COVID-19 spatialization by empirical Bayesian model in São Paulo, Brazil

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Abstract The new Acute Respiratory Syndrome, COVID-19, has affected the health and the economy worldwide. Therefore, scientists have been looking for ways to understand this disease. In this context, the main objective of this study was the spatialization of COVID-19, thinking in distinguishing areas with high transmissibility yet, verifying if these areas were associated with the elderly population occurrence. The work was delineated, supposing that spatialization could support the decision-making to combat the outbreak and that the same method could be used for spatialization and prevent other diseases. The study area was a municipality near Sao Paulo Metropolis, one of Brazil’s main disease epicenters. Using official data and an empirical Bayesian model, we spatialized people infected by region, including older people, obtaining reasonable adjustment. The results showed a weak correlation between regions infected and older adults. Thus, we define a robust model that can support the definition of actions aiming to control the COVID-19 spread.

Keywords SARS-CoV-2 · Mathematic model · Geographic information system (GIS) · Elderly occurrence · Disease spread

Introduction

Firstly, registered in Wuhan (Hubei Province, China) in December 2019, the new Acute Respiratory Syndrome (SARS-CoV-2), which causes COVID-19 disease, has produced wasting effects on world health and the economy, forcing the World Health Organization (WHO) declares a global pandemic (WHO, 2020). In Brazil, the disease has affected around 29 million people, having 656,425 deaths in a population of approximately 210 million (IBGE, 2020).

In this context, the COVID-19 pandemic presents itself as a challenge for health authorities, requiring the implementation of measures to control the spread. Therefore, understanding the aspects related to the spatialization of transmission is essential for disease control and harm reduction (De Jesus et al., 2020).

Research indicates that the most significant urban centers and regions with social vulnerability are the most affected by the disease (Castro et al., 2021). According to Rouse (2021), proximity among people comes as cultural belonging, shared ethical beliefs, and moral practices. However, the virus exposed
how people, groups, and different age groups, living side by side, can have radically different experiences, especially with state and institutional power (Martins-Filho et al., 2021, Santos et al., 2021, Baqui et al., 2020, Saavendra et al., 2020).

According to epidemiologists, age is the most critical factor in decreasing the chances of surviving COVID-19, especially for people over 65 years old (Jordan et al., 2020; Zhou et al., 2020). Despite this evidence, research reports a non-linear behavior between age groups and social distancing (Canning et al., 2020; Daoust, 2020). The most vulnerable population is not systematically more responsive regarding self-isolation or willingness to isolate themselves. The non-linearity identified in the studies corroborates with the discrepant results observed in countries such as the USA, where 80% of deaths were in people aged 65 and over, while in South Korea, it was only 2.1% (Yu, 2020).

Therefore, in addition to the attributes of the community, the biases produced by low budgets, insufficient resources destined to fight the disease, and the biases in the surveillance of COVID-19 can tend to underestimate the discrepancies in viral load and lead to errors in the definition of priorities, misallocation of resources, inaccuracies, and failure to identify a plausible worst-case scenario (Goldstein et al., 2021).

In this sense, the Geographic Information System (GIS) is a critical tool for examining the spatial distribution of infectious diseases (Mollato et al., 2019). Based on location, we can discuss how to distribute medical and human resources (Yoneoka et al., 2022), direct interventions for mass testing, isolation of cases to mitigate the spread of the disease, define priority groups for vaccination (Siqueira et al., 2021) and spread situational information on the transmissibility of the disease (Sarwar et al., 2020).

This reality opens a new paradigm of probabilistic modeling and GIS-based tools to understand the COVID-19 situation. Firstly consider that the spatial diffusion of cases is one of the COVID characteristics and that the device is associated with algorithms that can support future scenarios. In this way, GIS can facilitate the identification of the spatial clusters responsible for person-to-person transmission and is a source of localized infection (Meng, 2017).

The interpolation methods and spatial overlays (i.e., layer’s overlay in a GIS), based on regressions, figure among the procedures used by these evaluations and can be used to comprise the geographical distribution of the diseases (as the COVID-19), their patterns, or its significant risk aspects (Kaplan et al., 2019).

So, we can construct a statistical and spatial model of the diseases in the GIS environment, considering that the confirmed case data establishes a relation between model parameters and transmitting rate. However, a model with a good fit can result in a prevision different from the actual epidemic behavior, known in the literature as non-identifiable (Lintusaari et al., 2016).

Roda et al. (2020) indicated the Bayesian Inference (BI) when we have the presence of non-identifiable, especially when we have adequate parameter adjustments with a significant reduction of wide ranges and production of viable credible intervals.

BI is commonly employed to estimate dynamic system parameters (Ma and Berndsen, 2014). For example, Yoneoka et al. (2022) determined a positive correlation between the spread of COVID-19 and road allocation in Japan, while Lawson and Kim (2021) observed spatial dependence and disease transmissibility at a regional level in the United States, while Bherwani et al. (2021) applied Bayesian statistics to understand the link between COVID-19 cases and population density in India.

In this way, the first step to reaching an adequate model is to understand the data in terms of its magnitudes and time scale, which sometimes is a no easy task, considering that epidemiological information is not available in real time. On the other hand, public data cannot be forgotten since it can help us fill this gap (Arino, 2020). Thus, it is evident that cross-border transmission occurs at the local level, and ignoring this information should limit the predictive ability of the models.

Thus, the main objective of this study was the spatialization of COVID-19 through BI, thinking in distinguishing areas with high transmissibility and verifying if these areas were associated with the elderly population occurrence. Furthermore, we thought the method could support the spatialization of other diseases and their prevention.
Material and methods

Study area

The study area was the Sorocaba municipality in Sao Paulo state (SP), the southeastern region of Brazil (Fig. 1). Having 450,382 km$^2$, Sorocaba has an estimated population of 679,378 inhabitants (IBGE, 2020), who live predominantly in urban areas, that sum up 82.5% of the municipality (Mello et al., 2014). Initially covered by Atlantic and Savanna forests, the remnants of the municipality (around 5.6%) are scattered in this urbanized landscape (Mello et al., 2014).

Sorocaba is important in coronavirus spatialization because it is near Sao Paulo Metropolis (around 100 km), one of Brazil’s main disease epicenters. The proximity has transformed Sorocaba into a "dormitory city" of the metropolis for some of its inhabitants. Still, Sorocaba and neighboring municipalities (Fig. 1) form the Metropolitan region of Sorocaba, one of the more populous of the SP.

The municipality drainage has approximately 6830 km$^2$, belonging to the Sorocaba and Médio Tietê River’s Water Resources Management Unit, composed of 34 Sao Paulo municipalities. The main river that crosses the municipality is justly named Sorocaba river, which is the main tributary of the left bank of the Tietê River (IGC, 2014), which supplies fresh water for a populous region of the Sao Paulo state.

The regional climate is tropical, with rainy summer and dry winter periods (EMBRAPA, 2020).

According to the official institute of Brazil named "IBGE" (2020), the infant mortality rate in the municipality is 9.71 deaths per thousand live births, occupying the number 313 of 645 municipalities in the SP and 3193 of 5570 municipalities in the Brazilian territory. Still, according to IBGE, in the 2009 survey, the municipality had 75 health establishments linked to the Unified Health System (IBGE, 2020).

![Fig. 1 Location of Sorocaba and neighboring municipalities in Sao Paulo State, Brazil](image-url)
Statistics data and COVID-19 information

The COVID-19 information on Sorocaba and Neighboring municipalities (from 23 January to 17 May 2020) was obtained from the Epidemiological Surveillance Center of the São Paulo Health Secretaria - ESC/SPHS (CVE, 2020).

The region accumulated 468 (100%) infected people in the period studied, resulting in an average prevalence rate (PR) of 0.00038, which is equivalent to the ratio between the numbers of people infected by those at risk (Table 1) (CVE, 2020).

Having the largest population in the region for the studied period, Sorocaba also revealed the highest number of infected cases per hectare (ha; 10,000 m²) (n=0.0071) with 68.4% (n=320) of infected people and a PR of 0.00047 (Table 1). In the sequence, the ranking (having lower values) were Itu (10.3%; n=48), Votorantim (7.7%; n=36), Mairinque (3.6%; n=17), Araçoiaba da Serra (3.2%; n=15), Porto Feliz (3.2%; n=15), Salto de Pirapora (2.6%; n=12), Iperó (0.9%; n=4), and Alumínio (0.2%; n=1).

COVID-19 spatialization

The PR of the municipality (Table 1) supported identifying regions associated with a possible high virus transmission rate. We used the rate (PR) to estimate the number of people infected by IBGE census sectors (cs) (2010) divided by the area of the respective sector (Eq. 1). The IBGE defines the cs as equivalent to the territorial unit for census operations collecting, respecting the municipal limits (Fig. 2a).

\[
SI(\text{ha}) = \frac{PR \times \text{Pop cs}}{A \text{ cs}}
\]  

(1)

where: SI(\text{ha}) is the sector infected per ha; PR is the Prevalence Rate; Pop cs is the population in the census sector; A cs is the area in the census sector (IBGE, 2020).

In the same way, we used occurrence data of people over 60 years old, by cs (IBGE, 2020) to assess the correlation between this group of people and the SI (ha), which was divided by the area of the respective cs, according to Eq. 2 (Fig. 2b).

\[
EO = \frac{\text{Pop.60 cs}}{A \text{ cs}}
\]

(2)

where: EO is the Elderly Occurrence; Pop. 60 is the population over 60 years; A cs is the area in the census sector (IBGE, 2020).

After using interpolators based on an empirical Bayesian model, we spatialize the values resulting from applying Eqs. 1 and 2.

The Bayesian structure assumes that a probability model for the data observed a priori (i.e., SI

Table 1  Sorocaba and neighboring municipalities (SP, Brazil): statistical data and COVID-19 information, from January 23 to May 17, 2020

| Municipalities          | Statistical Data | COVID-19 Information* |
|-------------------------|-------------------|------------------------|
|                         | Pop               | Infected (n)           | Infected (%) | PR          | Munic. Area (ha) | Infected per ha |
| Sorocaba                | 679378            | 320                    | 68.4         | 0.00047     | 45038.2         | 0.0071          |
| Itu                     | 179939            | 48                     | 10.3         | 0.00027     | 64071.9         | 0.0007          |
| Votorantim              | 122480            | 36                     | 7.7          | 0.00029     | 18351.2         | 0.0020          |
| Mairinque               | 47150             | 17                     | 3.6          | 0.00036     | 21014.9         | 0.0008          |
| Araçoiaba da Serra      | 34146             | 15                     | 3.2          | 0.00044     | 25532.7         | 0.0006          |
| Porto Feliz             | 53098             | 15                     | 3.2          | 0.00028     | 55670.6         | 0.0003          |
| Salto de Pirapora       | 45422             | 12                     | 2.6          | 0.00026     | 28050.9         | 0.0004          |
| Iperó                   | 37133             | 4                      | 0.9          | 0.00011     | 17028.9         | 0.0002          |
| Alumínio                | 18628             | 1                      | 0.2          | 0.00005     | 17094.0         | 0.0001          |
| TOTAL                   | 1217374           | 468                    | 100.0        | 0.00038     | 291853.9        | 0.1604          |

Where: Pop.: Population in municipality in 2019 (IBGE, 2020); Infected (n): number of people with COVID-19 (CVE, 2020); Infected (%): percentage of disease registration by municipality; PR: Prevalence Rate, ratio between the number of infected per population at risk; Munic. Area (ha): Area of Municipality in hectare (IBGE, 2020); Infected per ha: number of people infected per hectare. *According to Epidemiological Surveillance Center of the São Paulo Health Secretaria (CVE, 2020)
(ha)) could estimate a posteriori the unknown parameters (Chen et al., 2000), i.e., generate a continuous surface, representing the occurrence probability of infected people per hectare and Elderly Occurrence.

Thus, in the Geographic Information System environment, empirical Bayesian kriging was used as an automated geostatistical interpolation method that calculates parameters (Eq. 3 and 4) through a subset of data (Eq. 1 and 2) and simulations.

During the simulations, the method considers the error introduced by the parameter estimation, making the results more accurate. Thus, the Bayesian kriging method uses the maximum likelihood technique to predict the unknown surface values through the sampled points, i.e., the values of Si and EO of Sorocaba city (Krivoruchko, 2012).

The model was adjusted for an empirical prediction of 100 points in the exponential variogram, with an overlapping distance of 1 unit for 100 simulations. The maximum and the minimum number of neighboring (i.e., Sorocaba Neighboring municipalities) points for interpolation were 15 and 10, respectively, covering a radius of 0.0064 units, resulting in Eqs. 3 and 4.

\[
\text{Si Model} = 0.00173 + 0.802 \times \text{SI(}ha) \tag{3}
\]

\[
\text{EO Model} = 0.30852 + 0.779 \times \text{EO} \tag{4}
\]

where: SI Model is the predictive model for the sector Infected per hectare (ha), and EO Model is the predictive model for the Elderly Occurrence.

We analyzed the model prediction magnitude through the Root Mean Square Error (RMSE), which should show low values to indicate a robust result, ensuring a correlation coefficient (R) between the empirical values and prediction greater than 0.70. For this, we compared the original data with the values estimated by the model, an automated procedure in the GIS environment.

Considering the surface robustness, the map was clipped with the Sorocaba municipality limits to know the COVID-19 spatialization for the study area.

In the same way, we verified the EO using 200 random points overlaid to the surface to know the point values.

Pearson’s correlation coefficient greater than 0.70 was used as a reference, with the data previously tested for normal distribution. This coefficient

\[
\text{EO Model} = 0.30852 + 0.779 \times \text{EO} \tag{4}
\]
considers that an absolute value of 1 indicates a perfect linear relationship. A correlation close to zero indicates no linear relationship between the variables. The sign indicates a sense of correlation. A positive value indicates that the variables increase simultaneously, and the line slopes upwards. A negative value indicates that as one variable increases, the other decreases, and the line slopes downwards.

**Results**

The models for the interpolation of the SI (ha) and EO data, based on the empirical Bayesian method, showed suitable adjustments, having RMSE and R coefficients of 0.13 and 0.76 (Fig. 3a) and 4.79 and 0.80 (Fig. 3b), respectively.

Figure 4 illustrates the spatial model of SI by COVID-19 in Sorocaba, having two main spots marked by the high probability of transmissibility in its south and central-west region (probability values (p) of 0.156). The south spot is larger than the second, with neighboring regions with lower p values than the central-west (p: 0.047 and p:0.028). However, the central-west patch is surrounded by regions with a p of 0.095, having the second value in classifying the probability of transmissibility. Thus, we have a region with a higher probability of transmission involved by another with a lower value, being a spatial pattern of the municipality (with p ranging from 0.156 to 0.013), except for the patch in the south of Sorocaba.

Having an SI average of 0.007 (Table 1) infected per hectare according to ESC/SPHS (CVE, 2020), Sorocaba showed 0.6% of the territory with an average probability of 19.3 (n=0.136) times greater than the average value of infected per ha in the municipality (Table 2), which can reach 22.3 times (n=0.156).

Then, the average estimates pointed to 5.0% of the municipality with 0.058 (± 0.0091) infected/ha, followed by 17.1% of the territory with 0.036 (± 0.0051), another 28.2% had 0.020 (± 0.0044) and the 49.0% of the territory presented 0.007 (± 0.0036) infected/ha, similar to the municipal rate published by the State Health Department (CVE, 2020).

Concerning the EO spatialization, Sorocaba showed regions with two individuals/ha and regions more populous (the elderly population) with 23 individuals/ha in the south of the municipality (Fig. 5). Similar to SI spatialization (Fig. 4), the highest probability region is involved by another associated with one level down, following this pattern until the region with the least number of elderly (2 ind./ha).

The correlation analysis between SI and EO resulted in a correlation coefficient (R) of only 0.49 (p < 0.0001; F2 = 61.66 and 124 gl) (Fig. 6).

**Discussion**

The model we used for interpolating the SII (ha) reveals the identification of regions with different transmissibility levels (Fig. 4; Table 2). Thus we can highlight that it is essential to know the population dynamics to plan mitigating actions aiming to combat a pandemic (Dowd et al., 2020). As we did in Fig. 4 and Fig. 5, the spatialization of the information can support the linkage between vulnerable populations and risk factors (Sarwar et al., 2020).
Therefore, public census data are essential but are not commonly used in routine infectious disease surveillance, especially by official agencies (SAR-WAR et al., 2020). As we noticed in Table 1, one reason is related to the poor detailing of data, which is caused by underreporting of infected by COVID-19, especially in developing countries (Redón and Aroca, 2020).

Even in this scenario, we obtained a good mathematical adjustment for our models without available data (i.e., data on COVID-19 infections and demographics).

In the same way, Roda et al. (2020) affirmed that the simple models are more robust than the complexes, considering the problem of its validation.
through data of confirmed cases, which influence the calibration of these complex models.

Knowing the model’s weight in the pandemic situation, even more about the data questions, Sarwar et al. (2020) pointed out the use of spatial statistics methods in these conditions. Methods that permit understanding the relationships between diseases and related hazards in different periods can allow us to identify their transmission mode, among other points.

In the case of SI spatialization, we can support the development of local estimators, which can indicate action. Ogen (2020) showed that graphics rates could highlight areas where control actions were well-organized.

So, a challenging task is modeling factors that have influenced the spread of COVID. According to our findings, age was not a factor, considering that there was no strong correlation between the distribution models of SI and EO (Figs. 4–6).

Based on this result, we can look at other factors such as income inequality (Mollalo et al., 2020), social mobility restrictions, individual protection measures, virus incubation time, transmission rate (Cássaro & Pires, 2020), other age groups, climatic...
conditions (Réndon and Aroca, 2020) and human behavior (Arino, 2020).

Cássaro and Pires (2020) mentioned that factors like these should be included in more realistic models, revealing reliable aspects of the outbreak evolution. Models, as we proposed, aiming at the definition of places with a higher probability of infected people prevalence, can be considered a special tool for the decision-makers to investigate how the actions are changing the evolution of COVID-19 cases.

Our finding obtained a result following Otoo et al. (2020), who showed a relationship between the spread of COVID and the infected population’s steep contact rate (symptomatic and asymptomatic individuals).

Unfortunately, socioeconomic inequalities have been a world problem of COVID, especially in developing countries (United Nations, 2020), where they are accentuated. According to Ahmed et al. (2020), the tendency of inequalities increases as the disease spreads, considering the health system vulnerabilities, a sharp decline in economies, and an increase in unemployment rates.

Conclusion

Considering the challenge to minimize the outbreak spread, we spatialize COVID-19 occurrence through the Bayesian model, having adequate results and good prospects.

Our findings highlight a Sorocaba region, representing 0.6% of the total area evaluated, having a probability of around 23 times plus people infected per ha than the medium of the municipality.

In addition, we obtained a weak correlation between sector infected per ha and Elderly Occurrence, evidencing that other factors (related to COVID dynamics) should be analyzed, such as the prevalence of the disease by age groups, spatialization of the population in other age groups, dynamics of movement of people, even the environmental factors, that can interfere in the behavior of the population, among others.

Finally, the results can support decision-makers in analyzing locations with higher transmissibility values in the municipality and identifying possible infections. Likewise, the method is replicable and can aid in the spatialization of other diseases and their prevention.

This way, we define robust mathematical parameters of occurrence estimation and actions to control the spread of COVID-19, supporting its applications in other situations.

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Data availability Data and materials may be made available.

Code availability Not applicable.

Declarations

Conflicts of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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