-CGCM3	1.06	1.92	5.16	9.08
Average Models	-0.08	0.80	4.01	6.98

Source: Elaborated by the authors using results from this research.

In general, we observed that, as expected, RCP 8.5 showed higher values than RCP 4.5, thereby indicating that in a scenario of increasing GHG emissions and with the absence of emissions reduction policies, the levels of urbanization could be greater. Additionally, the values for the period between 2046 and 2065 were higher than those for the period between 2016 and 2035, which meant that the adverse weather conditions that favor the decision to leave rural areas are likely to become stronger over time.

Given the scenarios of increasing temperature and decreasing precipitation with consequent increase in urbanization in the region considered in this study, the creation of public policies in order to ensure that smallholders do not have to leave rural areas forcedly is essential. In cases where the decision to move to urban areas becomes necessary due to adverse weather, the policies should ascertain that the migration to urban areas occurs under favorable conditions.

It is a major challenge for the government to create policies related to urbanization induced by climate change because both processes are dynamic and nonlinear. However, the creation of such policies could include the expansion of new agricultural technologies, introduction of crops with greater resistance to drought, greater access to water through irrigation, and greater supply of microcredit policies, among other policies.

As a result of the increased urbanization level, the exacerbation of environmental and economic problems is expected not only in the origin areas but also in the destinations. Climate change affects rural areas as well urban areas, which are facing increasing risks associated with the migrants' marginalization. Thus, policies should focus not only on people who remain in the original area, but also on those who decide to move to urban areas. Employment policies should be reformulated to guarantee the economic inclusion of marginalized groups of migrants, which are often submitted to lower wages.

Boosted urbanization related to climate change is likely to result in adverse health and security outcomes, both for the displaced and host population. Barnett and Adger (2007) and Reuveny (2007) pointed out that human displacement induced by climate change might lead to conflict in host communities. The former stated that "climate change may undermine human security by reducing access to, and the quality of, natural resources that are important to sustain livelihoods." Climate change is also likely to undermine the capacity of states to provide the opportunities and services that help people sustain their livelihoods, which might in turn increase the risk of violent conflict. The latter author stated that the arrival of environmentally displaced people could burden the economic and resource base of the receiving area, thereby promoting competition between native and newly arrived populations over resources, which would increase the risk of conflict. Thus, policies should ensure the proper provision of public services, such as security, health, and education.

Above all, considering that anthropogenic action is one of the main causes of climate change, behavioral changes regarding GHG emissions are pivotal to deal with all the adverse effects caused by climate change, including rural emigration. At the same time, it must be recognized that mitigation measures alone are not enough, since GHG emissions persist in the atmosphere for many years while maintaining climate change. Accordingly, policies that seek to keep farmers in the countryside are essential. Agricultural insurance and credit policies for adaptation in the agricultural sector could reduce urbanization resulting from rural-urban migration.

4. Conclusion

The analysis of the drivers involved in the urbanization process indicated that multiple factors, especially climate conditions, influence this process. Mainly in Brazil, the negative effects of climate variability are expected to occur more intensely in regions that are the most vulnerable and the most dependent on climate-sensitive resources. Studies indicate that the agricultural sector will be the most affected and have more evident economic losses. This is of pivotal importance, particularly when considering that a significant proportion of the national income comes from agricultural production. In addition, losses in agriculture could bring several consequences, including the issue presently analyzed.

When estimating all models, we verified that a spatially dependent panel data model fit the data better than a traditional econometric model. The results found in this study confirmed that the municipalities in the semi-arid region, which rely widely on agriculture, would be the most affected by climate, especially by temperature. Temperature was more prominent in determining the decision to leave rural areas for urban areas of these municipalities. In turn, addressing the effects of climate change in the economic sphere is a challenge for policymakers.

Regarding the projected urbanization, we have confirmed the expectation that it would increase with scenarios of higher GHG emissions. The results showed that, although at different magnitudes, it is expected that more individuals living in rural areas of semi-arid municipalities in Brazil will decide to move to urban areas by 2065.

In general, the results of this study reinforce the need to formulate public policies that seek an organized and planned development of urban centers and consider this type of intra-municipality migration as an adaptive strategy to address adverse climatic effects rather than an adaptation failure. Policies should properly guarantee the absorption of displaced people and ensure that they have access to basic public services. Therefore, given the expected worsening of climate change, policymakers should focus on adaptation policies that aim to make crops less sensitive to climate. Ultimately, if the decision to move to urban areas of the municipality becomes necessary, policies that emphasize the absorption of migrants in urban areas would reduce the social costs of climate variability.

It is noteworthy that although migration will continue to be the result of multiple factors in both the origin and destination areas in the future, the factors related to climate change are likely to become increasingly significant. Thus, the reduction in GHG emissions to reduce the number of people affected by climate change in the future is the main measure that governments should take to minimize the costs and maximize the benefits of urbanization increased by climate change. Hence, the priority order of actions to be taken should be as follows: (1) mitigation of GHG emissions, (2) investments in climate change adaptation measures, and (3) implementation of migration and urbanization policies.

The present study presented limitations regarding the definitions of urbanization and rural-urban migration. Although the literature agrees that the latter is one of the main causes of the former, especially in areas such as the semi-arid region of Brazil, future studies should consider analyzing the phenomena separately. Specifically, we suggest the characterization of rural-urban migration at an individual level. Finally, it is important to recognize that farmers in vulnerable climate situations can migrate to regions outside the semi-arid region. This issue, which was outside the research scope, should be addressed in future studies.

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Appendix

Table A1 – Tests for model specification, heteroscedasticity, and autocorrelation

	FE-OLS (Panel A)		**FE-OLS (Panel B)**		**SDM (Panel A)**		**SDM (Panel B)**	
Tests	**χ^2**	***p*-value**	**χ^2**	***p*-value**	**χ^2**	***p*-value**	**χ^2**	***p*-value**
Hausman	875.19	0.000	1097.68	0.000	53.08	0.000	55.44	0.000
White	2.8e+05	0.000	5.1e+05	0.000	-	-	-	-
Wooldridge	75.641	0.000	73.927	0.000	-	-	-	-

Source: Elaborated by the authors using results from this research.

Table A2 – Global autocorrelation indicators for the urbanization rate

Year	**Moran's I**	**Standard Deviation**	***z*-value**	***p*-value**
1991	0.2263	0.0247	9.2382	0.001
1996	0.2347	0.0250	9.3865	0.001
2000	0.2423	0.0246	9.8732	0.001
2007	0.2437	0.0242	10.1291	0.001
2010	0.2287	0.0247	9.3065	0.001

Source: Elaborated by the authors using results from this research.

Table A3 – Moran's I and Pesaran's CD tests on the OLS-FE residuals

Year	**Without interaction dummies**				**With interaction dummies**			
	Moran's I	**Standard Deviation**	***z*-value**	***p*-value**	**Moran's I**	**Standard Deviation**	***z*-value**	***p*-value**
1991	0.1475	0.0241	6.1802	0.001	0.1509	0.0241	6.3327	0.001
1996	0.1250	0.0236	5.3547	0.001	0.1214	0.0234	5.3975	0.001
2000	0.1075	0.0234	4.6751	0.001	0.1173	0.0237	4.9883	0.001
2007	0.1606	0.0250	6.5202	0.001	0.1650	0.0248	6.7076	0.001
2010	0.2539	0.0246	10.3873	0.001	0.2536	0.0243	10.4730	0.001
	Pesaran's CD			***p*-value**	**Pesaran's CD**			***p*-value**
Panel	101.181	-	-	0.000	95.256	-	-	0.000

Source: Elaborated by the authors using results from this research.

Table A4 –Direct and indirect marginal effects from the SDM

	Panel A		**Panel B**	
Variable	**Direct**	**Indirect**	**Direct**	**Indirect**
Wage	0.0195***	-0.0802***	0.0201***	-0.0815***
	(0.0068)	(0.0096)	(0.0068)	(0.0097)
School	-0.0471	-0.1161	-0.0629	-0.0948
	(0.0608)	(0.1433)	(0.0603)	(0.1333)
Age group	-0.6563***	2.2201***	-0.6710***	2.2389***
	(0.2301)	(0.2867)	(0.2301)	(0.2753)
Irrigation	0.0145	0.2053	0.0264	0.2085
	(0.0561)	(0.1446)	(0.0555)	(0.1337)
Temperature	0.1050***	-0.0833***	0.0665***	-0.0697***
	(0.0172)	(0.0171)	(0.0179)	(0.0187)
Precipitation	-0.0009	-0.0138	-0.0027	-0.0218
	(0.0112)	(0.0135)	(0.0113)	(0.0166)
Temp*Agri	-	-	0.0510***	-0.0060
			(0.0071)	(0.0154)
Rain*Agri	-	-	0.0039	0.0139
			(0.0072)	(0.0159)

Note: (***), (**), and (*) indicate significance levels of 1%, 5%, and 10%, respectively. Values in brackets refer to the standard errors. Obs: State dummy effects not reported.
Source: Elaborated by the authors using results from this research.

Table A5 – Marginal effects for the RE-SDM

Variable	**Panel A**			**Panel B**		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Wage	0.0291***	-0.0819***	-0.0528***	0.0293***	-0.0830***	-0.0536***
	(0.0080)	(0.0101)	(0.0057)	(0.0079)	(0.0101)	(0.0056)
School	-0.2192***	-0.1496	-0.3689**	-0.2279***	-0.1380	-0.3677**
	(0.0689)	(0.1205)	(0.1507)	(0.0682)	(0.1260)	(0.1582)
Age group	-0.5731***	2.1684***	1.5952***	-0.5893***	2.1848***	1.5954***
	(0.2146)	(0.2512)	(0.2968)	(0.2155)	(0.2510)	(0.2875)
Irrigation	0.0553	0.2461	0.2964*	0.0614	0.2684**	0.3299**
	(0.0551)	(0.1317)	(0.1512)	(0.0554)	(0.1280)	(0.1504)
Temperature	0.1045***	-0.0838***	0.0206***	0.0650***	-0.0696***	-0.0045
	(0.0174)	(0.0177)	(0.0051)	(0.0185)	(0.0196)	(0.0098)
Precipitation	0.0010	-0.0094	-0.0084**	-0.0026	-0.0133	-0.0160
	(0.0117)	(0.0138)	(0.0066)	(0.0118)	(0.0160)	(0.0106)
Temp*Agri	-	-	-	0.0523***	-0.0067	0.0456***
				(0.0074)	(0.0151)	(0.0167)
Rain*Agri	-	-	-	0.0071	0.0069	0.0141
				(0.0071)	(0.0157)	(0.0162)

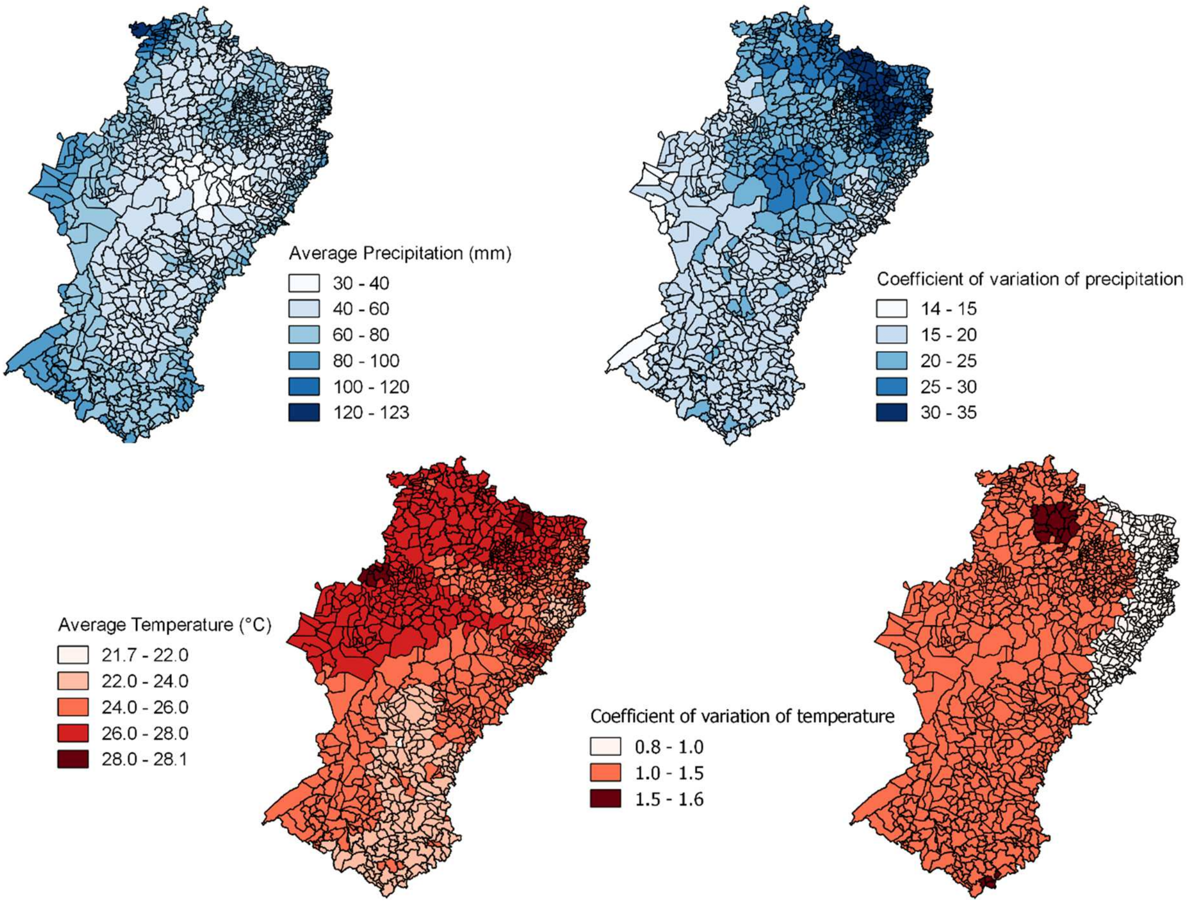
Note: (***), (**), and (*) indicate significance levels of 1%, 5%, and 10%, respectively. Values in brackets refer to the standard errors. Obs: State dummy effects not reported.
Source: Elaborated by the authors using results from this research.

Table A6 - Moran's I test on the RE-SDM and FE-SDM residuals

Year	**Without interaction dummies**		**With interaction dummies**	
	FE-SDM	RE-SDM	FE-SDM	RE-SDM
1991	-0.0630***	-0.1313***	-0.0190	-0.1033***
	(0.0249)	(0.0249)	(0.0250)	(0.0250)
1996	-0.0616***	-0.1302***	-0.0161	-0.1075***
	(0.0249)	(0.0248)	(0.0249)	(0.0248)
2000	-0.0558***	-0.1053***	-0.0069	-0.0812***
	(0.0249)	(0.0248)	(0.0249)	(0.0248)
2007	-0.0537***	-0.1008***	-0.0082	-0.0776***
	(0.0248)	(0.0246)	(0.0250)	(0.0246)
2010	-0.0768***	-0.1211***	-0.0429**	-0.1058***
	(0.0242)	(0.0242)	(0.0242)	(0.0240)

Note: (***) and (**) indicate significance levels of 1% and 5%, respectively.
Values in brackets refer to the standard errors.
Source: Elaborated by the authors using results from this research.

Figure A1 – Average precipitation (mm) and temperature (°C) and coefficient of variation of precipitation and temperature for the semi-arid municipalities (1980-2010)



Source: Elaborated by the authors using data from the CRU/CL3.21 database.