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An Analysis of the Gross Domestic Product of Municipalities: a Spatial Glance into the State of Paraná-Brazil

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Abstract

The vast relevance of applications of spatial regression models has recently captured the interest of Economics and Agriculture, in the sense of better understanding the spatial behavior of the region under study, in the different forms of approaches. It is interesting to understand why some regions show greater variability than others, and why some forms of regional development are better explained. It is up to the researcher to understand, explore, and organize a series of observations, so that it is possible to make predictions, diagnoses, and recommendations to public policy managers and regional development agents. The municipalities' Gross Domestic Product (Gdp) has driven studies involving spatial information. The objective of this study was to analyze the Gdp of the municipalities in Paraná-Brazil, in 2018, regarding soybean yield, corn yield, pig production, and the tax on the circulation of goods, through different approaches of spatial regression models. SAR and CAR models are global models, while the GWR model is considered a local one. Three spatial analysis models were used to perform this study: Spatial Autoregressive (SAR), Conditional Autoregressive (CAR), and Geographically Weighted Regression (GWR). The results were compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Cross-Validation Criterion (CVC), and the descriptive graphic of residual diagnoses-Worm Plot. The best result obtained was for the GWR model, which best explained the GDP of the state of Paraná-Brazil in terms of its covariates.

Keywords

Agribusiness, economic scenario, production chains, development, spatial regression models.

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This work's innovative and relevant approach is in using original georeferenced spatial data, considering economy and agriculture. The present work is justified by analyzing whether the impacts of soybean yield, corn yield, pig production, and the tax on the circulation of goods influence the Gross Domestic Product (GDP) of the municipalities. Previous works have proven such an influence and responded differently to this question. Therefore, the study intended to present and demonstrate the impact of economic growth interpreted as soybean yield, corn yield, pig production, and the tax on the circulation of goods in the GDP. The motivation for this approach is given by the fact that the agro-industrial growth in Paraná-Brazil is not just another means of generating wealth, but rather a vigorous activity that promotes values, citizenship, and economic sustainability, generating and promoting benefits in the different economic, social, and environmental areas, in society as a whole. The sector is present in all areas, whether innovative to improve its activity, or in the positive impact of innovation on the return of productive and economic gains, on constant improvement of this activity so necessary for the growth and development of the municipalities that make up the state of Paraná-Brazil.

Banacu et al. (2019) analyzed business economic management with emphasis on urban waste control management and its relationship with the GDP, through a linear regression model, in the European Union (EU). The authors concluded that public policies need to be focused on increasing the use of public and private investment in environmental control programs.

Fan and Hao (2020) analyzed, using regression models, economic growth, the environmental issue and its relationship with the GDP in China in the period 2000-2015. They concluded that there is a balanced relationship between that country's GDP and economic growth.

In studies developed by Banerjee et al. (2021) on the relationship between GDP and economic sustainability in Colombia, 2021, through Integrated Environmental Economic Modeling (IEEM), the influence of GDP was verified.

Matese et al. (2019) report that the approach to spatial data that takes into account the spatial structure is a robust and powerful technique in agricultural and economic data analysis as it constitutes a valuable element in decision-making.

Kánská et al. (2021) investigated the spatial analysis of data on agricultural properties through digital technologies and found that their use promotes the competitiveness of rural properties, thus favoring their growth and economic development. The agribusiness scenario shows that the increase in food productivity is directly bound to the development of agro-industrial production chains and the use of precision agriculture techniques – in agreement with Cima et al. (2021a).

Čechura et al. (2021) evaluated agricultural productivity in the Theca Republic by considering spatial analysis. The results showed that agricultural productivity follows technological progress and that productivity dynamics promote economic competitiveness.

The economic scenario found in Paraná has been presenting in the current decades trends of advancement and growth favored by the use of digital technologies that make the spatial analysis of geographic data possible, as is the case with regional development and precision agriculture, which promotes economic and strategic competitiveness to boost the economy, aiming to increase its participation in the internal and external market, with exports of agricultural and livestock products (Gaffuri and Alves, 2022).

In the agricultural field, analysis involving spatial data and their interactions can be used in several activities. On a regional scale, they can be used to represent production areas and agricultural enterprises in the same place over time (Macário et al., 2020). The use of geotechnologies in agribusiness is of great relevance for studies involving geographic space, allowing efficient diagnoses in large databases of information, and creating favorable conditions for analysis, given the accelerated changes that humanity has been experiencing (Cardoso et al., 2020).

The growing offer of agricultural production observed in Paraná-Brazil has presented interests and motivation for a better understanding of its variability concerning the Gross Domestic Product of the municipalities (GDP), which represents an estimate of the generation of goods produced in a state or country. Recently, the agricultural sector has grown at expressive annual rates (IBGE, 2021a). The reported locational indicators of economic growth lack clarity about the information they seek to explain (Ferrera de Lima, 2020). A key aspect that is important to know regarding spatial interaction is the relationship between its intensity with the distance among observations (Seibert and Silva, 2021).

In the Spatial Autoregressive (SAR) model (*Spatial Lag Model*), it is possible to capture the spatial correlation structure in a single parameter added to the regression model. It is assigned to spatial autocorrelation to a response variable (Y). Grifn and Lowenberg DeBoer (2019) analyzed agricultural data through spatial regression, including the SAR method, and concluded that spatial statistical methods can provide efficient estimates in the analysis and decision-making of rural producers.

For the Conditional Autoregressive (CAR) model, the spatial autocorrelation is attributed to the model's error term (Marconato et al., 2020). The behavior of different spatial patterns plays an important role in agricultural productivity. Hoef et al. (2018) report that the SAR (*Spatial Lag Model*) and the CAR (*Spatial Error Model*) were developed to model spatially autocorrelated data considering their neighboring regions.

In the model with local spatial effect represented by Geographically Weighted Regression (GWR), the interest is to regionalize the study area by obtaining subregions with their own pattern (Fotheringham et al., 2002; Fotheringham et al., 2017; Li et al., 2020; Bergs, 2021; Kedron et al., 2021). Wei et al. (2022) found that the GWR was advantageous and effective when analyzing climatic conditions in regions of China from 2001 to 2019.

In this context, the agro-industrial sector deserves to be better evaluated as it represents a major factor in local, regional, and national development.

Paraná-Brazil is considered promising in agricultural production, and incentives to the agro-industrial system must be provided by mechanisms that aim to optimize productive resources, which corroborates IBGE's (2021b) results.

Thus, as a contribution to the field of agricultural and socioeconomic research in Paraná and Brazil, the proposal of this study was to analyze the results obtained through different analyzes of spatial regression models (SAR, CAR, and GWR), which meet with the already documented literature, in which several studies focusing on the spatial econometric data are observed (Wang et al., 2019; Pimenta et al., 2021).

The objective of this paper was to show a spatial regression study from an original georeferenced database of the Gross Domestic Product (GDP) of the municipalities, obtained from the Paraná Institute for Economic and Social Development (IPARDES) [R$], based on the soybean yield (*Rendsoy*) [kg/ha], maize yield (*Rendcorn*) [kg/ha], pig production (*Prodpig*) [quantity/head], and the tax on the circulation of goods (*Gct*) [R$], covering the period from January to December 2018, in the 399 municipalities that make up the state of Paraná-Brazil.

Material and methods

The selection of the explanatory variables (soybean yield, corn yield, pig production, and the tax on the circulation of goods) was because they are highly relevant economic indicators for the economic and agro-industrial growth of Paraná-Brazil, since the profile of these variables refer to possible associations with the GDP, which represents a measure that indicates the sum of all final goods and services produced by a municipality, state, or country in a given year.

The global spatial correlation analysis of the Spatial Lag Model (SAR) was performed, allowing to capture the spatial correlation structure in a single parameter added to the spatial regression model. In that model, spatial autocorrelation is attributed to the response variable y. The SAR model hypothesizes that the variable y_i is affected by the values of the response variable in neighboring areas A_i (Equation 1).

$$y = \rho W y + X\beta + \mathcal{E}, \tag{1}$$

where,

ρ = the autoregressive spatial coefficient. It is a measure of spatial correlation;

W = the spatial proximity matrix;

$\mathcal{E}$ = the random error vector;

ρWy = the spatial dependence (Baller et al., 2001).

Being a matrix of spatial weights standardized by line W (that is, the weights are standardized so that W_{ij} = 1 for all i), this amounts to including the average of the neighbors as an additional variable into the regression specification. This variable, Wy, is referred to as a spatially lagged dependent variable.

Baller et al. (2001) state that another form of spatial dependence occurs when the dependence works through the error process, in that the errors from different areas may display spatial covariance called Conditional Autoregressive Model (CAR), which is a first-order spatial autoregressive process. The model hypothesizes that the observations are interdependent and spatially correlated, in which the spatial effects are a noise since it is not possible to model all the characteristics of a geographic unit that can influence the neighboring regions (Equation 2).

$$y = X\beta + \mathcal{E},$$
$$\mathcal{E} = \lambda W \mathcal{E} + \xi, \tag{2}$$

where,

$W\mathcal{E}$ = the error with spatial effect;

λ = the autoregressive parameter;

ξ = the error parameter with constant variance.

Lesage (2015) asserts that the CAR may be seen as a combination of a standard regression model with a spatial autoregressive model in the error term $\mathcal{E}$, and hence has an expectation equal to that of the standard regression model. In large samples, point evaluation for the β parameters of the CAR model and conventional regression will be the same, but in small samples there may be an efficiency gain when modeling the spatial dependence in terms of error. In the Geographically Weighted Regression model, the interest is to regionalize the study area by obtaining sub-regions with their own pattern. The model adjusts a regression line for each sub-region, so this method adjusts a regression model to each point observed, weighting all other observations based on the distance to this point (Fotheringhan et al., 2002). In the GWR method, the weighting function is considered constant throughout the study area and it is used to describe a family of regression models in which the parameters $\beta's$ can vary spatially (Equation 3).

$$Y(S) = \beta_0(S) + \beta_1(S)x_1 + \beta_2(S)x_2 \ldots + \beta_p(S)x_p + \mathcal{E}(S), \tag{3}$$

Where,

Y(S) = variable that represents the process at the point S;

β(S) = parameters to be estimated at the point S for each observation *i* of location $g_i = (u_i, v_i)$;

Ɛ(S) random error vector nx1, with zero mean and uncorrelated constant variance (Fotheringhan et al., 2002).

The study area comprises the municipalities in the Paraná (399 municipalities). The data were obtained from the Paraná Institute of Economic and Social Development (IPARDES) from January to December 2018. SAR (4), CAR (5), and GWR (6) spatial regression models were used to verify which model best adjusted the Gross Domestic Product (*Gdp*) of the municipality based on the soybean yield (*RendSoy*), corn yield (*Rendcorn*), pig production (*Prodpig*), and the tax on the circulation of goods (*Gct*) (Ipardes, 2021). The parameters of the models were estimated using the maximum likelihood-ML method, presented in equations (4) (5) and (6), respectively:

$$\hat{G}_{dp} = \widehat{\beta_0} + \widehat{\beta_l} Rendsoy + \widehat{\beta_2} Rendcorn + \widehat{\beta_3} Prodpig + \\ + \widehat{\beta_4} Gct + \hat{\rho} W G_{dp}, \quad (4)$$

$$\hat{G}_{dp} = \widehat{\beta_0} + \widehat{\beta_l} Rendsoy + \widehat{\beta_2} Rendcorn + \\ + \widehat{\beta_3}\, Prodpig + \widehat{\beta_4} Gct + \hat{\lambda} W_{\varepsilon}, \quad (5)$$

$$\hat{G}_{dp} = \widehat{\beta_0}(u_i, v_i) + \widehat{\beta_l}(u_i, v_i) Rendsoy + \\ + \widehat{\beta_2}(u_i, v_i) Rendcorn + \widehat{\beta_3}(u_i, v_i) Prodpig + \\ + \widehat{\beta_4}(u_i, v_i) Gct, \quad (6)$$

Where,

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

WG_{dp} = expresses the weighted spatial dependence (Baller, 2001);

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

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

W_{ε} = error component with spatial effects,

(u_i, v_i) = denotes the centroid coordinates of the ith area $i = 1,\dots, 399$;

$\widehat{\beta_y}(u_i, v_i), y = 0, \dots, 4$ = realization of the continuous function $\widehat{\beta_y}(u, v)$ on the centroid of ith area $^{i} = 1,\dots, 399$.

The hypothesis of normality of the spatial regression was verified using plots of normal probability (Draper and Smith, 1998), among them the Moran residues index test. The QQ-plot chart was elaborated to analyze the residues normality at 5% significance. The SAR model restriction on the spatial lag coefficient ρ is that it lies within the open range between -1 and 1 i.e. $|\rho| < 1$. (Almeida, 2012).

For the assumption of the SAR model, the random error vector *n* x1 has zero mean, constant variance, and is uncorrelated (Bailey and Gatrell, 1995). For CAR model restriction, the matrix $[I_n - \lambda W^{-1}]$ must not be unique. For this to be guaranteed, the matrix W must maintain the properties that the sum of its rows and columns is limited to a fixed number, provided that $|\lambda| < 1$ (Fingleton, 2008). In the assumption of the CAR model, the random error vector *n* x 1 has zero mean, constant variance, and is uncorrelated (Bailey and Gatrell, 1995).

For the GWR model, its limitations include multicollinearity problems in local coefficients (Wheeler, 2005). The GWR model assumes that the random error vector *n* x 1 has zero mean, constant variance, and is uncorrelated (Cima et al., 2021b).

For the comparison of linear models of spatial regression: SAR, CAR, and GWR, the best adjustment quality will be due to a higher logarithm value of the Maximum Log-Likelihood (MLL) to the data analyzed (Cima et al., 2021b). Another way to validate the results obtained is through the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Spring, 2003). In this study, the residues self-correlation was tested by means of the global residue Moran index (I_r), according to the Equation 7:

$$I_r = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(e_i - \bar{e})(e_j - \bar{e})}{s_0 \sum_{i=1}^{n} (e_i - \bar{e})^2}, \quad (7)$$

Where,

n = sample size;

e_i and e_j = the values of the residue considered in the areas *i* and *j*, respectively;

$\bar{e}$ = the average value of the residue in the study region;

w_{ij} = elements of the normalized matrix, in which weights 0 and 1 are attributed, being 0 the regions that do not border each other, and 1 the ones that do so;

s_o = sum of the elements ww_{ij} of the symmetric matrix of spatial weights W.

To prove the best adjusted model for GDP in 2018 among SAR, CAR, and GWR, the criterion of Cross-Validation (Uribe-Opazo et al., 2012) and the descriptive chart *Worm Plot* for residue analysis was used (Buurea and Fredriks, 2001). The data were analyzed using the free *software* R (Development Core Team, 2021). The following packages were used: Gamlss, Spdep, GISTools, and Spgwr.

Results and discussion

The results for the spatial regression models SAR, CAR, and GWR for Gross Domestic Product of the municipalities (*Gdp*) of the state of Paraná are shown in Table 1. The results show coefficients of determination (R^2) ranging from 77.7% to 80.8%, which shows an expressive adjustment of the models used, as well as the best adjustment quality according to the AIC and BIC criteria. Due to the results found (Table 1), it is observed that in all the models analyzed the estimated parameters $\hat{\beta}_1$ and $\hat{\beta}_2$ were negative in all models adjusted – a fact which produced an inversely proportional effect of the variables analyzed in the GDP of the municipalities in 2018, which means that there was an inversely proportional effect on soybean yield and corn yield in the GDP of the municipalities.

The results found in Table 1 express the vast importance and applicability of spatial data analysis for decision-making by public and private managers, in the sense of better understanding of events inherent to the object of study analyzed.

Recent studies such as Mykhnend and Wolff (2019) spatially analyzed the economic behavior in Europe, after 1970, using economic indicators such as Gross Domestic Product, and concluded that the analysis of spatial data is a method of wide relevance to explain the trends of European economic convergence.

The parameters estimated $\hat{\beta}_3$ and $\hat{\beta}_4$ were positive in all the adjusted models, which means that there was a directly proportional influence on pig production and on the tax on the circulation of goods in the GDP of the municipalities in the year studied (Ipardes, 2021).

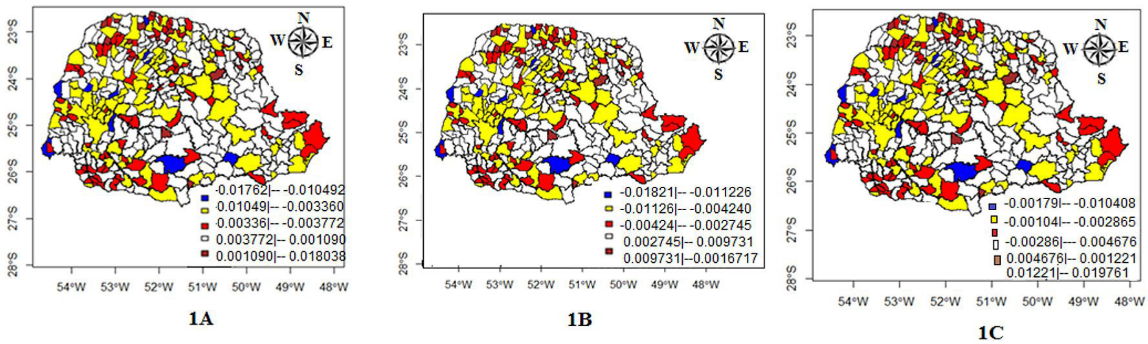
Through the SAR model, it was observed that the autoregressive coefficient ($\hat{\rho}$ = 0.362) was significant, in which the spatial autocorrelation was added to the explained variable. The CAR model showed that the autoregressive coefficient ($\hat{\lambda}$ = 0.418) was also significant, showing that the spatial dependence attributed to the term of the error was representative. And in the GWR model, it was observed that all parameters associated with covariates were significant at the 5% significance level (Table 1).

By observing the residues map ($\hat{G}_{dp}$) for SAR and CAR regression models (Figure 1A and Figure 1B), it is evident that the spatial

Model/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	0.046*	0.0312ns	-0.0341*	0.339*	0.238*	0.362*	-	1502	0.777	-2951.6	-2903.0
CAR	0.089*	0.0948ns	0.0352*	0.0742*	0.0197*	-	0.418*	1486	0.768	-2954.0	-2918.1
GWR	0.087*	0.0157*	0.0364*	0.0465*	0.0167*	-	-	0.065	0.808	-2998.5	-2918.7

Note: ns: not significant; *: significant at 5% probability level; $\hat{\rho}$, $\hat{\lambda}$: autoregressive coefficients estimates; $\hat{\beta}_i$: estimated parameters of models, for i = 0, 1,…,4; MLL: Maximum Log-Likelihood value of the likelihood function; AIC: Akaike information criterion; BIC: Bayesian information criterion
Source: own calculations

Table 1: Statistics of the best SAR, CAR, and GWR models for the Gross Domestic Product (GDP) of the municipalities in the state of Paraná, in 2018.



Source: own research

Figure 1: Residues map resulting from the application of the spatial model SAR (1A), CAR (1B), and GWR (1C).

autocorrelation added to the response variable was eliminated, which allowed to generate non-correlated residues along the region analyzed (Batistella et al., 2019).

Pegorare et al. (2018) state that studies involving the spatial econometric data are necessary and important and that spatial autoregressive models (SAR and CAR) can influence the regional and national agribusiness scenario.

Through the analysis of the global Moran residues index for the GWR model, it was possible to verify that the global Moran index (I_r = 0.01609) was close to zero and was not significant (p-value = 0.085), thus eliminating the model's spatial autocorrelation. Therefore, the GWR model also allowed to generate non-correlated residues in the study region (399 municipalities in Paraná-Brazil) (Figure 1C), which corroborates Alves and Galvani (2021) findings.

Balland et al. (2020) verified the productive spatial concentration in metropolitan areas of the United States (USA) using economic variables such as the GDP. The results suggest that economic activities were explained through the spatial investigation data.

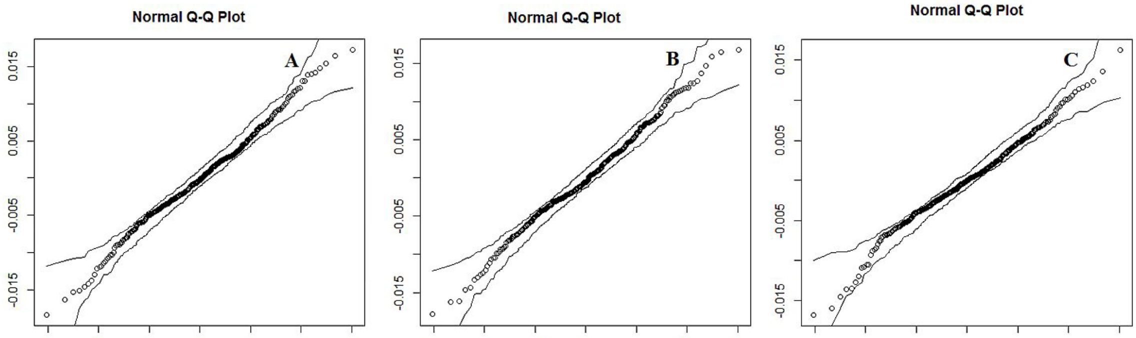
Huo et al. (2022) analyzed the characteristics of space-time variation of cultivated land and control factors in the Chinese delta region using Moran's spatial autocorrelation and the Geographically Weighted Regression (GWR) model. They concluded that both the analysis of the Moran's spatial autocorrelation and the GWR model explained the land characteristics associated with the GDP economic indicator.

According to the QQ-plot charts shown in Figure 2, it was observed that the points tend within the confidence bands, so this indicates that the residues of the SAR, CAR, and GWR models have a normal distribution, which means that the models suggest an indication of good adjustment because the points are aligned in the line that represents the identity of the theoretical and sampling quantiles – which corroborates Jaya and Chadidjah (2021) findings.

Through the cross-validation test for the Gross Domestic Product (GDP) of the municipalities, in 2018 SAR (0.0000298), CAR (0.0000319) and GWR (0.0000276), a better quality of fit was obtained for the GWR model when compared to the other models analyzed, which corroborates Uribe-Opazo et al. (2012) findings.

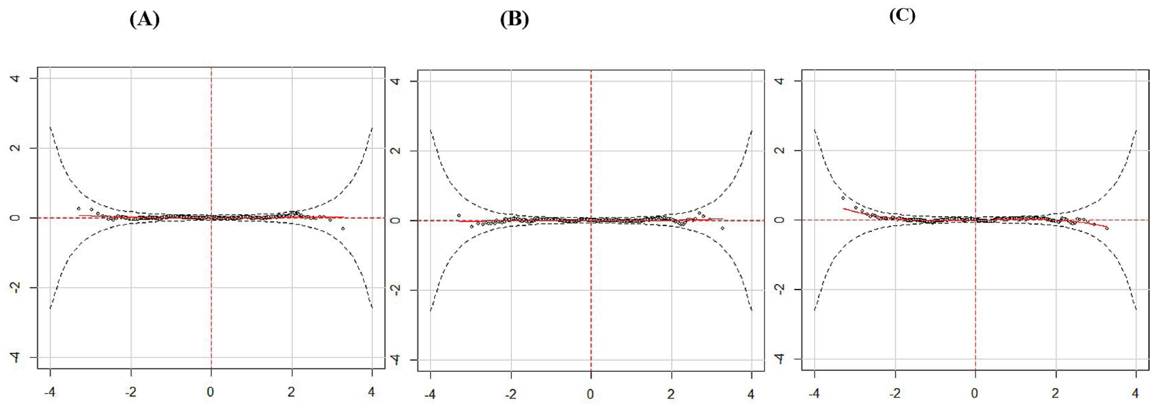
According to Harris (2019), the cross-validation test presents valuable performance mechanisms when comparing different spatial regression models, being fundamental for decision-making.

Figure 3(c) shows the worm plot for the GWR model, with the points and the red line within the confidence bands, showing a good goodness-of-fit of the GWR model. According to the results obtained through Cross Validation and the worm plot chart of residues, the local GWR model was the one that best explained the GDP of the municipalities and its relationship with soybean yield, corn yield, pig production, and with the tax on the circulation of goods. In this sense, the results found suggests that these variables contribute to the GDP of municipalities, which corroborates Cellmer et al. (2020) and Sikida et al. (2020) findings. In this focus of analysis, Zasaga et al. (2019) analyzed, through the spatial regression analysis of areas, agricultural yield and food economic growth in different regions of Europe. The results showed significant variations according to the analyzed locations and it was concluded that the analyzed spatial model explained the analyzed variables.



Source: own research

Figure 2: SAR QQ-plot (A), CAR QQ-plot (B), and GWR QQ-plot (C).



Source: own research

Figure 3: SAR worm plot (A), CAR worm plot (B), and GWR worm plot (C).

The results found through the GWR model make clear its predictive capacity to identify the spatial variability of the data, which corroborates Hu et al. (2018) findings. The same authors analyzed soybean yields in China using the GWR model in the 2015-2016 crop year and concluded that the GWR model had a significant goodness-of-fit and greater prediction accuracy in relation to other spatial regression models analyzed.

It is evident, from this information obtained, the broad driving capacity of generating wealth and foreign exchange that the state of Paraná presents. It is important to highlight the possibility of generating favorable mechanisms for the growth and economic development of the agricultural sector in the different municipalities. We emphasize the possibility of developing emerging public policies in favor of the economy that supports agricultural production in all its magnitude of coverage throughout the municipalities of Paraná-Brazil, in agreement with Vieira et al. (2019) and Evans et al. (2020) studies. In this regard Jank et al. (2020) report that Brazil's agricultural economic growth is highly complementary in relation to China and that agricultural productivity associated with economic growth indicators promote economic competitiveness between markets.

Conclusion

There were variations in the Gross Domestic Product (GDP) of the municipalities in 2018 and the effects of soy yield, corn yield, pig production, and the tax on the circulation of goods varied significantly in the 399 municipalities that make up the state of Paraná-Brazil.

The results found here suggest that it is likely that there are differences in the GDP in relation to the yield of soybean, corn, pig production, and the tax on the circulation of goods according to each location.

The SAR and CAR models showed significant goodness-of-fit, but the GWR model behaved better, being the one that best explained the GDP of the municipalities, according to the model validation tests.

The GWR model, considered a local model, was the one that presented more stability when compared to SAR and CAR models, and its use is more consistent in studies that focus on spatial econometrics.

The results show that the indicators: soybean yield, corn yield, pig production, and the tax on the circulation of goods explained the variabilities in the GDP of the municipalities that make up the state of Paraná-Brazil, since they presented statistical significance in the year analyzed. The GWR model was the one that best explained the GDP of the municipalities of the state of Paraná in 2018.

It should be noted that the originality of the article (ineditism) is in the way in which the econometric analysis was approached considering the economic and agricultural variables analyzed, as well as in the treatment that was given in each stage itself. The agricultural and economic scenario was considered in detail, aiming at the criteria and complexity that each statistical technique studied here presents. Thus, the welcoming way the research proposes to the researcher generates exemplary motivation in the universe of scientific knowledge.

It became clear during the work carried out that the overwhelming challenge was to understand, assimilate, and adapt the database according to the methodologies used.

It is suggested that the results found here do not exhaust the subject and that new scientific academic research will be necessary to understand the complexity that involves the spatial analysis of areas. Therefore, research of this scope benefits the economic system as a whole and it is suggestive of analysis in the decision-making of managers, whether in public or private institutions, thus contributing to the growth and development of the economy and promoting the dissemination of knowledge in the scientific community and the business sector.

Given this study, it is pertinent to suggest new works that focus on the spatial analysis of data, among them econometrics and spatial statistics of areas applied in different economic areas that emerges of great importance, considering that this relevance is regional, national, and worldwide.

Therefore, the research showed that the wealth of information contained, and which can be explored in the analysis of spatial data, acts in the sense of presenting accurate diagnoses of the possible events that can be analyzed, favoring scientific research and providing new forms of economic analysis in the broad universe of science.

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