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ORIGINAL ARTICLE

WHAT ROLE DO SOCIAL VARIABLES AND HEALTH PLAY IN THE SPREAD OF COVID-19 IN THE STATE OF MINAS GERAIS – BRAZIL? *

Qual o papel das variáveis sociais e de saúde na propagação da COVID-19 no estado de Minas Gerais – Brasil?

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Abstract

The high rates of COVID-19 lethality have made it necessary to identify groups potentially at risk from the disease. The spread of COVID-19 can be better understood with epidemiological studies combined with socioeconomic evaluations of the affected populations. This study aimed to use spatially explicit analysis to analyze the influence of socioeconomic and health attributes on the viral spread of COVID-19 in the state of Minas Gerais using multiple and spatial regressions. The socioeconomic data were collected using

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the platform of the Instituto de Pesquisa Econômica Aplicada (institute of Applied Economic Research). Subsequently, regression models were constructed, which included spatial error models (SEMs) and spatial lag models (SLMs) for the numbers of COVID-19 cases and deaths. For the socioeconomic and pandemic conditions found in the state of Minas Gerais, the SEM was the most suitable for the dependent variable Cases, while the SLM was the most suitable for the dependent variable Deaths. The results show that municipalities with greater longevity among the citizens, better municipal urban infrastructure, and a lower flow of people on public transport had fewer deaths from COVID-19. This study provides support to pandemic risk mitigation policies and better management of medical resources.

Keywords: Epidemic outbreak; Infection spread; Social-demographic attributes; Epidemiologic models.

Resumo

A alta letalidade da COVID-19 traz evidente a necessidade da identificação dos potenciais grupos de risco da doença. A disseminação da COVID-19 pode ser melhor compreendida com estudos epidemiológicos combinados com avaliações socioeconômicas das populações afetadas. O objetivo desta pesquisa foi usar análise espacialmente explicitas para analisar a influência de atributos socioeconômicos e de saúde na disseminação viral de COVID-19 no estado de Minas Gerais por meio de regressões múltiplas e espaciais. Os dados socioeconômicos foram coletados na plataforma do Instituto de Pesquisa Econômica Aplicada, e posteriormente, foram construídos modelos de regressão incluindo modelos de erro espacial “spatial error models” (SEMs) e de defasagem espacial “spatial lag models” (SLMs) para as variáveis número de casos “Cases” e óbitos “Deaths” por COVID-19. Para as condições socioeconômicas e pandêmicas encontradas no estado de Minas Gerais, o SEM adequou-se melhor para variável dependente ‘Cases’ e o SLM para a variável dependente ‘Deaths’. Os resultados mostram que municípios com maior longevidade, infraestrutura urbana municipal, e menor fluxo de pessoas em transportes públicos apresentam menores ocorrências de óbitos por COVID-19. Este trabalho fornece subsídios a políticas de mitigação de risco de pandemia e melhor gerenciamento de recursos médicos.

Palavras–chave: Surto epidêmico; Propagação da infecção; Atributos sociodemográficos; Modelos epidemiológicos.

1. INTRODUCTION

COVID-19 is an acute respiratory disease originating from China, which was officially declared a public health emergency of international concern (PHEIC**)** by the World Health Organization (WHO) on January 30, 2020 (CAPODEFERRO; SMIDERLE, 2020; MATTHEW; ELUDOYIN; OLUWADIYA, 2021). More quickly than expected, the severe acute respiratory syndrome (SARS) caused by coronavirus was recognized as a disease of global medical interest, being declared a pandemic as of March 11, 2020. By June 28, 2021,

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data demonstrated 180,817,269 infected individuals and 3,923,238 deaths from the disease (WHO, 2021).

Viruses from the family *Coronaviridae* are capable of infecting mammals and other vertebrates. Among the microorganisms able to infect humans, most are responsible for flu-like symptoms (LANSIAUX *et al.,* 2020). However, the SARS-CoV and MERS-CoV viruses cause serious, potentially fatal infections due to the lesions caused to the respiratory tract (HENNING *et al.,* 2021).

Considering the high rates of COVID-19 lethality, attention should be given to the need to identify groups potentially at risk from the disease, and, consequently, promote socioeconomic data evaluation of the affected populations (KHALATBARI-SOLTANI *et al.,* 2020). Moreover, the use of social indicators should be adopted alongside the evaluation of epidemiological data, in view of the possibility of supporting pandemic risk mitigation policies and improving management of medical resources (HENNING *et al.,* 2021).

In its most serious form, COVID-19 is most significant for the elderly population. One of the reasons is the greater occurrence of severe pulmonary infection among older patients, in addition to the increased levels of blood sugar hindering control of the infection, and the risk of cardiac death, according to Liu *et al.,* (2020), who also suggest higher rates of comorbidities in this group.

Furthermore, the immunological system of an elderly individual is not as efficient as that of a young adult. When in a situation of comorbidity (such as obesity or arterial hypertension), the immunological system of the elderly establishes a condition of chronic inflammation, and when the patient is subjected to an infection, such as that caused by SARS-CoV-2, an exaggerated immunological response known as cytokine storm syndrome can occur (MEFTAHI *et al.,* 2020). Thus, longevity represents a social indicator for the epidemiological dynamic of coronavirus.

Other social indicators such as low income and poor education may be related to increased vulnerability to COVID-19, as workers with this profile have greater difficulty carrying out their work in home-office and, therefore, are more exposed to viral transmission (ATCHISON *et al.,* 2021; DE LAROCHELAMBERT *et al.,* 2020).

Brazil has 27 federal states, among which, Minas Gerais (MG) stands out as the second most populous in the country, being composed of 853 municipalities (IBGE, 2021). By June 28, 2021, 1,788,725 cases and 45,924 deaths from COVID-19 had been confirmed in MG (SES-MG, 2021). Studies suggest that the Metropolitan Region of Belo Horizonte (RMBH) and the Vale do Rio Doce Mesoregion were the main epidemic focuses at the

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beginning of the expansion process and had an important influence on the spread of SARS-CoV-2 in the state of Minas Gerais. Regions such as the Triângulo Mineiro and Alto Paranaíba also presented elevated risk of infection from the disease (COURA-VITAL *et al.,* 2021).

In this context, the aim of this study was to analyze the influence of socioeconomic and health attributes on the viral spread of COVID-19 in the state of Minas Gerais through multiple spatial regressions. While many studies have focused on public health variables, exploring the role of comorbidities in the spread of and deaths from COVID-19 (DE LUCENA *et al.,* 2020; EJAZ *et al.,* 2020; SANYAOLU *et al.,* 2020; WANG *et al.,* 2020a, 2020b), studies exploring the role of socioeconomic variables are less frequent (BAYODE *et al.,* 2022; BENITA; GASCA-SANCHEZ, 2021; GREKOUSIS; WANG; LIU, 2021). The relevance of the theme is guided by better understanding of the influence of socioeconomic variables on the spread of COVID-19. This is information that could be used to assist public agents in the identification of regions with greater need for medical and hospital resources (BENITA; GASCA-SANCHEZ, 2021; GREKOUSIS; WANG; LIU, 2021).

2. METHODS

2.1. Characterization

This is an ecological, analytical study that evaluates how social context interferes in the health of the population in the Brazilian state with the second highest population in the country in relation to infection from COVID-19.

2.2 Description of the Study Area

The state of Minas Gerais is located in the southeast of Brazil (Figure 1), between 14º13’58” and 22º54’00” S and 39º51’32” and 51º02’35” W (Gov-MG, 2021). The state covers an area of 586,528.293 km² and is territorially divided into 853 municipalities, with a total population of 21,292,666 inhabitants and a demographic density of 36.30 inhab/km².

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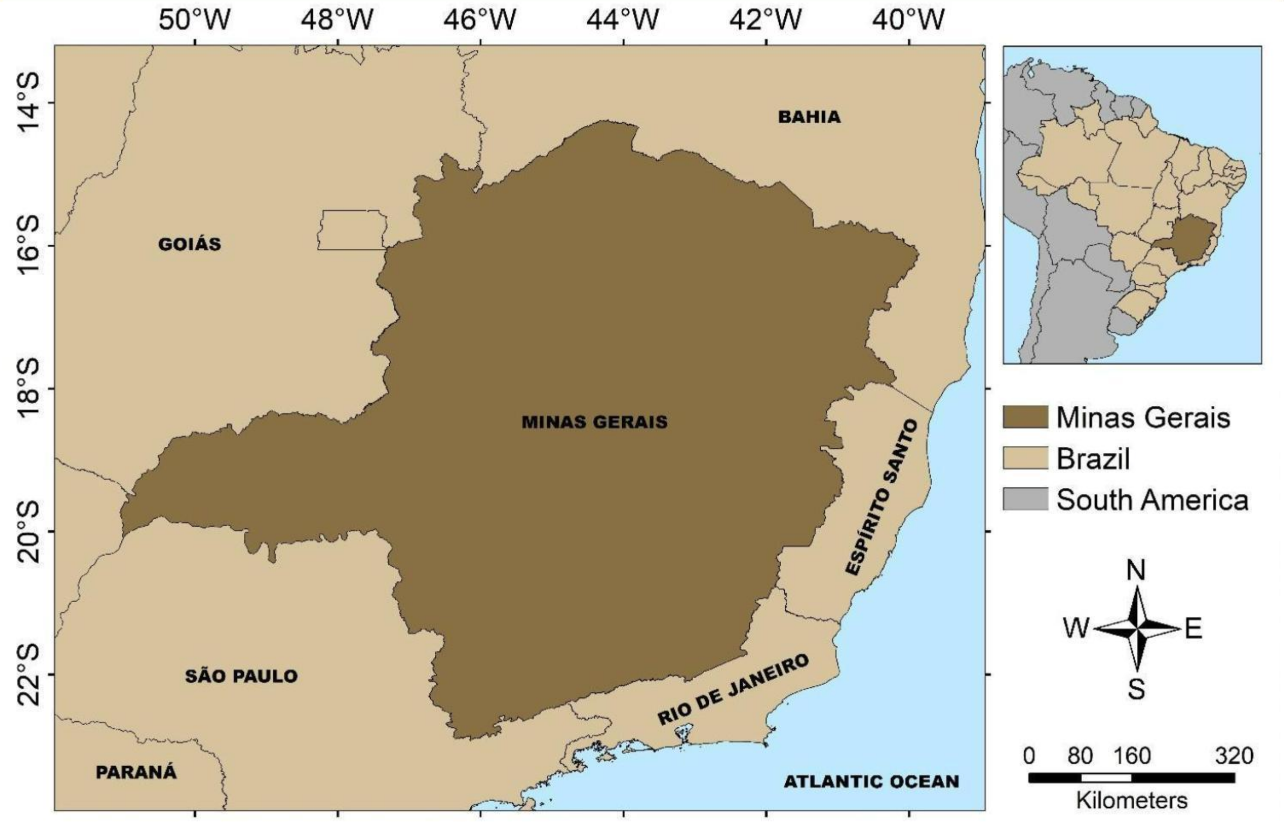

Figure 1 – Map of the location of Minas Gerais, Brazil.
Source: Prepared by the authors.

2.3. Variables considered in the study

Initially, documental research was carried out on the epidemiological attributes of the state of Minas Gerais (MG) (SES-MG, 2021), the socioeconomic data, which was collected from the platform of the Instituto de Pesquisa Econômica Aplicada (Institute of Applied Economic Research) (IPEA, 2021), and the data referring to the population of the municipalities of Minas Gerais (FJP, 2019) (Table 1).

Table 1 – Summary of the variables.

Variable	Abbreviation	Source	Scale
Vulnerability Rate	VR	(COSTA; MARGUTI, 2015)	Municipal
Urban infrastructure - Social Vulnerability Index	UI-SVI	(COSTA; MARGUTI, 2015)	Municipal
Longevity - Municipal Human Development Index	L-MHDI	(PINTO; COSTA; MARQUES, 2013)	Municipal
Aging Rate	AR	(PINTO; COSTA; MARQUES, 2013)	Municipal
COVID-19 cases	Cases	(SES-MG, 2021)	Municipal
COVID-19 Deaths	Deaths	(SES-MG, 2021)	Municipal
Standardized population	STD-P	Adapted from FJP (2019)	Municipal

Source: Prepared by the authors.

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Among the variables made available by IPEA, the following were selected and evaluated: vulnerability rate (VR); the subindex of the municipal human development index (MHDI): MHDI-Longevity (L-MHDI); the subindex of the social vulnerability index (SVI): Urban Infrastructure (UI-SVI); and the Aging Rate (AR).

The VR and UI-SVI variables were developed by Costa and Marguti (2015) and are defined as follows: (i) VR is related to the percentage of people that live in households with a per capita income of less than half a minimum wage (R$255,00 or $141,50 in 2010, the year when the raw data was obtained through the demographic census) and that spend more than an hour to get to work in relation to the total number of people that live in households with a per capita income of less than half a minimum wage; (ii) the UI-SVI subindex is composed of indicators related to basic sanitation, garbage collection, and the urban mobility available to low-income families.

The L-MHDI subindex is related to life expectancy at birth (PINTO; COSTA; MARQUES, 2013), while the AR variable is composed of the percentage of people aged 65 and older in relation to the total municipal population.

Municipal population data updated by the Tribunal de Contas da União (Federal Court of Auditors) in 2019 (FJP, 2019) were also used. The population data were standardized (STD-P) to prevent the absolute population number from interfering in the statistical analysis. This variable was standardized using the Z-score method, whereby the values of each observation were subtracted from the mean of the variable and the result was divided by the value of the standard deviation. The result of these calculations is the Z value associated with the observation of interest.

The data referring to COVID-19 were obtained through the epidemiological bulletins of the Secretaria de Estado de Saúde de Minas Gerais (Minas Gerais State Health Secretary) (SES-MG, 2021). This database refers to the social and epidemiological data of the 853 municipalities in the target state. The data were individually organized and separated by each municipality. The number of cases and the number of deaths accumulated as a result of COVID-19 refer to the period of the first wave of infection in Brazil, from March to October 2020 (CERQUEIRA *et al.,* 2022).

A database was created from the obtained data, which was subsequently used to execute the multivariate regression analysis using R Core Team software (R Core Team, 2021)**.**

No missing values were found among the data used. The absolute quantities of cases and deaths in the most populous municipalities are linked to the larger number of inhabitants

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in these places, which explains the outliers that were found. Removing these outliers from the function would result in a low degree of adjustment of the functions, as such, they were maintained in the analysis. Outliers are values that go beyond the upper and lower limits of the variable, which commonly occurs through typing errors or during data collection; however, in this case, the outlier occurs because Belo Horizonte is the city with the highest absolute numbers of COVID-19 cases and deaths in the state of Minas Gerais.

2.4. Statistical analyses

2.4.1. Spatial autocorrelation of the COVID-19 cases and deaths dependent variables

Global Moran's I was obtained using GeoDa software (ANSELIN; SYABRI; KHO, 2010) and a spatial association (autocorrelation) was verified between COVID-19 Cases and Deaths. Maps were then generated using Local Moran I (LISA), on which significant autocorrelated groupings were highlighted. The tests used the localizations *yi* and the weighted mean of the neighboring values *wyi*, which resulted in the Moran scatter plot represented by a straight line centered on the point of coordinates *yi* = 0 and *wyi* = 0, being thus divided into four quadrants. The upper-right quadrant and the lower-left quadrant correspond to positive associations, there being positive values surrounded by positive values in the upper-right quadrant and negative values surrounded by negative values in the lower-left quadrant. The lower-right and upper-left quadrants demonstrate negative associations, that is, in the lower-right quadrant there are positive values surrounded by negative values and in the upper-left quadrant, negative values surrounded by positive values (ANSELIN, 1995; CHI; ZHU, 2008).

2.4.2. Regression models

For the regression models, number of COVID-19 cases (Cases) and number of COVID-19 deaths (Deaths) were used as dependent variables, and the other variables were introduced through the Stepwise method (THOMPSON, 1995), as explanatory variables. Subsequently, the multiple linear regression (MLR) predictions were verified, and no transgression was found.

Global Moran's I was verified in the residuals of the two ordinary least squares (OLS) regression models for verification of spatial dependence in the errors, using the neighbors matrix for contiguity in the queen model. The Lagrange multiplier test (ASTAIZA-GÓMEZ, 2020) was then applied to select the spatial regression models to be applied to each of the

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two dependent variables. Significance at a level of 1% on the robust Lagrange multiplier test was adopted as selection criteria for the modelling method to be used for each set of variables. As such, the spatial error model (SEM) and the spatial lag model (SLM) were adjusted for the response variables of Deaths and Cases. The spatial error model adjustments were verified using the Hausman spatial test (KELLEY PACE; LESAGE, 2008). The spatial lag model adjustments were verified using simulation of the significance of direct and indirect impacts attributed to the independent variables used in each of the SLMs.

3. RESULTS

The spatialization of COVID-19 cases and deaths accumulated during the period corresponding to the first wave of infection (March to October 2020) for the municipalities in the state of Minas Gerais is presented first (Figure 2).

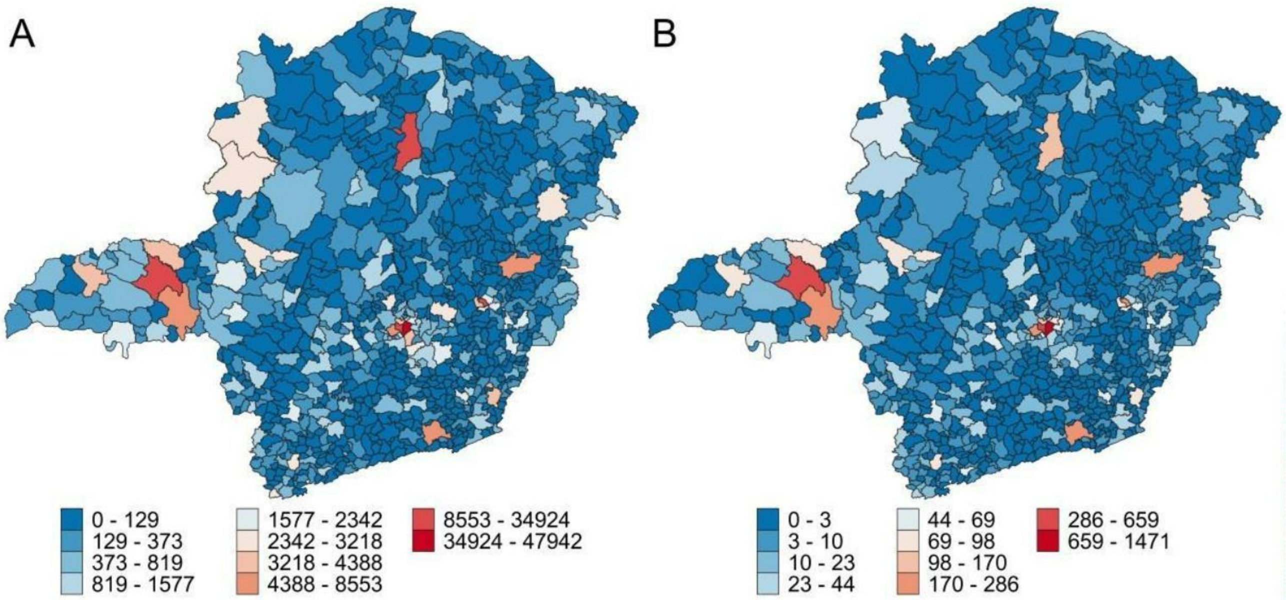

Figure 2 – Spatialization of COVID-19 data in the state of Minas Gerais, Brazil. Data accumulated from March 2020 to the end of October 2020. A) Distribution of cases due to SARS-CoV-2 infection. B) Distribution of deaths.
Source: Prepared by the authors.

Through the application of Global Moran's I, the existence of a spatial autocorrelation was found in the data on number of COVID-19 cases and deaths in relation to the populations of the municipalities of Minas Gerais (Figure 3).

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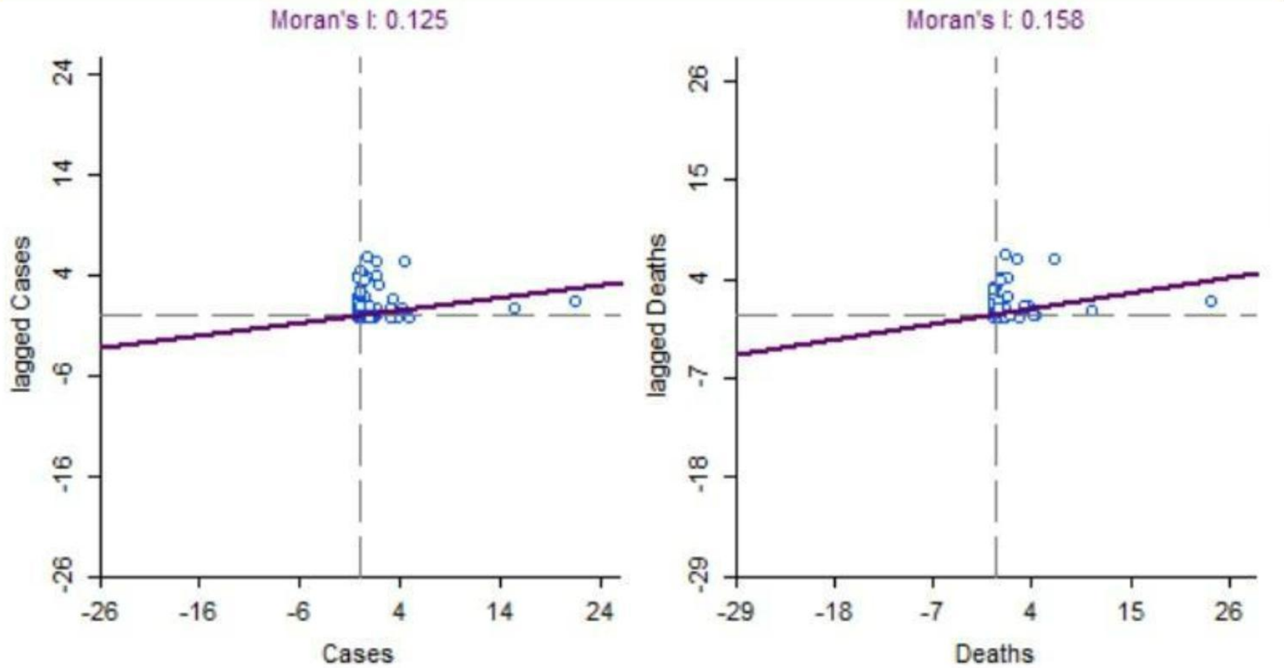

Figure 3 – Global Moran scatter plot for variables of cases and deaths from SARS-CoV-2 in the state of Minas Gerais, Brazil (Mar-Oct. 2020).
Source: Prepared by the authors.

Through analysis of the Moran scatter plots, a positive spatial autocorrelation was found, in which municipalities with high numbers of COVID-19 cases or deaths tended to be surrounded by neighboring municipalities also with high numbers of cases or deaths. The same principle can be observed for municipalities with low numbers of COVID-19 cases or deaths. For better visualization of the spatial autocorrelation, Local Moran's Is were calculated (Figure 4).

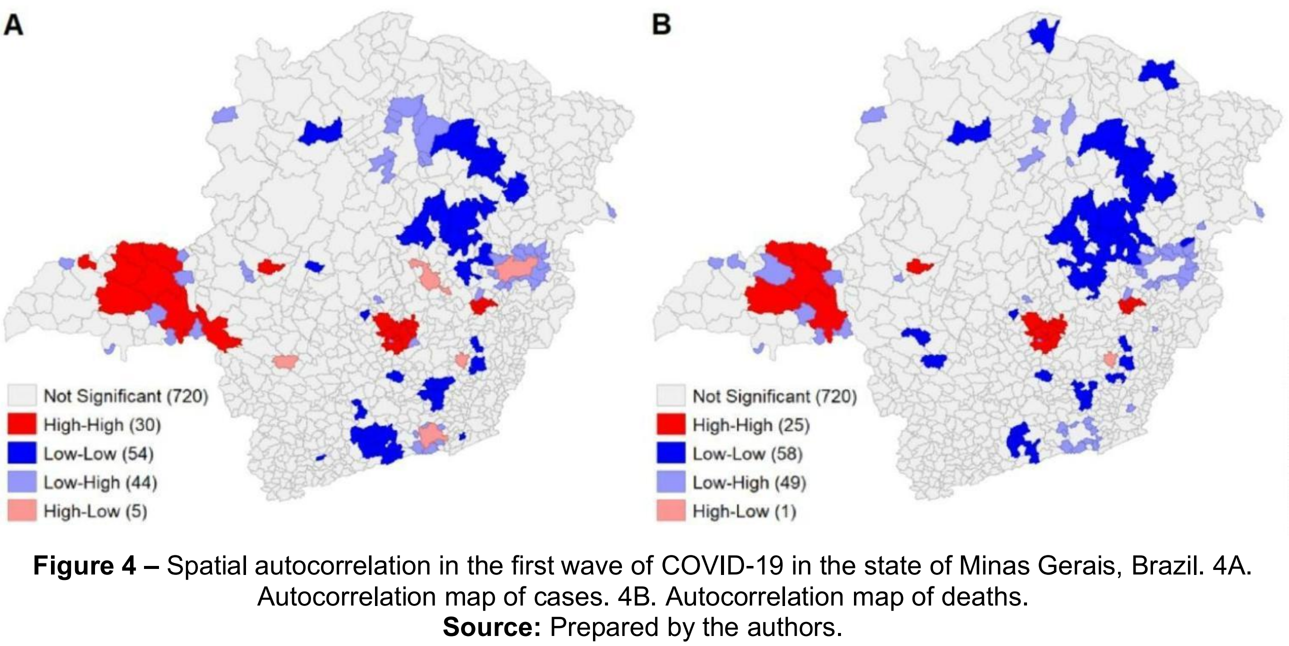

Figure 4 – Spatial autocorrelation in the first wave of COVID-19 in the state of Minas Gerais, Brazil. 4A. Autocorrelation map of cases. 4B. Autocorrelation map of deaths.
Source: Prepared by the authors.

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The multiple linear regression models (MLRs) for the different sets of variables were better adjusted when the Stepwise method was used. The MLR models have distinct explanatory variables (independent) for the response variables (dependent) of numbers of COVID-19 cases and deaths.

The model defined for the number of cases indicated two significant independent variables. This model and the explanatory variables can be seen in Table 2.

Table 2 – OLS regression for the dependent variable Cases.

	Estimate	Std. Error	t value	Pr(>|t|)	Tolerance	VIF
Intercept	167.2840	45.3670	3.6870	0.0002	-	-
STD-P	2071.6560	29.6130	69.9580	0.0000	0.9639	1.0374
VR	-15.4870	5.6620	-2.7350	0.0064	0.9639	1.0374
Multiple R-squared: 0.8549, Adjusted R-squared: 0.8546						
F-statistic: 2505 on 2 and 850 DF, p-value: < 2.2e-16						

Source: Prepared by the authors.

The first MLR model was significant, explaining the behavior of 85.46% of the number of cases through these two independent variables. According to the variance inflation factor (VIF) value for each explanatory variable, there was no multicollinearity between the variables.

For the MLR model with COVID-19 deaths as the dependent variable, five independent variables were found. The model had adjusted R^2 of 94.04% (Table 3).

Table 3 – OLS regression for the dependent variable Deaths.

	Estimate	Std. Error	t value	Pr(>|t|)	Tolerance	VIF
Intercept	41.4169	16.5355	2.5050	0.0124	-	-
Cases	0.0266	0.0002	112.3020	0.0000	0.9377	1.0664
VR	0.7081	0.1733	4.0860	0.0000	0.3169	3.1551
AR	0.5855	0.2635	2.2220	0.0265	0.9602	1.0415
L-MHDI	-58.7739	19.4907	-3.0150	0.0026	0.7707	1.2976
UI-SVI	-18.6187	7.3303	-2.5400	0.0113	0.2904	3.4434
Multiple R-squared: 0.9408, Adjusted R-squared: 0.9404						
F-statistic: 2691 on 5 and 847 DF, p-value: < 2.2e-16						

Source: Prepared by the authors.

The variable with the greatest impact on the function was the number of COVID-19 cases, given that it is not possible to have deaths from the disease without having cases of the same. The second most important explanatory variable was VR, followed by L-MHDI,

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UI-SVI, and AR, respectively. It is noteworthy that the explanatory variables of Cases, VR, and AR are directly proportional, contrasting with the variables L-MHDI and UI-SVI.

After confirming the existence of a spatial autocorrelation in the residuals of the OLS models through Global Moran's I (Cases = 0.1033; Deaths = 0.0949), the Lagrange multiplier test was applied to verify the method of the spatial model to be applied (Table 4).

Table 4 – Lagrange multiplier test.

	Test	Result	p-value
Deaths	Lmerr	20.1940	7.00E-06
	Lmlag	22.4120	2.20E-06
	RLMerr	10.4500	1.23E-03
	RLMlag	12.6680	3.72E-04
Cases	Lmerr	23.9100	1.01E-06
	Lmlag	0.0998	7.52E-01
	RLMerr	31.4910	2.00E-08
	RLMlag	7.6810	5.58E-03

Source: Prepared by the authors.

There was a greater level of significance for the spatially lagged spatial dependence structure for the dependent variable Deaths than for the autocorrelation structure in errors, when robust diagnostic tests were taken into consideration (MLRlag and MLRerr, respectively). The opposite was observed for the dependent variable Cases.

Considering the criterion of 1% significance on the robust Lagrange multiplier diagnostic test, both spatial models, SEM and SLM, were selected to model the dependent variables of Cases and Deaths. Adjustments to the spatial models were found from the sets of variables that best modelled the respective dependent variables through MLR (Tables 5, 6, 7, and 8). The result of the Hausman spatial test for validation of the adjusted SEM models can be observed in Tables 5 and 6.

Table 5 – Spatial Error Model for the dependent variable Cases.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	153.5790	51.1049	3.0052	0.0027
STD-P	2085.6600	29.6845	70.2609	0.0000
VR	-12.8595	5.8593	-2.1947	0.0282
Lambda: 0.20437, LR test value: 18.363, p-value: 0.000018256				
Wald statistic: 16.034, p-value: 0.00006221				
Spatial Hausman test = 5.1663, df = 3, p-value = 0.16				

Source: Prepared by the authors.

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Table 6 – Spatial Error Model for the dependent variable Deaths.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	31.3724	16.9979	1.8457	0.0649
Cases	0.0265	0.0002	113.0656	0.0000
VR	0.3518	0.1812	1.9414	0.0522
AR	0.7191	0.2844	2.5282	0.0115
L-MHDI	-47.9822	20.1030	-2.3868	0.0170
UI-SVI	-7.2494	7.6786	-0.9441	0.3451
Lambda: 0.24093, LR test value: 19.906, p-value: 0.0000081342				
Wald statistic: 23.194, p-value: 0.0000014648				
Spatial Hausman test = 64.599, df = 6, p-value = 5.21e-12				

Source: Prepared by the authors.

Table 7 – Spatial Lag Model for the dependent variable Cases.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	167.6076	45.2865	3.7010	0.0002
STD-P	2073.4858	30.2929	68.4479	0.0000
VR	-14.9066	6.0197	-2.4763	0.0133
Rho: -0.0074912, LR test value: 0.096132, p-value: 0.75652				
Wald statistic: 0.092352, p-value: 0.76121				

Source: Prepared by the authors.

Table 8 – Spatial Lag Model for the dependent variable Deaths.

	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	37.3502	16.2514	2.2983	0.0215
Cases	0.0264	0.0002	111.9597	0.0000
VR	0.3195	0.1827	1.7483	0.0804
AR	0.7694	0.2611	2.9471	0.0032
L-MHDI	-56.5489	19.1499	-2.9530	0.0031
UI-SVI	-8.5403	7.3824	-1.1568	0.2473
Rho: 0.079466, LR test value: 23.117, p-value: 0.0000015241				
Wald statistic: 24.66, p-value: 0.00000068404				

Source: Prepared by the authors.

In addition, the impacts of the independent variables used in the spatial lag models were measured (Tables 9 and 10). Inferences on the direct and indirect impacts related to the parameters obtained for the independent variables of the spatial lag model were simulated using the Markov Chain Monte Carlo (MCMC) estimation method for Bayesian inference (GELFAND *et al.,* 1990; LESAGE, 1997; LESAGE; PACE, 2009).

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Table 9 - Spatial Lag Model impact tests for Cases.

	Variables	Direct	Indirect	Total
Impact measures	STD-P	2073.5060	-15.4376	2058.0684
	VR	-14.9067	0.1110	-14.7957
Simulated z-values	STD-P	70.5097	-0.3429	40.5894
	VR	-2.5453	0.2114	-2.4965
Simulated p-values	STD-P	0.0000	0.7316	0.0000
	VR	0.01092	0.83261	0.012542

Source: Prepared by the authors.

Table 9 shows the simulated p-values for the SLM impacts for the dependent variable Cases. The independent variables STD-P and VR had significant direct impacts and insignificant indirect impacts.

Table 10 - Spatial Lag Model impact tests for Deaths.

	Variables	Direct	Indirect	Total
Impact measures	Cases	0.0264	0.0022	0.0287
	VR	0.3198	0.0272	0.3471
	AR	0.7703	0.0655	0.8358
	L-MHDI	-56.6127	-4.8178	-61.4306
	UI-SVI	-8.5500	-0.7276	-9.2776
Simulated z-values	Cases	118.3050	5.0383	58.6114
	VR	1.7849	1.7663	1.7962
	AR	2.8907	2.3556	2.8704
	L-MHDI	-2.9474	-2.5188	-2.9458
	UI-SVI	-1.0653	-1.0241	-1.0656
Simulated p-values	Cases	0.0000	0.0000	0.0000
	VR	0.0743	0.0773	0.0725
	AR	0.0038	0.0185	0.0041
	L-MHDI	0.0032	0.0118	0.0032
	UI-SVI	0.2867	0.3058	0.2866

Source: Prepared by the authors.

However, the impact tests in relation to the SLM for the dependent variable Deaths (Table 10) demonstrated that the variables UI-SVI and VR were not significant at the 5% level of probability. On the other hand, the independent variables Cases, AR, and L-MHDI had significant direct and indirect impacts.

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4. DISCUSSION

Through the analysis of the results, it was possible to perceive that there was no great spatial dependence in the disposition of the numbers of COVID-19 cases and deaths. However, clusters were identified in certain regions of the state through positive spatial autocorrelation, that is, locations with positive values were surrounded by neighbors with positive values and locations with negative values were surrounded by neighbors with negative values. Moreover, the variables that were significant in the Linear Regression Models indicate that the independent variables influenced the numbers of cases and deaths.

It is noteworthy that the variables that explain the behavior of the variables Cases and Deaths were different when the multiple regression models were analyzed. For the dependent variable Cases, the number of inhabitants and the vulnerability rate managed to explain 85.46% of the observations; whereas for Deaths (adjusted r^2 = 94.04%), the independent variable with the greatest significance was Cases, followed by VR.

Through the application of the Lagrange multiplier test on the OLS residuals, significant values were obtained in relation to the spatial dependence structure (Table 3). The SLM and SEM were selected for Cases and Deaths due to the robust diagnostic test results. With the application of the robust tests, possible interference of the spatial autocorrelation in the errors was considered, when spatially lagged dependence of the variables and vice-versa were evaluated (ANSELIN *et al.,* 1996).

Evaluation of the OLS and SEM models through application of the Hausman spatial test, enabled the inference that the analogue coefficients estimated for the set of variables with the dependent variable Deaths were statistically different (p-value = 0.00). However, the insignificant p-value (0.16) of the Hausman spatial test for the OLS and SEM models for the dependent variable Cases indicated that the coefficients of the parameters did not differ statistically (KELLEY PACE; LESAGE, 2008). Therefore, it was considered that the adjustment of the OLS and SEM models was suitable for Cases and unsuitable for Deaths. Nevertheless, it is worth emphasizing that the OLS models resulted in high R^2 values and that the p-values of the autoregressive coefficients of the SEM models were significant (λ_{Cases} = 0.000018256 and λ_{Deaths} = 0.0000081342).

When analyzing the variables of the SLM models after carrying out the tests, the direct and indirect impacts of the variables can be interpreted separately. According to LeSage and Pace (2009), the changes observed in the independent variables in relation to a given municipality can potentially affect the dependent variable in the other municipalities.

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In the SLM for Cases, the variables STD-P and VR only led to an increase in the number of COVID-19 cases within the municipalities; there was no indirect impact. However, in the SLM model for Deaths, the independent variables VR and UI-SVI did not have a significant impact at the 5% level of probability. It can be observed that as with the SLM model for Deaths, the independent variables VR and UI-SVI were not significant for the SEM model for Deaths. This contrasted with the significance of these independent variables in the model obtained through MLR to model Deaths.

The independent variable STD-P only had a direct impact on transmission of SARS-CoV-2, indicating that in municipalities with larger populations, there was a larger number of cases of the pandemic disease. Within the SLM model for Cases, the direct impact of VR demonstrated that there was greater transmission of the virus in municipalities with an increased flow of people with low income on public transport. According to Moreno *et al.,* (2021), genetic material from different genomes of SARS-CoV-2 was found in underground trains and on buses in the city of Barcelona, demonstrating the risk of using public transport during the pandemic. In Brazil, collective public transport is used mainly by people with medium and low incomes (CARVALHO; PEREIRA, 2012).

The independent variable L-MHDI, related to longevity of the population, had significant direct and indirect impacts in the SLM model for Deaths. The result indicates that in municipalities where the population achieves greater longevity, and in the neighboring municipalities, there was a reduced number of COVID-19 deaths as the coefficient of the variable had a negative value. According to Pinto *et al.,* (2013), a higher L-MHDI value in a given municipality may suggest that there are better living conditions and access to health services for the resident population. As such, the direct and indirect impacts of the variable L-MHDI may be associated with the hospital infrastructure existing in each municipality and the access available to the resident and floating population (from neighboring cities).

Also regarding SLM for the dependent variable Deaths, it was found that the independent variable AR directly and indirectly impacts the number of deaths in the municipalities of the state of Minas Gerais. The direct impact of the variable was the most significant for the model (p-value = 0.0032 against 0.0118) and demonstrates that in municipalities with a higher aging rate there was a greater number of COVID-19 deaths. This result reiterates the findings of Liu *et al.,* (2020) and Mefhati *et al.,* (2020), who stated that the increased frailty (cellular and systemic) of the elderly, combined with contamination from the disease, can lead to more severe pulmonary infections and trigger immunological complications, which increases the chance of lethality for these individuals.

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COVID-19 spread throughout the state of Minas Gerais and, as reported by Oronce *et al.,* (2020), certain socioeconomic factors have been identified as relevant to increasing the probability of transmission and deaths from the disease. Regions with larger populations where a considerable portion of the population are found in a situation of vulnerability (SANNIGRAHI *et al.,* 2020; YILDIRIM; GEÇER; AKGÜL, 2021), as in the Metropolitan Region of Belo Horizonte and the west of the state, were severely affected by the disease.

The present study shows that municipalities with populations with greater longevity, better municipal urban infrastructure, and a lower flow of people on public transport present less COVID-19 deaths. Therefore, this study provides support to mitigating the spread of the disease, emphasizing the need for investment in the cleaning and maintenance of transport infrastructure in areas with higher transmission rates. A study carried out in Turkey identified prominent preventative practices against COVID-19, such as limitations on the use of collective transport and the frequent washing of hands. In the United States, Karmakar *et al.,* (2021) identified that in counties where there was greater social vulnerability, there were higher rates of transmission and death from the disease.

It can be observed through this study that each dependent variable was best explained by distinct spatial regression models. For the socioeconomic and pandemic conditions found in the state of Minas Gerais, SEM was most suitable for the dependent variable Cases, and SLM was most suitable for the dependent variable Deaths.

4. CONCLUSIONS

It was observed in this study that spatial regression models are important for studies involving socioeconomic variables and their relationships with COVID-19, especially SLM, due to the possibility of individual evaluation of the direct and indirect impacts associated with each independent variable used in the models. It has been conclusively demonstrated that municipalities with greater longevity, better municipal urban infrastructure, and a lower flow of people on public transport had less COVID-19 deaths. These findings value the evaluation of socioeconomic data for the contention of diseases such as COVID-19, or even for directing healthcare and financial resources to places of risk.

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