Modifiable Areal Unit Problem (MAUP): Analysis of Agriculture of the State of Paraná-Brazil

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Abstract

The way the researcher groups his research data will influence the result of his work. In the literature, this phenomenon is treated as a Problem of the Modifiable Areal Unit. The objective of this article was to analyze the three spatial levels by Municipalities, Regional Centers and Mesoregions using the following data: gross domestic product, effective agricultural production, grain production and gross value of agricultural production for the state of Paraná-Brazil in the period since 2012 until 2015. The methodological procedure studied data from the Paranaense Institute for Economic and Social Development of the above-named variables collected on the website of the Paranaense Institute for Economic and Social Development of the 399 municipalities, 23 regional centers and 10 mesoregions. The results found show the presence of the Modifiable Areal Unit Problem, presenting different results for each level of grouping. The study revealed the problem of the modifiable areal unit is a relevant occurrence and it should be disregarded by researchers who work with clusters of spatial data in their studies. The results found allow a better understanding of the scale effect and demonstrate the efficiency of spatial analysis in socioeconomic data.

Keywords

Introduction

Following the development of science, new challenges are imposed on researchers, once new problems arise, consequently, new resolutions are proposed, according to Kupriyanova et al. (2019). Surveys work with different spatial boundaries for the analysis of the most varied themes, in which the relationship between time and space is analyzed, the size of the clusters changes and the phenomenon entitled Modifiable Areal Unit Problem (MAUP) can present different results according to the spatial boundaries are changed. Observation and evaluation of the effects of the Modifiable Areal Unit Problem become a relevant issue in the modeling, because if the appropriate levels of geographic scale and zone configuration are not defined and identified; statistical models based on spatial data can induce the misleading conclusions.

Thus, considering the same population under study, the spatial definition of its borders affects the results will be obtained. The estimations obtained within a system of area units are directly related to different ways in which they can be grouped and consequently different results can be obtained by simply alteration of the boundaries established (Janelle et al., 2004; Wei et al., 2017; Duque et al., 2018; Didier and Louvet, 2019).

Some studies, already carried out, realized the importance of MAUP in spatial data (Lee et al., 2015; Cabrera-Barona et al., 2018; Pietrzak, 2019). Investigating the effect of MAUP aims to study various sizes of spatial resolutions that can lead researchers to determine the most appropriate scale to be used for analysis purposes, Wei et al. (2017) report that the effects of MAUP can be completed through statistical results.

Chaves et al. (2018) report that the problem modifiable areal unit can alter the support of soybean cultivation, inform that is not possible to cultivate soybean and other crops in the same environment simultaneously, highlight that MAUP is related to two specific problems, namely:

the scale effect and zoning effect, economically this result may compromise the planning of soybean productivity.

Lee et al. (2018) in their studies found that the problem of the modifiable areal unit has a clear and evident scale effect for the uncertainties surrounding its relations with spatial autocorrelation, identified in their experiments with simulation, that in an initial level, autocorrelation spatial plays an important role in the nature and extent of the effects of MAUP.

According to the United Nations Program for Sustainable Development - UNDP (2020) suggest that researchers should work with disaggregated data in economic analyzes according to the 2030 Agenda that addresses the Sustainable Development Goals (SDGs).

Salmivaara (2015), Santo et al. (2015), Cabrera-Barona et al. (2016) and Burdziej (2019) studied and evaluated the scale effect (MAUP) at different levels of spatial units. Recent studies consider the scale effect in decision-making (Xu et al., 2018; Tunson et al., 2019).

Anselin (2018) presents Geary's global univariate index (c) and Geary's local (c_i) to study the spatial autocorrelation of quantitative characteristics considering the location of the data. Spatial regression models, such as spatial autoregressive (SAR), conditional autoregressive (CAR) and geographically weighted spatial model (GWR), are established to study the relationship of an interested variable to its covariables and considering the location of the data and from your close neighbors. (Anselin and Bel, 2013; Araújo et al., 2014; Meyappan et al., 2014; Javi et al., 2015; Zou and Wu, 2017). The SAR and CAR models are considered global models; their results are valid for the entire study area, whereas the GWR explores local variations and estimates the regression coefficients at the local level. The spatial regression methods allow taking into account the dependence between the sample elements collected in regions considering the location of the data (Lesage, 2015; Duan et al., 2015).
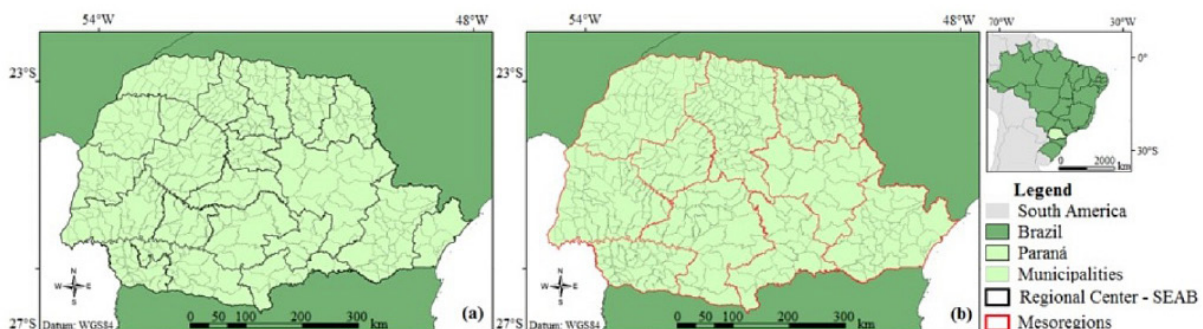
This article presents a study of MAUP from a database of the gross domestic product, effective of agricultural production, total grain production and gross value of agricultural production, obtained through the Paranaense Institute of Economic and Social Development (IPARDES) in the years 2012 to 2015. The analysis focused on three levels: Municipalities, Regional Centers and Mesoregions. The objective of this study was to analyze the MAUP, in the state of Paraná-Brazil, using different spatial resolutions and to show the extent to which the different scale effects can directly reflect in the decision making of regional analyzes of public and private institutions in the agribusiness economics.

Materials and methods

The study area comprises 399 municipalities, 23 regional development centers (Figure 1a) and 10 mesoregions (Figure 1b) in the state of Paraná. Socioeconomic data from the years 2012 to 2015 and the variables were used: gross domestic product [R$], effective agricultural production [quantity/unit], gross value of agricultural production [R$], Total grain production (soybeans, corn 1st harvest, corn 2nd harvests, and wheat) [t].

For the analysis of spatial autocorrelation, the hypothesis test was used by means of the $Z(c)$ pseudo-significance statistic (Almeida, 2012).

Exploratory Spatial Data Analysis was applied to this database to identify its global spatial associations and clusters. Then, the spatial regression models SAR, CAR and GWR were

Source: Adapted from SEAB-DERAL (2015)

Figure 1: Delimitation of study area (Figure 1a and Figure 1b).

applied to verify which model best explains the gross value of agricultural production (V_{pb}). For the analysis of spatial autocorrelation, the global Geary index (c) (Equation 1) was used, which allows the assessment of global autocorrelation.

The Geary global index (c) assumes the spatial autocorrelation depends on the distance between two or more observations, assumes the values between 0 and 2 (ANSELIN, 2018), and if $c = 0$, it indicates direct positive spatial autocorrelation; if $c = 1$, it indicates absence of autocorrelation and if $c > 1$, it indicates negative spatial autocorrelation (Anselin, 2018).

$$c = \frac{(n-1)}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\ (x_i - x_j)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2}, \quad (1)$$

on what,

n: number of spatial units (areas);

x_i and x_j: values of attribute X considered in regions i and j;

$\bar{x}$: average value of attribute X in the studied region;

w_{ij}: element of the normalized neighborhood matrix, corresponding to the spatial weights 0 and 1, being 0 for areas i and j that do not border between themselves and 1 for areas i and j that border between each other. In this work, the Queen Contiguity criteria (Anselin, 2018) was used.

Considering the following hypothesis test H_0: There is no association between the observed value in a region and the observed value in nearby regions, c values are close to 1; versus H_1: There is an association between nearby regions, c values are close to 0. In order to verify the significance of the global Geary index (c), if there is no association between the value observed in a region and the value observed in nearby regions, it is done through the pseudo-significance statistic $Z(c)$ (Equation 2) (Anselin, 2018).

$$Z(c) = \frac{[c - E(c)]}{Sd(c)}, \quad (2)$$

where, $E(c)$ is the expected value of the Geary global index (c); $Sd(c)$ is the standard deviation of Geary's global index (c). About H_0, the $Z(c)$ statistic has a standard normal distribution with mean 0 and variance 1 (Almeida, 2012).

Geary's local autocorrelation index (c_i) (Equation 3), which measures the degree of spatial correlation at each specific location (Anselin, 2018). The local statistic c_i is an indicator of spatial association called LISA because it satisfies two requirements, namely: the ability for each observation to signal statistically

significant spatial clusters, and the property that the sum of c_i for all regions is proportional to the indicator of global spatial autocorrelation c by Geary (Anselin, 2018).

$$c_i = \sum_{j=1}^{n} w_{ij}\ (x_i - x_j)^2, \quad (3)$$

The linear spatial models SAR, CAR and GWR estimated by maximum likelihood for gross value of agricultural production (V_{pb}) as a function of the total quantity of bovine production (*QTbovine*), total quantity of pig production (*QTpig*), total quantity of production of poultry (*QTpoultry*) and total amount of grain production (*Totgrain*) are presented in Equations (4), (5) and (6), respectively:

$$\widehat{V_{pb}} = \widehat{\beta_0} + \widehat{\beta_l}QTbovine + \widehat{\beta_2}QTpig + \widehat{\beta_3}\ QTpoultry \\ + \widehat{\beta_4}\ Totgrain + \hat{\rho}\ WV_{bp}, \quad (4)$$

$$\widehat{V_{pb}} = \widehat{\beta_0} + \widehat{\beta_l}QTbovine + \widehat{\beta_2}QTpig + \widehat{\beta_3}\ QTpoultry \\ + \widehat{\beta_4}\ Totgrain + \hat{\lambda}\ W_{\varepsilon}, \quad (5)$$

$$\widehat{V_{pb}} = \widehat{\beta_0}(u_i, v_i) + \widehat{\beta_l}(u_i, v_i)QTbovine \\ + \widehat{\beta_2}(u_i, v_i)QTpig + \widehat{\beta_3}(u_i, v_i)QTpoultry \\ + \widehat{\beta_4}(u_i, v_i)Totgrain, \quad (6)$$

$\hat{\beta}_y$: estimated parameters of each model (SAR, CAR and GWR), y = 0,…, 4;

WV_{pb}: expresses the weighted spatial dependence with weight allocation of the spatial neighborhood;

$\hat{\rho}$: estimated autoregressive spatial coefficient;

$\hat{\lambda}$: estimated autoregressive coefficient;

W_{ε}: error component with spatial effects,

(u_i, v_i): denotes the coordinates of the centroid of the i-th area, i = 1, ..., 399;

$\widehat{\beta_y}(u_i, v_i), y = 0, …, 4$: realization of the continuous function $\widehat{\beta_y}(u, v)$ on the ketoid of the i-th area, i = 1,…, 399 (Fotheringhan et al., 2002).

Lopes et al. (2014) employed, in the comparison of the SAR, CAR and GWR models, the highest value of maximum likelihood logarithm (MLL), which represents the best fit to the observed data. The Akaike Information Criterion (AIC) and the Baysian Criterion (BIC) were also used in this study, considering the best model is which has the lowest value of AIC and BIC (SPRING, 2003).

The data analysis was performed with the aid of free software R (R Core Team, 2018). The following packages were used: GISTools, Spdep, Spgwr, Rgeos and Nortest.

Results and discussion

On Table 1, they are presented Geary global spatial autocorrelation indexes (*c*) and Z(*c*) significance tests, for Gross Domestic Product (GDP), bovine production, Pig production, Poultry production, Production of milk, Gross value of agricultural production, Grain production for the municipalities belong to Paraná state (Brazil).

It is possible to check in the 2012's GDP, Geary's global spatial autocorrelation index was not significant, realized the absence of spatial autocorrelation.This result is justified according as inform IBGE (2012) this period there were climatic problems such as the drought in the first half, affecting crops and the retraction of factory production in the state of Paraná-Brazil. For 2013, 2014 and 2015, there are some significant positive spatial autocorrelation of the GDP.

There was a significant positive spatial autocorrelation for all variables studied. This behavior shows that in the Paraná state, there are municipalities with high and /or low livestock production, total grain production and gross value of agricultural production surrounded by municipalities that have similar characteristics, with the mean spatial autocorrelation being $\bar{c}$ = 0.5016. (Table 1).

Economically it is observed through the results found, specifically for the production of milk and production of poultry, values close to zero, which implies that municipalities economically with high and or low production of these commodities are surrounded by neighbors also with high and or low productions, this information is economically very necessary and important because it allows showing the reality of the economic and agricultural scenario of these locations, thus highlighting their productive and economic potential.

With this information, it is possible to develop public policies in municipalities with disparate results and in municipalities with low productivity detect problems and improve production. The information can thus subsidize state agricultural policies in the municipalities with the greatest difficulties, in the case of milk there is a very high contingent of family farmers.The global Geary index (*c*) for each year studied by the Regional Centers (Table 2) indicated positive spatial autocorrelation of 5% significance for the production of bovine, pig and poultry, and gross value of agricultural production.

However, in the product gross domestic product and in the total production of grains (soybeans, corn 1st and 2nd harvest and wheat) there were no significant spatial autocorrelation because the indices were close to one, presenting the data are randomly distributed over the analyzed years.

From this point, the presence of the problem of the modifiable areal unit (MAUP) begins to be perceived in which by changing the spatial level of area, different statistical results are obtained (Table 2). Jiawei et al., (2020) comment that the spatial scale is also a major concern in the research on grain production and so, as you highlight Chen (2018),when choosing analytical units to quantify regional economic structure for a specific study, future research should pay attention to scale-related problems.

Comparing the spatial level of the regional centers and the spatial level of the municipalities, through Geary's global analysis (*c*) the results show the presence of a MAUP effect in the Gross Domestic Product and in the Total grain production, as it is possible to check in the Tables (1) and (2).

Variables	2012	2013	2014	2015
GDP	0.928[Ns]	0.794*	0.790*	0.827*
Bovine production	0.525*	0.522*	0.510*	0.509*
Pig production	0.421*	0.421*	0.402*	0.412*
Poultry production	0.590*	0.592*	0.629*	0.613*
Milk Production	0.397*	0.395*	0.369*	0.361*
Gross value of agricultural production	.	0.668*	0.621*	0.674*
Grain production	0.408*	0.410*	0.403*	0.456*

Note: Ns - not significant values; * statistically significant at the level of 5% probability; . - absence of information in the official database.

Source: own calculations

Table 1: Global Geary Index (*c*) of gross domestic product (GDP), actual agricultural production (bovine, pig, poultry, milk), gross value of agricultural production and total grain production (soybeans, corn 1st and 2nd harvest) and wheat) since 2012 until 2015 of the three hundred and ninety-nine municipalities in Paraná-Brazil.

Variables	2012	2013	2014	2015
GDP	0.900[Ns]	0.920[Ns]	0.895[Ns]	0.954[Ns]
Bovine production	0.514*	0.515*	0.541*	0.536*
Pig production	0.557*	0.557*	0.560*	0.572*
Poultry production	0.610*	0.611*	0.561*	0.548*
Milk Production	0.418*	0.415*	0.405*	0.391*
Gross value of agricultural production	.	0.751*	0.683*	0.701*
Grain production	0.850[Ns]	0.868[Ns]	0.900[Ns]	0.861[Ns]

Note: Ns - not significant values; * statistically significant at the level of 5% probability; . - absence of information in the official database.
Source: own calculations

Table 2: Global Geary Index (c) of gross domestic product (GDP), effective agricultural production (bovine, pig, poultry, milk), gross value of agricultural production and total grain production (soybeans, corn 1st and 2nd harvest) and wheat) from the years 2012 to 2015 of the twenty-three regional centers of SEAB-Paraná-Brazil.

Therefore, it shows the problem of the modifiable areal unit can reflect negatively on the decision-making process of public and private agencies (Table 2).

In the Table 3, the global index of Geary (c) by Mesoregions belonging to Paraná state demonstrates the presence of MAUP, because all indexes c presented values close to 1, a value indicative of a random spatial pattern, a fact corroborated by the test of pseudo-significance Z(c), which indicates absence of significant spatial autocorrelation.

In the analysis of Geary's global autocorrelation (c) for the Mesoregions of Paraná, Table (3) shows a high effect of the Modified Areal Unit Problem (MAUP) in all studied variables, it means that the statistical results found were quite different from those found in municipalities and regional centers. All values of the Geary index (c) which were close to 1 characterized absence of spatial autocorrelation.

This spatial behavior shows how serious the Modifiable Area Unit Problem (size of the spatial resolution) is, considering the same study population. Comparing the three studied spatial levels (municipalities, regional centers and mesoregions) (Table 1, Table 2 and Table 3), it is required the decision-making process must respect to the different results found and the decision should be made cautiously, in the sense order to better understand the different results of the spatial levels analyzed associated with the real study scenario. Considering the same population of studies, the different scales tested must be consistently evaluated, begin that many studies point to the use of disaggregated data. It is suggested non-generalization of the facts, it means, they all share a similar characteristic.

The Modified Areal Unit Problem in the three verified spatial levels had a relevant presence, mainly in the regional centers and mesoregions when compared to municipalities, evidences of it were the values analyzed in the mesoregions where were not significant for any variable studied (Table 3).

These results showed the importance of the MAUP study in the decision-making process and it suggests how necessary is consider the possibility of individual differences between the analyzed variables and the individual difference cannot be generalized, which is corroborated by Burdziej (2019).

Geary's local autocorrelation indexes (c_i) are presented using the LISA Cluster Map for poultry production from 2013 to 2015 by municipality, in Figure 2. The result shows spatial grouping of points in the studied regions, namely: West, Southwest, Central South and part of the North Central region, suggesting significant positive spatial autocorrelation, having regions with high or low production of birds surrounded by regions with similar characteristics (dark red color and pink color in Figure 2).

It was also observed the presence of negative spatial autocorrelation during 2013, 2014 and 2015; it suggests regions with high and/or low poultry production surrounded by neighbors with similar characteristics and regions with low poultry production, surrounded by regions with high poultry production, in the light blue color of Figure 2.
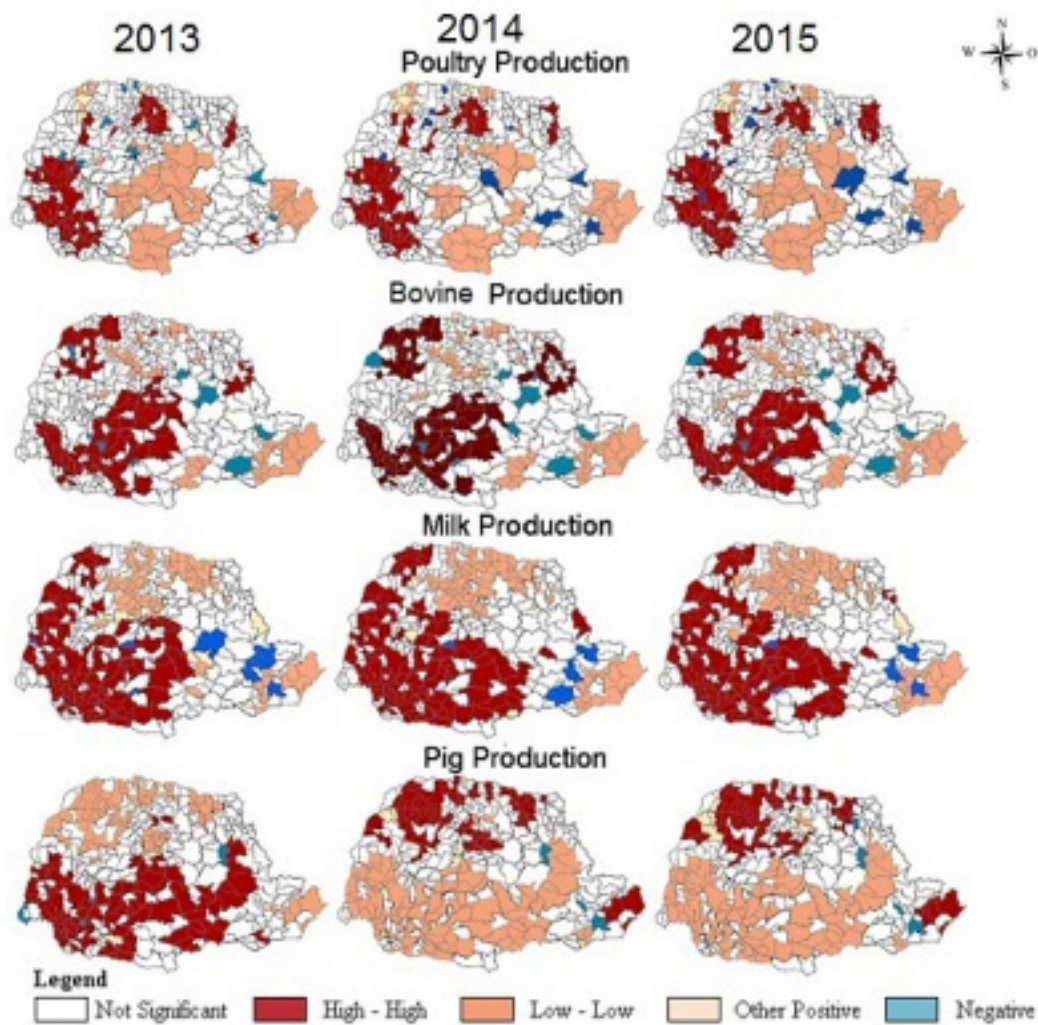
It is observed the Modifiable Areal Unit Problem (MAUP) is very visible when comparing the Municipal Map (Figure 2) to the Regional Centers Map (Figure3), there is a significant

Variables	2012	2013	2014	2015
GDP	1.160^{Ns}	1.159^{Ns}	1.128^{Ns}	1.211^{Ns}
Bovine production	0.943^{Ns}	0.943 Ns	1.002^{Ns}	0.995^{Ns}
Pig production	0.959^{Ns}	0.959 Ns	0.977^{Ns}	1.028^{Ns}
Poultry production	0.759^{Ns}	0.759 Ns	0.794^{Ns}	0.802^{Ns}
Milk Production	0.702^{Ns}	0.702Ns	0.755 Ns	0.759^{Ns}
Gross value of agricultural production	.	1.234 Ns	1.181 Ns	1.216^{Ns}
Grain production	1.142^{Ns}	1.151^{Ns}	1.165^{Ns}	1.118^{Ns}

Note: Ns - not significant values; * statistically significant at the level of 5% probability; . - absence of information in the official database.
Source: own calculations

Table 3: Global Geary Index (c) of gross domestic product (GDP), effective agricultural production (bovine, pig, poultry, milk), gross value of agricultural production and total grain production (soybeans, corn 1st and 2nd harvest) and wheat) from the years 2012 to 2015 of the twenty-three regional centers of SEAB-Paraná-Brazil.

Source: own research

Figure 2: LISA Cluster Map maps, related to poultry production, bovine, milk and pig by municipalities for the years 2013 to 2015.

difference between them. This results corroborates with the results obtained by Zen et al., (2019), who accessed the sensitivity to the MAUP, by calculating global statistics over there grid displacements.

Through Geary's local autocorrelation index (c_i), it is observed, in the bovine production from 2013 to 2015 (Figure 2), spatial patterns of clusters occur. In which, it is present positive spatial

autocorrelation and negative spatial autocorrelation, it means, the producing regions are similar to each other and they are close to each other, as well as regions distant from each other, allowing the identification of significant clusters (5%) shown in Figure 2, light pink.

In the 399 municipalities of Paraná state, it was observed clusters of municipalities with high bovine production surrounded by neighbors with similar characteristics (dark red color in Figure 2). The pattern of spatial concentration was observed most frequently in the municipalities of Guarapuava, Pitanga, Laranjeira do Sul, Catanduvas, Boa Vista de Aparecida, Guaraniaçu and Umuarama. Municipalities with significant negative spatial autocorrelation were observed, it means, municipalities with high bovine production surrounded by municipalities with low bovine production (light blue color in Figure 2) and municipalities with low cattle production surrounded by neighbors with high bovine production, this behavior signals spatial outliers, showing low spatial interaction between the municipalities.

Between 2014 and 2015, it was observed that there was a greater spatial concentration of data showing similar characteristics (High-High) in the municipalities of Guarapuava, Laranjeira do Sul, Loanda, Altonia, Três Barras, Catanduvas, Campo Bonito, Umuarama, Altamira do Paraná and Quedas do Iguaçu. This behavior may be related to the incentive in the use of confinement technique, which allows greater control over production costs.

The adoption of the bovine confinement system allows greater gains in production and signals that it is a profitable and viable livestock activity (Barbieri; Carvalho and Sabbag, 2016). This technique allows to concentrate more animals per area and consequently to have a larger scale reducing costs, besides obtaining bigger gains when providing more concentrated food without generating the movement of the animal generating greater added value to the product at the time of commercialization, allowing greater gains to the producers.

Regions that are not prone to agricultural cultivation due to steep topographic conditions, relief demographics, among others, which do not favor the planting of agricultural crops, are destined for other activities such as bovine raising. Cultivation techniques, no-till techniques are restricted in these environments.

Considering milk production, in most of the municipalities, there was a greater frequency of significant positive spatial autocorrelation, represented by the colors dark red and pink in Figure 2, with a predominance of regions with high milk production, surrounded by neighbors also with high milk production, mainly in the West, Southwest and Center South regions.

Regions with significant negative spatial autocorrelation were also observed, mainly in the Metropolitan Region and Eastern Center, in Figure 2, identified as light blue color. The results demonstrate the pig production, for the years studied presented, in its great majority, positive spatial autocorrelation (Figure 2, in dark red and pink colors), emphasizing on the mesoregions, namely, Centro Oriental, North Central, South Center, West and Northwest.

It is important to note, for the year 2013, there were municipalities with high pig production surrounded by neighbors with this same characteristic, in the West, Center South and part of the Central Eastern region, for 2014 and 2015, these same similarities were observed in parts in the municipalities belonging to the Northwest and North Pioneiro regions. In 2014 and 2015, there was a decrease in pig production in the municipalities (Low-Low) represented in pink. This fact may be related to the high production costs of this herd, which corroborates Embrapa, (2016) who studied the costs of pig production in the main states of Brazil, including Paraná and as a result, he found the variable most influencing the costs of pig production is the cost of labor, this result is relevant, since agricultural production also fluctuates according to the prices practiced in the markets associated with the production costs borne by rural producers, if the price to be paid to the finished final product is not attractive, the tendency is that much producers choose to migrate to other more profitable activities.

Considering that livestock production is economically demanding, a viable alternative would be to add technologies, investments in labor (technical and professional education) in order to improve good agricultural practices by promoting greater incentives to the activity that requires a lot of experience and planning on the part of rural producers.
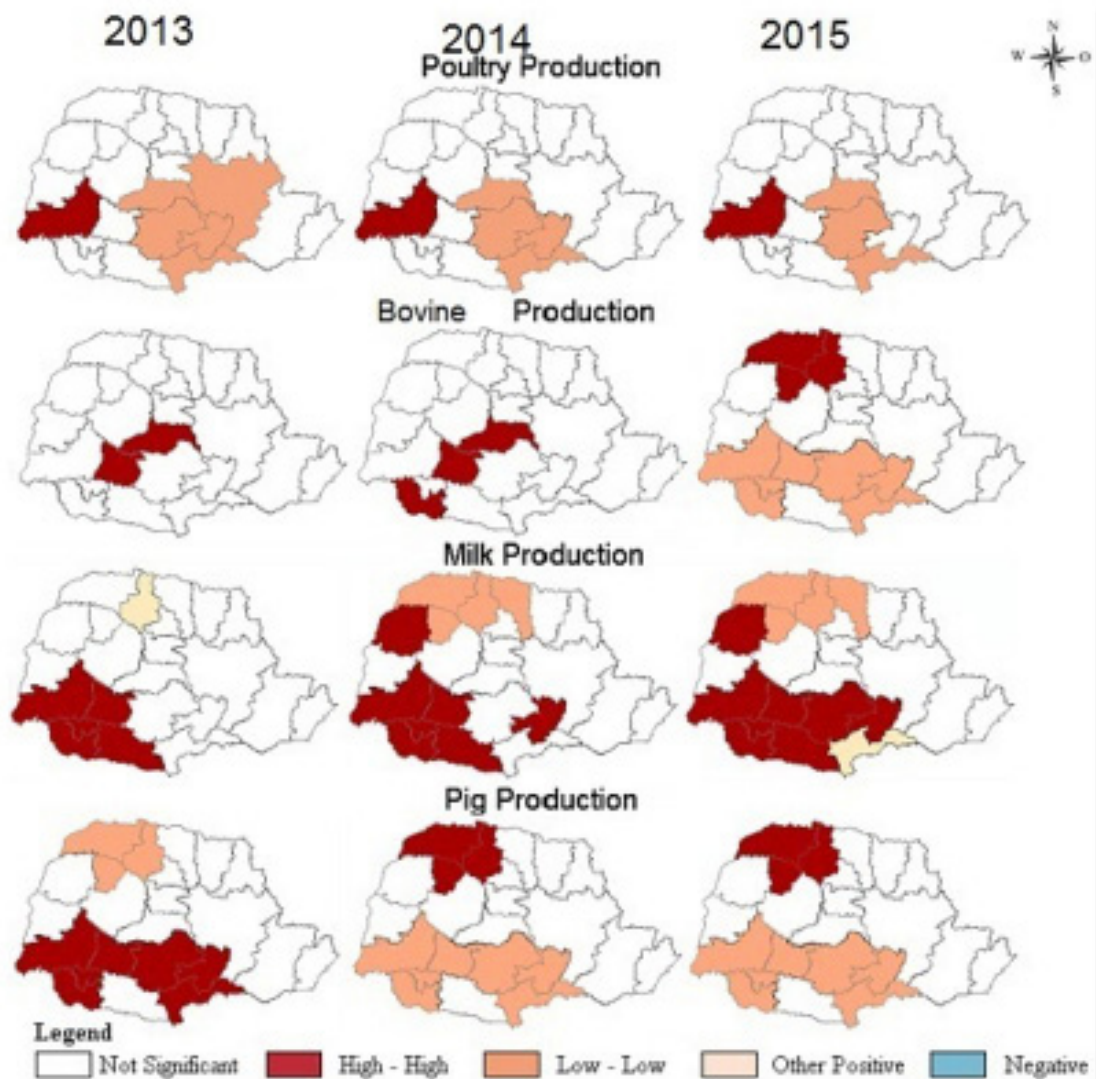
The results presented in Figure 3, for poultry production, point out three significant clusters (High-High) just for the regional centers of Cascavel, which differentiates it in great relevance to the map of the municipalities (Figure

2 in the dark red shade). This difference is accentuated when compared to the results of the mesoregions, as shown in Figure 4, for the year 2013, which characterizes the MAUP, in which there was a high-high cluster just for the North Central mesoregion, already for the years 2014 and 2015 there were no clusters with significant results. The statistical results are different. There was the presence of a Low-Low group, mainly in the Regional Centers of Pitanga, Guarapuava, Irati and União da Vitória (Figure 3 in pink).

The MAUP is clearly observed, comparing the maps made from the same database, the results of the significant clusters of the Regional Centers and Mesoregions are quite different from those observed in the municipal map (Figure 3 and Figure 4). The significant cluster agglomeration suggesting positive spatial autocorrelation for bovine production appears in the regional centers of Pitanga, Laranjeira do Sul, Francisco Beltrão, Paranavaí, Maringá and Cianorte (Figure 3 in brown). The regional centers that make up the municipalities of the West region practically disappear in 2013 and 2014 (Figure 3 in white).

The same fact occurs in the mesoregions (Figure 4). On the other hand, in 2015, the regional center of Cascavel, Toledo, Guarapuava and União da Vitoria presented a cluster (Low-Low), and their
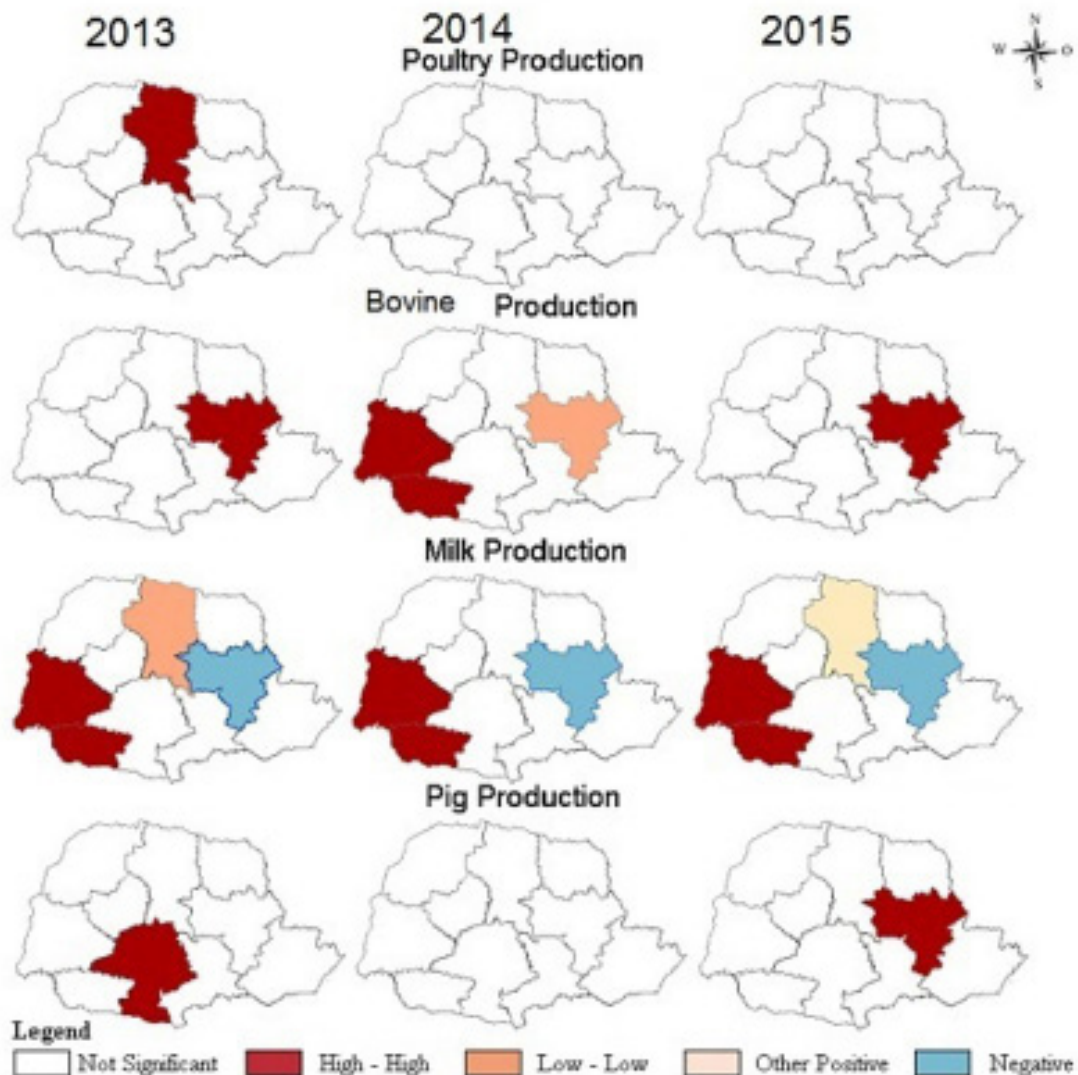

Source: own research

Figure 3: LISA Cluster Map maps, relative to the production of poultry, bovine, milk and pig by Regional Centers for the years 2013 to 2015.

municipalities were not identified on the municipal map, suggesting the difference between these maps. For milk production, the result also shows the presence of MAUP, demonstrating significant differences between maps of municipalities and maps of regional centers, Roces-Díaz et al. (2018) comment that when analyzing spatial data in different scales, they found different results between the levels studied, concluded that the use of spatial data in different resolutions, the results found showed significant differences.

The result points to significant clusters, suggesting positive spatial autocorrelation (High-High) just for the regional centers of: Cascavel, Laranjeira do Sul, Francisco Beltrão, Dois Vizinhos, Pato Branco, Irati and Umuarama. Toledo regional center (major producer milk from Western Paraná) simply disappeared from the map (Figure 3).

Therefore, as it appears in the municipal data, it is necessary to have coherence and consideration when analyzing the data by regional centers. The MAUP is clearly visible in these presented results. The group considering different spatial resolutions can generate complications in decision-making process, which in fact shows it in this analysis. For the production of pigs in 2013, significant clusters (High-High) were observed in the following regional centers: Toledo, Cascavel, Dois Vizinhos, Laranjeira and Guarapuava (Figure 3 in dark red). In 2014 and 2015, there were significant regional clusters in these same regions (Low-Low), which is very different from the municipal map and map by mesoregion (Figure 3), once other regions had this characteristic.

The results found make sense, because there was a slowdown in pig production in 2014 and 2015 due

Source: own research

Figure 4: LISA Cluster Map maps, relative to the production of poultry, bovine, milk and pig by Mesoregions for the years 2013 to 2015.

to the high production costs (EMBRAPA, 2016). It was observed constant productions in these periods. The results presented in Figure 4 demonstrate the MAUP to the production of poultry, bovine, milk and pig. Comparing the maps made through the three levels of differentiated spatial resolutions, the results of the significant clusters of the Mesoregions are different from those observed in the maps of the Municipalities and maps of the Regional Centers (Figure 4).

The municipality agglomeration in the West Mesoregion practically disappeared to the effective production of poultry and pig production in 2014 and 2015 in the state of Paraná (Figure 4), which suggests how worrying the problems were, which can occur mistaken decision-making process, when analyzed through the same study population considering a single level of analyzed spatial resolution.

For each year (2013, 2014 and 2015), SAR, CAR and GWR models of the gross value of agricultural production (V_{pb}) were built in relation to livestock production and total grain production for each year, considering the existence of spatial autocorrelation. The results to the municipalities in the state of Paraná are presented in Tables 4, 5 and 6.

The SAR, CAR and GWR forecast models for the gross value of agricultural production (V_{pb}) considering the explanatory variables: total amount of bovine production (*QTbovine*), total amount of pig production (*QTpig*), total amount of poultry production (*QTpoultry*) and total amount of grain production (*Totgrain*) for the year 2013, are shown in Table 4.

All the estimated parameters $\widehat{\beta}'s$ are observed in all models are positive, which implies a directly proportional influence of the herds of the livestock production and total grain production in 2013.

The result indicated the response variable: the SAR autoregressive model at R^2 = 77.32% explained gross value of agricultural production (V_{pb}) in 2013 (coefficient of determination). The Maximum logarithm value of the likelihood

function - 160.670. The other indexes point to a model adjusted with the addition of spatial dependence on the response variable $\hat{\rho}$ = 0.45283. The results inherent to the application of the CAR model to estimate the gross value of agricultural production (V_{pb}) to 2013 explains R^2 = 77.8%, presenting a significant autoregressive coefficient λ (Lambda) (0.490*), showing that spatial autocorrelation attributed to the error was significant at the 5% level of significance (Table 4).

Table 4 also shows the estimated GWR model for the gross value of agricultural production (V_{pb}) with a determination coefficient R^2 = 83.3%. It shows that there was, through the analysis of the GWR model, the best fit, considering the SAR and CAR models, once it presented the highest MLL value and the lowest values for AIC and BIC. Therefore, the local GWR model was the best explanation to the gross value of agricultural production (V_{pb}) for the year 2013.

Table 5 shows the results of the SAR, CAR and GWR models of the gross value of agricultural production (V_{pb}) in 2014 for the municipalities. In all models, the estimated parameter $\widehat{\beta}_2$ is negative, which implies an inversely proportional effect of the total quantity of pigs (*QTpig*) in the gross value of agricultural production (V_{pb}) for the year 2014, in the years 2014 to 2015 there was retraction in the production of pig, which may be related to the high production costs in this activity (IBGE, 2016).

The results also showed, for 2014, the best model, which explains the estimate of the gross value of agricultural production (V_{pb}), was the GWR model. As it is a local model, it attributed a significant improvement to the spatial regression process in the studied region (Table 5).

In 2015, it was observed, similarly to previous years, the GWR model was the best explanation to the gross value of agricultural production (V_{pb}) as a function of cattle production, pig production, poultry production and total grain production of the 399 municipalities of Paraná (Table 6).

Statistics	$\widehat{\beta}_0$	$\widehat{\beta}_1$	$\widehat{\beta}_2$	$\widehat{\beta}_3$	$\widehat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R^2	AIC	BIC
SAR	2.734	0.043	0.081	0.452	0.076	0.452*	-	- 160.670	0.774	343.340	387.163
CAR	4.32	0.053	0.080	0.451	0.074	-	0.490*	- 165.013	0.778	344.026	371.913
GWR	4.55	0.042	0.093	0.430	0.067	-	-	**0.310**	**0.833**	**322.957**	**311.735**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R^2 adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 4: Statistical results of the SAR, CAR and GWR models for the gross value of agricultural production in 2013 for municipalities.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R²	AIC	BIC
SAR	10.970	0.0097	-2.461	0.287	0.065	0.451*	-	-195.165	0.773	412.329	456.153
CAR	17.259	0.0901	-2.825	0.283	0.064	-	0.492*	-199.548	0.768	413.095	440.983
GWR	18.109	0.073	-3.580	0.262	0.057	-	-	**0.340**	**0.831**	**354.374**	**343.152**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R² adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 5: Statistical results of the SAR, CAR and GWR model for the gross value of agricultural production in 2014 for municipalities.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R²	AIC	BIC
SAR	6.627	0.138	-2.369	0.381	0.062	0.400*	-	-243.147	0.793	508.295	552.118
CAR	7.710	0.118	-2.862	0.373	0.064	-	0.469*	-252.732	0.783	519.464	547.351
GWR	7.744	0.025	0.341	-0.036	0.089	-	-	**0.393**	**0.840**	**400.421**	**393.021**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R² adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 6: Statistical results of the SAR, CAR and GWR model for the gross value of agricultural production in 2015 for municipalities.

In similar way of studies based on municipal database, the SAR, CAR and GWR models to Regional Centers of the state of Paraná-Brazil were studied.

It is observed according to the results presented in Tables 7 to 9 that the parameters $\hat{\rho}$, $\hat{\lambda}$ of the SAR and CAR models are not significant. The geographically weighted spatial regression model (GWR) was the best representation of the gross value of agricultural production (V_{pb}) in the three years 2013 to 2015. Therefore, the result shows the SAR and CAR models of the gross value of agricultural production (V_{pb}) is associated to the study unit that are the municipalities.

Whereas just in the regional centers and mesoregions, the GWR model is significantly related to production of bovine, pigs, poultry and grains. In this sense, the MAUP effect is observed in the database of regional centers and mesoregions. This result corroborates the results obtained by Jonatan and Brewer (2017), who, in their findings, verified that the aggregated data are sensitive to MAUP, and the levels of aggregation, sizes and zones, affect the validity and reliability of the results. Their findings suggest that researchers need to choose the most appropriate scale for specific problems analyzes.

It is evident the presence of MAUP (Table 7, Table 8 and Table 9) in the analysis of the spatial level by regional centers. MAUP is also observed in the mesoregions for the models (SAR and CAR), once the parameters related to the spatial level were not significant in any studied year. Considering

the GWR model, it was possible to adjust a model for the gross value of agricultural production (V_{pb}) for the studied years, this fact is justified because the estimation of the parameters takes into account the spatial information, Table 10, Table 11 and Table 12.

In accordance with Table 11 and Table 12, it was observed the SAR and CAR models were also not significant, showing the spatial structure is not being incorporated into the model, which resulted in a multivariate regression model, with a significant degree of explanation for the studied variables. Indeed, this fact confirms the scale effect, characterizing the presence of MAUP in the studied mesoregions.

Therefore, the MAUP is visible in the study, considering the comparative analysis of the SAR, CAR and GWR models. The GWR model was the one that explained the variable response gross value of agricultural production.

In the analysis of these models, it was clear the presence of MAUP in the comparison among the results based upon municipal, regional center and mesoregions databases.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R^2	AIC	BIC
SAR	11.150	-0.039	0.393	0.137	-0.045	-0.341[Ns]	-	2.797	0.829	16.405	28.895
CAR	5.450	-0.022	0.316	0.313	-0.021	-	0.030[Ns]	0.181	0.785	13.636	21.584
GWR	5.485	-0.022	0.316	0.310	-0.022	-	-	**0.234**	**0.795**	**24.392**	**13.170**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R^2 adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 7: Statistical results of the SAR, CAR and GWR model of the gross value of agricultural production by regional centers in 2013.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R^2	AIC	BIC
SAR	37.323	-0.042	-11.486	0.033	-0.040	-0.537[Ns]	-	7.605	0.90	6.788	19.278
CAR	25.106	-0.013	-9.817	0.106	-0.027	-	-0.164[Ns]	4.768	0.873	4.462	12.410
GWR	25.013	-0.013	-9.851	0.111	-0.022	-	-	**0.193**	**0.877**	**20.563**	**9.341**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R^2 adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 8: Statistical results of the SAR, CAR and GWR model of the gross value of agricultural production by regional centers in 2014.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R^2	AIC	BIC
SAR	25.03	-0.05	-12.76	0.18	-0.05	-0.39[Ns]	-	1.56	0.88	18.87	31.36
CAR	17.58	-0.03	-11.39	0.23	-0.03	-	0.05[Ns]	-1.92	0.84	17.85	25.80
GWR	5.485	-0.022	0.316	0.310	-0.022	-	-	**0.234**	**0.795**	**24.392**	**13.170**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R^2 adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 9: Statistical results of the SAR, CAR and GWR model of the gross value of agricultural production by regional centers in 2013.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R^2	AIC	BIC
SAR	13.34	-0.007	0.30	0.497	-0.11	-0.47Ns	-	8.44	0.94	5.10	8.43
CAR	8.73	-0.04	0.26	0.549	-0.21	-	-1.39Ns	4.04	0.86	5.90	8.02
GWR	5.91	0.02	0.37	0.053	-0.06	-	-	**0.16**	**0.86**	**14.20**	**2.98**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R^2 adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 10: Statistical results of the SAR, CAR and GWR model of the gross value of agricultural production by regional centers in 2013.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R^2	AIC	BIC
SAR	13.01	0.19	-6.837	-0.35	0.23	-0.17[Ns]	-	14.24	0.93	-6.48	-3.15
CAR	25.64	-0.01	-8.22	0.10	-0.11	-	-1.49[Ns]	8.52	0.91	-3.04	-0.93
GWR	25.76	0.03	-10.64	0.01	-0.04	-	-	**0.12**	**0.85**	**12.08**	**0.86**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R^2 adjusted coefficient of determination; AIC: Akaike information criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 11: Statistical results of the SAR, CAR and GWR model of the gross value of agricultural production by regional centers in 2013.

Statistics	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\rho}$	$\hat{\lambda}$	MLL	R^2	AIC	BIC
SAR	16.83	0.09	-9.91	0.07	-0.03	-0.18[Ns]	-	10.48	0.94	1.02	4.35
CAR	17.69	0.03	-13.36	0.11	0.01	-	0.47[Ns]	3.06	0.89	7.87	9.98
GWR	17.10	0.04	-12.06	0.06	0.00	-	-	**0.17**	**0.88**	**14.80**	**3.58**

Note: * significant probability level of 5 %; $\hat{\rho}$, $\hat{\lambda}$ auto-regressive coefficients; MLL: maximum likelihood logarithm ratio; R^2 adjusted coefficient of determination; AIC: Akaike information priation criterion; BIC: Bayesian information criterion; bold: best adjusted model.

Source: own calculations

Table 12: Statistical results of the SAR, CAR and GWR model of the gross value of agricultural production by regional centers in 2013.

Conclusion

The result indicates Geary's global and local spatial association indicators were more intense when analyzing municipalities in detriment of regional centers and mesoregions.

There were variations among municipalities, regional centers and mesoregions in the gross value of agricultural production from 2013 to 2015 and the effects of the effective agricultural production varied strongly in the universe of regions in the study. It shows there is a difference in the gross value of agricultural production related to the number of agricultural production according to their location.

The geographically weighted spatial regression model (GWR) was the best representation of the gross value of agricultural production (V_{pb}) in the three analyzed years, this evidence is all comparisons made.

The SAR and CAR models were highly sensitive when using different spatial resolutions, demonstrating their instability.

The GWR model remained stable with the changes in the different spatial resolutions analyzed, and its use in studies involving Spatial Area Statistics is more prudent.

A general recommendation is to work using different levels of spatial analysis and compare their results, whenever possible. Maintaining, throughout a research, a single territorial delimitation of the object of study, it may not be ideal for decision-making process.

Therefore, the resources for analyzing spatial data and spatial regression models, which we have only a snapshot of what can be analyzed, act in the direction of providing a more accurate picture of such dynamics. The use of these techniques does not provides just a new visualization resources, but also new regional performance indicators that presuppose the use of georeferenced databases, this situation may allow regional researchers to consider spatial aspects in their empirical analyzes.

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