A spatial analysis of the COVID-19 epidemic spreading over time in two of the most populous brazilian states

Uma análise espacial do espalhamento da epidemia de COVID-19 ao longo do tempo nos dois estados brasileiros mais populosos

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Jorge Garcia Filho
Doutorando em Estatística e Experimentação Agropecuária
Institution: Universidade Federal de Lavras
Address: Trevo Rotatório Prof. Edmir Sá Santos, s/n, Lavra - MG, CEP: 37200-900
E-mail: garcia.jorge.j@gmail.com

Thelma Safadi
Doutora em Estatística
Institution: Universidade Federal de Lavras
Address: Trevo Rotatório Prof. Edmir Sá Santos, s/n, Lavras - MG, CEP: 37200-900
E-mail: safadi@ufla.br

Deive Ciro Oliveira
Doutor em Bioinformática
Institution: Universidade Federal de Alfenas
Address: Avenida Alfredo Braga de Carvalho, 303, Industrial JK, Varginha - MG, CEP: 37062-440
E-mail: deive.oliveira@unifal-mg.edu.br

Angélica Sousa da Mata
Doutora em Física
Institution: Universidade Federal de Lavras
Address: Trevo Rotatório Prof. Edmir Sá Santos, s/n, Lavras - MG, CEP: 37200-900
E-mail: angelica.mata@ufla.br

Elias Silva Medeiros
Doutor em Estatística e Experimentação Agropecuária
Institution:Universidade Federal da Grande Dourados
Address: Rua João Rosa Góes, nº 1761, Vila Progresso, Dourados - MS, CEP: 79825-070
E-mail: eliasestatistica@gmail.com

Renato Ribeiro de Lima
Doutor em Estatística e Experimentação Agronômica
Institution: Universidade Federal de Lavras
Address: Trevo Rotatório Prof. Edmir Sá Santos, s/n, Lavras - MG, CEP: 37200-900
E-mail: rrlima@ufla.br

ABSTRACT
The entire world is still trying to understand and stop the spread of the COVID-19 disease. It is known that the evolution of human mobility associated with economic, geographic and demographic factors have caused differences in the spatial spread of the new coronavirus in distinct countries and regions and has also contributed to the rapid spread of the disease. The characterization of the spatial patterns of disease spreading involves environmental and social factors. In this context, we used statistical tools to investigate the spatial distribution of the incidence and mortality rates over time in two of the most populous Brazilian states: São Paulo and Minas Gerais. Our results show an spatial dependence among micro-regions related to incidence and mortality rates but with different spatial autocorrelations in both states. We used the VAR model to verify this causal relationship among the micro-units that showed spatial dependence. We found that there is a feedback relationship and also causality between some investigated areas. We also show that the heterogeneity of the spatial distribution of ICU beds, associated with the age stratification of the population, can explain the difference of the mortality rate in each subregion. Our findings indicate that government agencies should consider these regional differences when planning specific public health policies for each region.

Keywords: Coronavirus, VAR Model, spatial spreading, incidence rate, mortality rate.

RESUMO
O mundo inteiro ainda está tentando entender e impedir a propagação da doença COVID-19. Sabe-se que a evolução da mobilidade humana associada a fatores econômicos, geográficos e demográficos tem causado diferenças na propagação espacial do novo coronavírus em países e regiões distintas e também tem contribuído para a rápida propagação da doença. A caracterização dos padrões espaciais de propagação da doença envolve fatores ambientais e sociais. Neste contexto, utilizamos ferramentas estatísticas para investigar a distribuição espacial das taxas de incidência e mortalidade ao longo do tempo em dois dos estados brasileiros mais populosos: São Paulo e Minas Gerais. Nossos resultados mostram uma dependência espacial entre micro-regiões relacionadas a taxas de incidência e mortalidade, mas com diferentes autocorrelações espaciais em ambos os estados. Utilizamos o modelo VAR para verificar esta relação causal entre as micro-regiões que demonstraram dependência espacial. Constatamos que existe uma relação de feedback e também uma causalidade entre algumas áreas investigadas. Mostramos também que a heterogeneidade da distribuição espacial dos leitos de UTI, associada à estratificação etária da população, pode explicar a diferença da taxa de mortalidade em cada subregião. Nossas descobertas indicam que os órgãos governamentais devem considerar essas diferenças regionais ao planejar políticas de saúde pública específicas para cada região.

Palavras-chave: Coronavírus, Modelo VAR, propagação espacial, taxa de incidência, taxa de mortalidade.

1 INTRODUCTION

In Brazil, the first case of COVID-19 disease was confirmed in February 26th, 2020, in the city of São Paulo [1]. Thereafter the epidemic spread fast throughout the entire country, despite of the implementation of social distancing measures. Until August

8th, 2020, which is the last day of the analyzed data in this paper, Brazil presented 2,394,513 confirmed cases and 86,449 deaths caused by the COVID-19, according to the Ministry of Health [2].

The spatial and temporal evolution of the epidemic in different Brazilian states can present distinct and complex patterns, as many researchers have reported [1, 3, 4, 5, 6, 7, 8, 9]. For this reason, the use of statistical methods is very important to understand this spreading process. We investigated the two most populous Brazilian states, São Paulo and Minas Gerais, with 45.9 and 21.1 million inhabitants, respectively, which in total corresponds to 32.2% of the brazilian population, according to IBGE (Instituto Brasileiro de Geografia e Estatística) [10].

The data set corresponds to the period from March 22th, 2020 until August 8th, 2020. First, we analysed how the density of intensive care beds (per 105 inhabitants) are spatially distributed in every healthy micro-regions of both states [11]. The micro-regions of each Brazilian state are formed by a set of cities, which are organized according to their features, such as location and the social and economic relations among the municipalities [12].

Then, we investigated the dispersion of the disease by using the analysis of spatial autocorrelation over time, the incidence and the mortality rates (both per 105 inhabitants). Finally, we verified the Granger's causal relationship between these regions with spatial autocorrelation by using the vector autoregressive (VAR) model [13].

The manuscript is divided as follows: in the section 2, we presented the dataset and the statistical methodology of this research, in the section 3, we described our results related to both states: São Paulo and Minas Gerais. Finally, in the section 4, we discussed the main points of our results and we presented our final remarks. We hope that our results provide insights for understanding the dynamics of the COVID-19 disease, and help in the prevention and control of new outbreaks.

2 DATA AND METHODOLOGY

2.1 DATASET

The micro-regions of the States of São Paulo and Minas Gerais were defined by considering information from the IBGE (free availabe at https://biblioteca.ibge.gov.br) [12], updated by using information obtained from the Ministry of Health (free available at http://www.saude.mg.gov.br) [14] used to characterize the administrative health units regionally. There are 89 and 63 micro-regions in the states of Minas Gerais and São Paulo, respectively. For more details see appendix A where it is shown on a table with all micro-regions (administrative micro health units) of both states, named by the main city of each of them.

With data from the subdivisions of both states, we analysed the spread of the COVID-19 in these regions from March 22th, 2020 to August 8th, 2020. The database was provided by the Brazilian Health Government and organized by Brasil.io platform [15], which can be freely accessed. We analysed the number of cases and the death rate during the period mentioned, that corresponds to 19 epidemiological weeks.

2.2 METHODOLOGY

We considered spatial and time analysis independently. Although there are methods for spatio-temporal analysis in lattice data [16, 17], the inferential methods for spatio-temporal dependency indicators still have limitations, and they can present different results depending on the premise adopted [17]. Therefore, the spatial analysis of incidence and mortality rates over time was chosen as a more plausible methodology for the analysis of our data. In the following, we describe how such approaches were made.

2.3 SPATIAL ANALYSIS

The main types of spatial data, as described in [18], are the random surface data, point process data and lattice data, with different methods to describe or analyze them. For our purpose, the lattice data is the most suitable because we obtained all quantities for every partition or micro-region considered in this study. Therefore, the data generating process is modeled through an spatial stochastic process in the perspective of lattice data.

The lattice data is characterized by the spatial stochastic process where we have an R region that will be partitioned in i polygons Ai, with i = 1, 2, …, n, and in each area is measured variable y_i, so that:

$$\{Y(A_i): A_i \in R \subset \mathbb{R}^d\}$$

where: $Y(A_i)$ is the vector of random variables, $Y(A_i) = \{y_1, y_2, \dots, y_n\}$, A_i are the partitioned areas of the studied region.

The neighborhoods areas of A_i are denominated A_j with $i = 1, 2, \dots, n$ and $j = 1, 2, \dots, n$, being that the interaction geography of areas is defined per $i \neg j$. This neighborhood relation generates two implications for the partitioned areas:

- $\bigcup_{i=1}^{n} A_i = R$
- $A_i \cap A_j = \emptyset$

As the variable will be measured in each area of region R, the exact location of the occurrence of the variable is not given, but a representative value for each area Ai is obtained. Therefore, it becomes necessary to use tools that are able to capture and to measure the spatial relationship among the areas. The spatial proximity matrix **W** represent the neighborhood relationship among the areas in the studied region. There are several ways of constructing the **W** matrix, which can be found described in detail in references [19, 20]. In this paper, the **W** matrix was built considering the "queen" contiguity criterion in which all areas are considered as neighborhood if they have physical borders in common.

To investigate the behavior of the incidence and mortality rates, focusing on the descriptive analysis of spatial autocorrelation, we used the global and local Moran's I indexes. The global Moran's coefficient (Moran's I) was used to quantify and to verify the significance of the spatial dependence among the micro- regions, for each week. The global Moran's I captures spatial autocorrelation for the entire study region, but cannot detect the formation of spatial patterns among the areas [21]. We also used the local Moran's I, which is important to detect clusters with similar areas or composed by areas which present different patterns inside the study region. Both indicators generally have values between [-1,1]. where values close to zero indicate no spatial dependence among the areas, negative values mean negative autocorrelation (dissimilarity) and positive values mean positive autocorrelation (similarity) among the areas.

The global Moran's I [22] is given by:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(y_i - \bar{Y})(y_j - \bar{Y})}{\sum_{i=1}^{n} w_{ij}\,(y_i - \bar{Y})^2}$$

while its local version, proposed by [21], is given by:

$$I_{(i)} = (y_i - \bar{Y}) \frac{\sum_{i=1}^{n} w_{ij}\,(y_i - \bar{Y})}{\frac{\sum_{i=1}^{n}(y_i - \bar{Y})^2}{n}}$$

where: y_i is the value of the y attribute observed in the i^{th} area, y_j is the value of the y attribute observed in the j^{th} area, $\bar{Y}$ is the mean of the Y attributes of the studied region; and w_{ij} is the element of the spatial proximity matrix referring the interaction between the areas i and j.

Now, we need to calculate the statistical significance of the global and local Moran's I. According to [19], there are two main approaches to testing the values observed from Moran's I index, assuming there is no spatial autocorrelation in the data: the asymptotic normality test and the random permutation test. The inference for the global and local Moran's I was performed by using the random permutation test, because as reported in the literature, it presents better results when compared to the asymptotic normality test [23, 24], in addition to control satisfactorily the type I and type II error rates [25].

The spatial autocorrelation analysis provides the areas that have a spatial dependency relationship for the same variable under study. However this measurement does not show a causal relationship between the variables in the areas of the studied region, that can be investigated by means of a temporal analysis, using the Granger indicator, as explained below.

2.4 TEMPORAL ANALYSIS

For temporal systems, Granger [13] investigated causality in terms of predictability. Consider that the variable Y causes the variable Z, with respect to a given universe of information (includes Y and Z). There is causality if present values of Z, (Z_t), can be predicted more efficiently using past values of Y, (for example Y_{t-1} and Y_{t-2}), rather than using any other available information (including past values of Z) [26].
Considering a vector autoregressive model, VAR, and a multivariate series Y_t= (y_{1t}, y_{2t}, ..., y_{mt})′ composed for m times components t, a VAR(p) model is given by:

$$Y_t = \bar{Y} + \sum_{k=1}^{p} \Phi Y_{t-k} + a_t$$

where $\bar{Y}$ is an averages vector of dimension m of $\mathbf{Y}$, Φ are matrix of model coefficients $m \times m$, Y_{t-k} is an vector of Y in time $t-k$, with k = 1, ..., p and a is a non correlated variable with zero mean and constant variance.

Let us consider in a practical way a VAR of order 1, in which it seeks to analyze the causal relationship of cumulative number cases, represents for variable Yt and the neighbor relationship between micro-regions $'i'$ and $'j'$, $Y_t = (y_{i,t}, y_{j,t})'$ that is,

$$\begin{bmatrix} y_{i,t} \\ y_{j,t} \end{bmatrix} = \begin{bmatrix} y_i \\ y_j \end{bmatrix} + \begin{bmatrix} \emptyset_{11} & \emptyset_{12} \\ \emptyset_{21} & \emptyset_{22} \end{bmatrix} \begin{bmatrix} y_{i,t-1} \\ y_{j,t-1} \end{bmatrix} + \begin{bmatrix} a_t \\ a_{2t} \end{bmatrix}$$

We can also rewrite this system as

$$y_{i,t} = \bar{y}_i + \emptyset_{11} y_{i,t-1} + \emptyset_{12} y_{j,t-1} + a_t$$
$$y_{j,t} = \bar{y}_j + \emptyset_{21} y_{i,t-1} + \emptyset_{22} y_{j,t-1} + a_{2t}$$

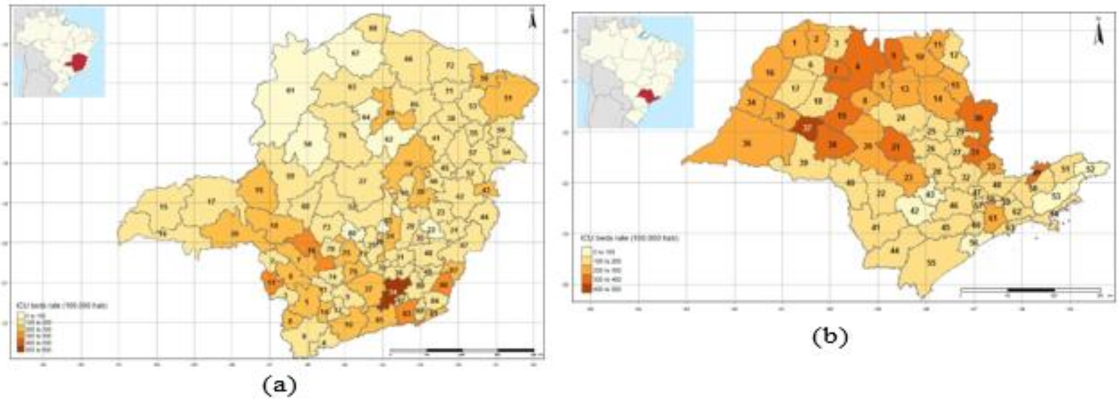
where: $y_{i,t}$ and $y_{j,t}$ is the variable y measure on micro-regions $'i'$ and $'j'$,respectively, in time t, $\bar{y}_i$ and $\bar{y}_j$ is the mean of attribute Y on region i and j respectively, $y_{i,t-1}$ and $y_{j,t-1}$ is the variable y measure on micro-regions “i” and “j”, respectively, in time t − 1.

Analysing $\mathbf{\Phi}$ the matrix coefficients on equations, we say that: if $\emptyset_{12} \neq 0$, the cases in the micro-region “i” causes the cases in micro-region “j”; if $\emptyset_{21} \neq 0$ micro-region “i” causes “j”.. If $\emptyset_{12} \neq 0$ and $\emptyset_{21} \neq 0$ we say that there is a feedback relationship between the micro-regions “i” and “j”, it means that, the number of cases on micro-region “i” causes the number of cases on micro-region “j” and “j” causes “i”. In this work, it means that, the number of cases in the micro-region “i” is better explained when we consider the number of cases on “j” neighbor micro-regions, and vice-versa.

3 RESULTS

In Minas Gerais state, since the beginning of the pandemic until August 08, 2020, the government contabilized 150, 213 cases and 3, 410 deaths occasioned by COVID-19 [2]. In according to the data of DataSUS [27], in march, when the COVID-19 outbreak had started in the state, there was 40, 699 beds available in intensive care, 26, 913 of which belonged to public health care and 13, 786 of which belonged to private health care. In the state of São Paulo, until the same date, it has confirmed 621,595 positive cases with 25, 016 resulting in death, for COVID-19 [2]. In March 2020, second data of DataSUS [27], this state had 90, 603 beds in intensive care, 52, 505 beds from public health care and 38, 098 beds from private health care. Figure 1 shows the spatial distribution of intensive care units beds per 105 inhabitants on the micro heath units for both states.

Figure 1: Spatial distribution of ICU beds rate for both states (a) Minas Gerais and (b) São Paulo. The numbers in the figure represent the micro units (see table in appendix A for more details).



Source: Authors, 2022

In Minas Gerais state, the ICU beds rate varies from 69, in the micro-region number 64, called "Coração de Jesus", to 502 in the micro unit number 34, "Barbacena". The mean in the state is 179 beds per 105 inhabitants. For São Paulo state, the mean ICU beds rate in the micro units is approximately 206 beds per 105 inhabitants, varying from 61 beds per 105 inhabitants in "Bananal", micro unit number 52, to 472 beds per 105 in "Tupã", micro unit number 37.

It is worth mentioning that the World Health Organization (WHO) recommendation is 2 to 3 beds per 10,000 inhabitants [28]. Although there was no value lower than that recommended in the state's micro-regions in both states, the data aggregation in micro health units hinder the visualization of bed rate in municipal level. In Minas Gerais, with 853 municipalities, 461 of them do not have intensive care beds, neither public nor private. Although these municipalities are quite small, it represents 54.04% of the the total of counties that have to move their population to neighboring cities when someone needs intensive care [27, 29]. The same problem happens in São Paulo where 347 of 645 municipalities do not have intensive care beds in the private health care system, 298 of them do not have beds in the public system and 291 counties do not have neither in the private nor in the public system [27].

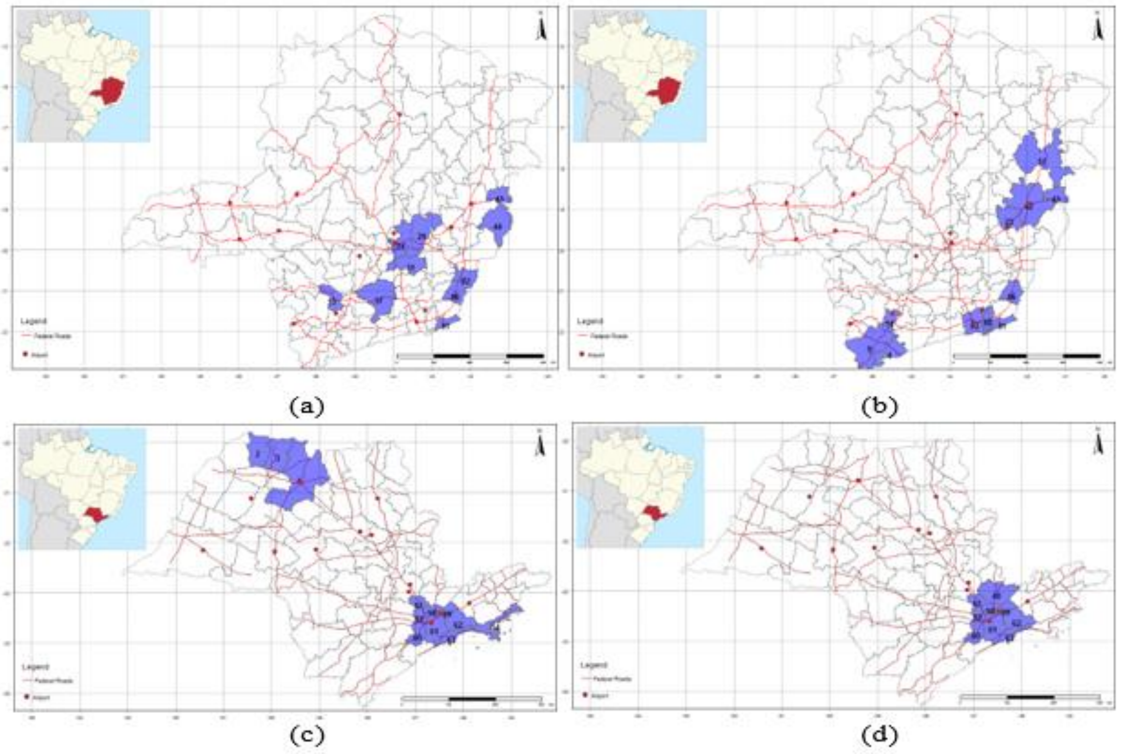
Table 1: Global Moran's I time dispersion for both states. Our analysis starts in the thirteenth week of the year (March 22th).

Week	Incid. rate	p.value	Death rate	p.value	Incid. rate	p.value	Death rate	p.value
13	0.1187	0.028	-	0.001	0.1663	0.001*	0.1375	0.024
14	0.0457	0.177	0.0193	0.094	0.3856	0.001*	0.2120	0.007*
15	0.1065	0.048	0.0820	0.075	0.4358	0.001*	0.3396	0.001*
16	0.1518	0.012	0.01	0.325	0.4792	0.001*	0.4251	0.001*
17	0.1694	0.005*	-0.028	0.553	0.5443	0.001*	0.5325	0.001*
18	0.1655	0.009*	0.0254	0.296	0.5779	0.001*	0.5859	0.001*
19	0.1810	0.006*	0.0829	0.098	0.5718	0.001*	0.6013	0.001*
20	0.2910	0.001*	0.0754	0.10	0.5886	0.001*	0.5926	0.001*
21	0.3374	0.001*	0.2431	0.004*	0.5975	0.001*	0.6009	0.001*
22	0.2261	0.002*	0.2559	0.002*	0.5923	0.001*	0.6218	0.001*
23	0.1541	0.011	0.2922	0.001*	0.5336	0.001*	0.6183	0.001*
24	0.1453	0.014	0.2560	0.001*	0.4819	0.001*	0.6209	0.001*
25	0.1665	0.011	0.1676	0.004*	0.4094	0.001*	0.6052	0.001*
26	0.1614	0.008*	0.1285	0.026	0.3737	0.001*	0.5651	0.001*
27	0.1857	0.009*	0.1478	0.016	0.3402	0.001*	0.5568	0.001*
28	0.2259	0.001*	0.1894	0.006*	0.2951	0.001*	0.5357	0.001*
29	0.2441	0.001*	0.1999	0.003*	0.2879	0.002*	0.5076	0.001*
30	0.2476	0.001*	0.1989	0.001*	0.2543	0.001*	0.4804	0.001*
31	0.2643	0.001*	0.1992	0.005*	0.2430	0.005*	0.4490	0.001*
32	0.2768	0.001*	0.2110	0.001*	0.2584	0.002*	0.4364	0.001*

Note: * statistical significance.

In table 1 we show the values of the global Moran's I for incidence and mortality rates for both (a) Minas Gerais and (b) São Paulo states. As we detect the presence of spatial dependence between the micro-regions, we investigated those micro units that interact with each other, using the local Moran's I index. In figure 2a, we presented the micro units health which has spatial dependence, to incidence rate, at some time in the studied period, for Minas Gerais state, and 2c shows the results for São Paulo. And the figures 2b and 2d shows the mortality rate spatial dependence's for the supracited states, respectivelly.

Figure 2: COVID-19 analyses in health micro units of Minas Gerais (above) and São Paulo (below). Significance detected in Local Moran's I: (a) and (c) incidence rate, (b) and (d) mortality rate.



Based on these results, some health micro units were chosen to analyze the causal relationship of the number of cases and deaths between them. In Minas Gerais: 'Belo Horizonte (BH) / Nova Lima / Caeté" (number 24), "Itabira" (number 29) and "Ouro Preto" (number 31) - located in metropolitan region of the state; "Itajubá", "Pouso Alegre" and "Varginha" (numbers 4, 9 ans 14 respectively) - in the southern region; 'Além Paraíba" (number 81),"Juiz de Fora" (number 83) and "Bicas" (number 88) - in the southeastern; and 'Governador Valadares", "Mantena", "Ipatinga" and "Teófilo Ottoni" (numbers 42, 43, 23 and 57, respectively) - in the eastern of the state. For the São Paulo state the micro-regions, the micro units analyzed are "São Paulo", "Santos", "Mogi das Cruzes", "Guarulhos", "Franco da Rocha", "Osasco", "Jundiaí" and "Itapecerica da Serra" (number 61, 63, 62, 59, 58, 57, 47 and 60,respectively), in the metropolitan region.

Hereafter we considered the logarithm of the cumulative number of the cases in these 20 weeks. The results of adjusted the vector autoregressive (VAR) model with the estimation of parameters and their statistics significance, are show in the appendixes. For Minas Gerais state in the appendix B and for São Paulo in the appendix C. The VAR(p) model estimated consider $p \leq 2$ due to the characteristics of disease transmission.

In short, on Minas Gerais state, in the metropolitan region, “Itabira” and “Ouro Preto” presents feedback relationship and “Belo Horizonte” causes “Itabira”. The southern region presents feedback relationship between “Pouso Alegre” and “Varginha” and “Itajuba” causes “Varginha”. In the southeastern of state, “Governador Valadares” and “Ipatinga” presents feedback relationship, and “Governador Valadares” causes “Teófilo Otoni” and “Mantena” causes “Governador Valadares”. Finally, in the in the eastern region of Minas Gerais, “Juiz de Fora” causes “Além Paráıba” and causes “São João Nepomuceno/Bicas”, but none of the microregions causes “Juiz de Fora”. Only in the southern region the causal relationship is of the one week, in the other analysed regions this relation is the of up two weeks.

In the state of São Paulo, in the metropolitan region, the results of models fitted shows the two feedback relationships between “Guarulhos” and “Osasco” and between “Guarulhos” and “São Paulo”. And the micro-region “Santos” causes “Guarulhos” and causes “São Paulo” but none of the micro-regions causes “Santos”.

4 DISCUSSIONS AND FINAL REMARKS

The spatial distribution of the incidence rates of COVID-19 in the states of Minas Gerais and São Paulo presented formation of clusters in the micro-units close to their respective metropolitan regions Belo Horizonte/MG and São Paulo/SP. This result corroborates with similar analyzes made for other states of the country, such as Ceará [30, 31], Paraná, Santa Catarina [32] and Espírito Santo [33].

Our study showed that the number of cases of COVID-19 in the micro-unit of the capital São Paulo (number 61) was influenced by the number of cases in the micro units of Guarulhos, Osasco and Santos (number 59, 57 and 63 respectively) with time delays of up to two weeks. A reasonable explanation is found when we analysed the recurrent mobility [34] in metropolitan regions due to studies or jobs. The micro unit of São Paulo and its neighboring micro regions, which constitute the São Paulo metropolitan region, are responsible for the major mobility of people from one city to another. There are 1,801,878 people moving between municipalities, performing a total of 506 daily connections [35].

In the metropolitan region of Minas Gerais there is a flow of 573,780 people in daily movements from the capital, Belo Horizonte, to its neighboring cities, performing a total of 190 links [35]. But the large proportion of this recurrent mobility occurs between municipalities inside the same micro-region. This can explain why the number cases of micro region of Belo Horizonte was not influenced by the micro-regions of the metropolitan region of the state.

Regarding the spatial distribution of the mortality rates of COVID-19, São Paulo and Minas Gerais presented different patterns. While the former shows a cluster formation more concentrated in the metropolitan region, the latter presents clusters in the micro-units close to the state's borders with the states of São Paulo, Rio de Janeiro and Espírito Santo. This is justified because Minas Gerais is much larger than São Paulo and has micro-regions that have greater autonomy and independence from the capital. This suggests that the mortality rate may be being influenced by demographic and economic factors, availability/offer of treatment and geographic location [36, 37].

Researches have shown that factors such as age and the presence of comorbidities can aggravate the disease, increasing the chance of the patient dying [38, 39]. According to the last brazilian census carried out in 2010 [40], the microregions of Minas Gerais and São Paulo, with spatial dependence on the mortality rate in some period, have more than 10% of the population with 60 years old or over. This portion of the population is generally the one most in need of intensive care at the beginning of the pandemic [39].

We observed that the spatial distribution of intensive care beds by micro health units in the states of São Paulo and Minas Gerais is very heterogeneous. An emergency government recommendation 1 endorses the managers of the Brazilian Unified Health System to request private beds when necessary to ensure equal treatment during the pandemic. However, this resolution cannot be fully attended because there are micro-regions that do not have private beds. Consequently, the minimization of regional inequalities and the expansion of service capacity are compromised [29], compelling the population to search for hospital assistance in neighboring regions, when there is overcrowding of public hospitals. This displacement increases the circulation of people and the risk of contagion.

The present study spatially characterized the spread of COVID-19 in the two most populous states in Brazil. While in Minas Gerais the disease first arrived in the interior and after in the capital, in São Paulo the opposite happened. The mortality rate due to COVID-19 also showed a different behavior in both states. In São Paulo, the micro-regions with spatial dependence for the mortality rate, as with the incidence rate, are close to its metropolitan region. In Minas Gerais, the micro-regions that presented spatial dependence for the mortality rate are located near the borders of the states of São Paulo, Espírito Santo and Rio de Janeiro. Although these micro-regions have available beds, they have an older population when compared to other state micro-regions and are intercepted by important roads, responsible for the flow of people across the state. Our results indicate that the spread of the disease can be influenced by economic, social and demographic factors. Public health policies must take these regional differences into account, as well as the flow of people and the age stratification of the population.

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APPENDIX A

Table A. 1: Micro-regions (administrative micro health units) index of both states - São Paulo and Minas Gerais - named by the main city of each of them.

Index	Micro health unit - Minas Gerais	Micro health unit - São Paulo
1	Alfenas	Jales
2	Cássia	Fernandópolis
3	Guaxupé	Votuporanga
4	Itajubá	São José do Rio Preto
5	Lavras	Catanduva
6	Passos	Auriflama
7	Piumhi	Nhandeara
8	Poços de Caldas	Novo Horizonte
9	Pouso Alegre	Barretos
10	São Lourenço	São Joaquim da Barra
11	São Sebastião do Paráıso	Ituverava
12	Três Corações	Franca
13	Três Pontas	Jaboticabal
14	Varginha	Ribeirã Preto
15	Ituiutaba	Batatais
16	Patrocínio/Monte Carmelo	Andradina
17	Uberlândia/Araguari	Araçtuba
18	Araxá	Birigui
19	Frutal	Lins
20	Uberaba	Bauru
21	Caratinga	Jaú
22	Coronel Fabriciano	Avaré
23	Ipatinga	Botucatu
24	BH/Nova Lima/Caeté	Araraquara
25	Betim	São Carlos
26	Contagem	Rio Claro
27	Curvelo	Limeira
28	Guanhães	Piracicaba
29	Itabira	Pirassununga
30	João Monlevade	São João da Boa Vista
31	Ouro Preto	Mogi Mirim
32	Sete Lagoas	Campinas
33	Vespasiano	Amparo
34	Barbacena	Dracena
35	Congonhas	Adamantina
36	Conselheiro Lafaiete	Presidente Prudente
37	São João Del Rei	Tupã
38	Araçuáı	Marília
39	Diamantina	Assis
40	Serro	Ourinhos
41	Turmalina/Minas Novas/Capelinha	Itapeva
42	Governador Valadares	Itapetininga
43	Mantena	Tatúı
44	Resplendor	Capã Bonito
45	Santa Maria do Suaçúı	Piedade
46	Peçanha/São João Evangelista	Sorocaba

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47	Manhuaçu	Jundiaí
48	Ponte Nova	Bragança Paulista
49	Viçosa	Campos do Jordão
50	Águas Formosas	São José dos Campos
51	Almenara/Jacinto	Guaratinguetá
52	Itambacuri	Bananal
53	Itaobim	Paraibuna/Paraitinga
54	Nanuque	Caraguatatuba
55	Padre Paraíso	Registro
56	Pedra Azul	Itanhaém
57	Teófilo Otoni	Osasco
58	João Pinheiro	Franco da Rocha
59	Patos de Minas	Guarulhos
60	São Gotardo	Itapecerica da Serra
61	Unaí	São Paulo
62	Bocaiúva	Mogi das Cruzes
63	Brasília de Minas/São Francisco	Santos
64	Coração de Jesus	-
65	Francisco Sá	-
66	Janaúba/Monte Azul	-
67	Januária	-
68	Manga	-
69	Montes Claros	-
70	Pirapora	-
71	Salinas	-
72	Taiobeiras	-
73	Bom Despacho	-
74	Campo Belo	-
75	Divinópolis	-
76	Formiga	-
77	Itaúna	-
78	Lagoa da Prata/Santo Ant. Do Monte	-
79	Oliveira	-
80	Pará de Minas	-
81	Além Paraíba	-
82	Carangola	-
83	Juiz de Fora	-
84	Leopoldina/Cataguases	-
85	Lima Duarte	-
86	Muriaé	-

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APPENDIX B

Table B. 1:VAR(2) models fitted for Belo Horizonte (BHt) and Itabira (ITBt) and Ouro Preto (OPt), respectively.

(a) Belo Horizonte micro unit

Parameter	Estimate	Std. Error	p-value
Cases BH_{t-1}	0.470453	0.343475	0.2008
Cases ITB_{t-1}	0.000854	0.064559	0.9897
Cases OP_{t-1}	0.020775	0.094689	0.8308
Cases BH_{t-2}	-0.10621	0.155342	0.5097
Cases ITB_{t-2}	-0.00587	0.093438	0.9512
Cases OP_{t-2}	0.040328	0.065818	0.5537
Const.	4.309519	2.189143	0.0773
Trend	0.154463	0.098184	0.1467

(b) Itabira micro unit

Parameter	Estimate	Std. Error	p-value
Cases BH_{t-1}	0.05162	0.81759	0.950898
Cases ITB_{t-1}	0.87856	0.15367	0.000194*
Cases OP_{t-1}	1.10136	0.22539	0.000636*
Cases BH_{t-2}	1.51625	0.36976	0.002143*
Cases ITB_{t-2}	-1.44076	0.22241	7.09e-05*
Cas*es OP_{t-2}	0.26983	0.15667	0.115741
Const.	-8.92546	5.21089	0.117518
Trend	-0.41153	0.23371	0.108751

c) Ouro Preto micro unit

Parameter	Estimate	Std. Error	p-value
Cases BH_{t-1}	0.8677	0.8195	0.314593
Cases ITB_{t-1}	0.8443	0.154	0.000269*
Cases OP_{t-1}	0.6583	0.2259	0.015461
Cases BH_{t-2}	1.0556	0.3706	0.017303
Cases ITB_{t-2}	-0.7144	0.2229	0.009422*
Cases OP_{t-2}	0.1471	0.157	0.370862
Const.	-11.4948	5.2231	0.052372
Trend	-0.5519	0.2343	0.040216*

Note: * statistics significance at nivel of 5%.

Table B. 2: VAR(1) models fitted for Itajubá(ITAt) and ouso Alegre (PAt) and Varginha (VGAt), respectively.

(a) Itajubámicro unit.

Parameter	Estimate	Std. Error	p-value
Cases ITA_{t-1}	-0.54185	0.09032	3.26e-05 *
Cases PA_{t-1}	1.45287	0.26253	7.36e-05 *
Cases VGA_{t-1}	-0.62413	0.30213	0.0579
Const.	-0.36587	0.14439	0.0239 *
Trend	0.19442	0.02583	2.76e-06 *

(b) Pouso Alegre micro unit.

Parameter	Estimate	Std. Error	p-value
Cases ITA$_{t-1}$	0.01374	0.04673	0.7730
Cases PA$_{t-1}$	0.14345	0.13583	0.3088
Cases VGA$_{t-1}$	0.36	0.15632	0.0371 *
Const.	3.28546	0.07471	<2e-16 *
Trend	0.13109	0.01336	1.18e-07 *

(c) Varginha micro unit.

Parameter	Estimate	Std. Error	p-value
Cases ITA$_{t-1}$	0.26699	0.08354	0.00647 *
Cases PA$_{t-1}$	-0.71106	0.24282	0.01101 *
Cases VGA$_{t-1}$	1.06637	0.27944	0.27944 *
Const.	2.84571	0.13355	4.55e-12 *
Trend	0.0905	0.02389	0.002 *

Note: * statistics significance at nivel of 5%.

Table B. 3: VAR(2) models fitted for Governador Valadares (GV_t) and Ipatinga (IPA_t) and Teofilo Otoni (TO_t) and Mantena ($MANT_t$), respectively.

(a) Governador Valadares micro unit

Parameter	Estimate	Std. Error	p-value
Cases GV_{t-1}	1.31993	0.26585	0.0011*
Cases IPA_{t-1}	-0.42271	0.20026	0.06779
Cases TEO_{t-1}	-0.02408	0.07844	0.76665
Cases $MANT_{t-1}$	0.24798	0.07316	0.0095*
Cases GV_{t-2}	-0.52994	0.20112	0.02995*
Cases IPA_{t-2}	0.5981	0.16053	0.00582*
Cases TEO_{t-2}	-0.08901	0.07449	0.26633
Cases $MANT_{t-2}$	-0.04253	-0.649	0.53454
Const.	1.39066	0.3755	0.00601*
Trend	-0.08586	0.05509	0.15775

(b) Ipatinga micro unit

Parameter	Estimate	Std. Error	p-value
Cases GV_{t-1}	1.0166	0.23351	0.002434*
Cases IPA_{t-1}	0.19477	0.1759	0.300344
Cases TEO_{t-1}	0.16556	0.0689	0.042973
Cases $MANT_{t-1}$	0.332	0.06426	0.000856*
Cases GV_{t-2}	-0.89239	0.17665	0.000987*
Cases IPA_{t-2}	0.418	0.141	0.018022*
Cases TEO_{t-2}	-0.22563	0.06542	0.008712*
Cases $MANT_{t-2}$	0.07147	0.05756	0.249547
Const.	1.50297	0.32982	0.001857*
Trend	-0.07157	0.04839	0.17742

(c) Teofilo Otoni micro unit

Parameter	Estimate	Std. Error	p-value
Cases GV_{t-1}	0.76579	0.89816	0.4187
Cases IPA_{t-1}	-0.05566	0.67656	0.9365
Cases TEO_{t-1}	-0.17387	0.265	0.5302
Cases $MANT_{t-1}$	-0.42764	0.24715	0.1218
Cases GV_{t-2}	1.81755	0.67946	0.0281*
Cases IPA_{t-2}	-0.48537	0.54234	0.3969
Cases TEO_{t-2}	0.55641	0.25164	0.058*
Cases $MANT_{t-2}$	0.26079	0.2214	0.2727
Const.	-0.39616	1.26859	0.7628
Trend	-0.66095	0.18613	0.0075*

(d) Mantena micro unit

Parameter	Estimate	Std. Error	p-value
Cases GV_{t-1}	-0.5196	1.3683	0.714
Cases IPA_{t-1}	-0.3994	1.0307	0.708
Cases TEO_{t-1}	0.5132	0.4037	0.239
Cases $MANT_{t-1}$	0.122	0.3765	0.754
Cases GV_{t-2}	0.8739	1.0351	0.423
Cases IPA_{t-2}	-0.6069	0.8262	0.484
Cases TEO_{t-2}	0.25	0.3834	0.533
Cases $MANT_{t-2}$	0.3328	0.3373	0.353
Const.	1.2064	1.9326	0.55
Trend	0.2037	0.2836	0.493

Note: * statistics significance at nivel of 5%.

Table B. 4: VAR(2) models fitted for Além Paraíba (ALPt) and Juiz de Fora (JFt) and São João Nepomuceno/Bicas (SJNt), respectively.

(a) Além Paraíba micro unit

Parameter	Estimate	Std. Error	p-value
Cases ALP$_{t-1}$	0.13272	0.16069	0.42809
Cases JF$_{t-1}$	0.53633	0.48813	0.29763
Cases SJN$_{t-1}$	0.05057	0.15082	0.74434
Cases ALP$_{t-2}$	0.36945	0.11191	0.00799*
Cases JF$_{t-2}$	0.85597	0.23136	0.00411*
Cases SJN$_{t-2}$	-0.27021	0.13936	0.08122
Const.	-4.78124	1.87272	0.02871*
Trend	-0.18577	0.06444	0.0163*

(b) Juiz de Fora micro unit

Parameter	Estimate	Std. Error	p-value
Cases ALP$_{t-1}$	0.007909	0.095162	0.9354
Cases JF$_{t-1}$	0.930457	0.289082	0.0092*
Cases SJN$_{t-1}$	-0.01298	0.089321	0.8873
Cases ALP$_{t-2}$	0.065902	0.066273	0.3435
Cases JF$_{t-2}$	-0.13032	0.137016	0.364
Cases SJN$_{t-2}$	-0.04087	0.082529	0.6311
Const.	1.535525	1.109056	0.1963
Trend	0.021104	0.038161	0.5924

(c) São João Nepomuceno/Bicas micro unit

Parameter	Estimate	Std. Error	p-value
Cases ALP$_{t-1}$	0.12403	0.21153	0.5706
Cases JF$_{t-1}$	1.86951	0.64257	0.0156*
Cases SJN$_{t-1}$	0.19277	0.19854	0.3545
Cases ALP$_{t-2}$	0.1014	0.14731	0.5069
Cases JF$_{t-2}$	-0.83378	0.30456	0.0209*
Cases SJN$_{t-2}$	0.18317	0.18345	0.3416
Const.	-4.36455	2.46522	0.1071
Trend	-0.18449	0.08482	0.0547

Note: * statistics significance at nivel of 5%.

APPENDIX CA

Table C. 1: VAR(2) models fitted for Guarulhos and Osasco and São Paulo and Santos, respectively, named region B of SP in our study.

Parameter	Estimate	Std. Error	p-value
Cases GRU_{t-1}	0.1547	0.26848	0.58031
Cases OSA_{t-1}	0.54431	0.17061	0.0128*
Cases SP_{t-1}	-1.3716	0.5752	0.04423*
Cases STS_{t-1}	0.35818	0.19684	0.1063
Cases GRU_{t-2}	-0.75347	0.17665	0.00274*
Cases OSA_{t-2}	0.14028	0.23152	0.56137
Cases SP_{t-2}	1.82476	0.52105	0.00805*
Cases STS_{t-2}	-0.30442	0.10351	0.01868*
Const.	1.65418	3.02642	0.59958
Trend	0.07866	0.02234	0.00783*

(c) São Paulo micro unit

Parameter	Estimate	Std. Error	p-value
Cases GRU_{t-1}	-0.29502	0.11225	0.03026*
Cases OSA_{t-1}	0.70089	0.07133	9.68e-06*
Cases SP_{t-1}	-0.30161	0.24049	0.24519
Cases STS_{t-1}	0.14871	0.0823	0.10839
Cases GRU_{t-2}	0.02266	0.07386	0.76688
Cases OSA_{t-2}	0.22249	0.0968	0.05059
Cases SP_{t-2}	0.09315	0.21785	0.68022
Cases STS_{t-2}	-0.03123	0.04328	0.49112
Const.	4.72046	1.26535	0.00578*
Trend	0.05063	0.00934	0.00063*

(d) Santos micro unit

Parameter	Estimate	Std. Error	p-value
Cases GRU_{t-1}	-0.12156	0.16293	0.47696
Cases OSA_{t-1}	0.07018	0.10353	0.517
Cases SP_{t-1}	0.0129	0.34906	0.97142
Cases STS_{t-1}	0.34665	0.11945	0.01983*
Cases GRU_{t-2}	-0.27677	0.1072	0.03253*
Cases OSA_{t-2}	0.38629	0.1405	0.02508*
Cases SP_{t-2}	0.23073	0.3162	0.48639
Cases STS_{t-2}	-0.10331	0.06281	0.13864
Const.	6.07366	1.83659	0.01075*
Trend	0.0479	0.01356	0.00769*

Parameter	Estimate	Std. Error	p-value
Cases GRU_{t-1}	0.29039	0.58536	0.6332
Cases OSA_{t-1}	-0.76555	0.37198	0.0736
Cases SP_{t-1}	0.54122	1.25413	0.6775
Cases STS_{t-1}	0.77332	0.42916	0.1092
Cases GRU_{t-2}	-0.15522	0.38516	0.6975
Cases OSA_{t-2}	0.46687	0.50479	0.3821
Cases SP_{t-2}	0.22046	1.13606	0.851
Cases STS_{t-2}	-0.23043	0.22568	0.3371
Const.	-2.47075	6.59858	0.7178
Trend	-0.03137	0.04871	0.5376

Note: * statistics significance at nivel of 5%.