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Coronavirus Pandemic

COVID-19 risk areas associated with social vulnerability in northeastern Brazil: an ecological study in 2020

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Abstract

Introduction: COVID-19 is a major public health concern in this century. The causative agent SARS-CoV-2, is highly contagious and spreads continuously across territories. Spatial analysis is of enormous importance in the process of understanding the disease and its transmission mechanisms. We aimed to identify the risk areas for COVID-19 and analyze their association with social vulnerability in Maceió, Alagoas. The study was conducted in 2020.

Methodology: This is an ecological study to evaluate the incidence, mortality and case fatality rate of COVID-19 and their relationship with 12 indicators of human development and social vulnerability. Multivariate and spatial statistics were applied. A 95% confidence interval and a 5% confidence level were considered.

Results: The spatial scan statistic revealed the existence of six high-risk clusters for the incidence of COVID-19. The regression model showed that social indicators, such as literacy of people, residents of private households, households with more than four residents, and resident brown population, were associated with COVID-19 transmission in Maceió-AL. The disease affected localities whose populations are exposed to a context of intense socioeconomic vulnerability.

Conclusions: Based on the results, it is necessary to adopt measures that take into account the social determinants of health in order to minimize the damage caused by the pandemic.

Key words: SARS-CoV-2; vulnerability; epidemiology; COVID-19.

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Introduction

Social conditions have a direct impact on the incidence, mortality and case fatality rates of COVID-19. Studies have shown that living in high density housing increases the risk of infection [1]. Such living conditions limit the effectiveness of social distancing measures promoted by health authorities around the world. This situation is evidenced by the vulnerable population, who live in places with inadequate socioeconomic conditions [2].

In the absence of public housing policies, this population lives in informal living arrangements leading to the formation of slums. This leads to increasing irregular employment opportunities, and aggravates the social inequality process [3]. In addition, spaces with low quality of life are created. This process directly impacts access to health services, since the less developed regions have fewer resources and poor infrastructure, thereby depending exclusively on presence of the state-sponsored health and welfare programs [4].

Therefore, understanding the spatial dispersion process of the virus allows the identification of hotspots of disease transmission, providing an accurate knowledge of the epidemiological reality and improving the decision-making process by public health managers [5]. Using geostatistical analysis, it is possible to map and track cases so that the actions taken are effective [6]. This study is justified by the lack of studies addressing the spatial distribution of SARS-CoV-2 in the state of Alagoas.

The conventional literature on COVID-19 uses states and municipalities as the unit of analysis to observe the territorial dispersion of the disease. This study is innovative since it examines the phenomenon of spatial diffusion with the neighborhoods of Maceió as the unit of analysis. Finally, it allows a clearer and more precise understanding of the epidemiological dynamics of COVID-19 in space, since territorial units with a lower level of disaggregation and more homogeneous social characteristics are used [7]. Thus, the aim of this study was to identify risk areas for COVID-19 and analyze its association with social vulnerability in Maceió, Alagoas, Brazil, 2020.

Methodology

Study design, population and period

In this ecological study we included all confirmed cases and deaths due to COVID-19 registered in Maceió between March 8 and August 10, 2020.

Area of Study

The municipality of Maceió has a population of 1,025,360 people (Figure 1). A total of 47.1% of the households have adequate sanitation, 57.1% of urban households are on public roads with afforestation and 32.7% of urban households are on public roads with adequate urbanization (presence of sewage system, sidewalk, pavement and curb).

Study variables, data sources and collection

Two sets of variables were included in the study.

The first was composed of three epidemiological indicators: coefficient of accumulated incidence of COVID-19/100,000 inhabitants, coefficient of accumulated mortality by COVID-19/100,000 inhabitants and case fatality rate (proportion of fatal cases). All data were extracted from the public database of the state (http://www.dados.al.gov.br/dataset/painel-covid19-alagoas). In addition, population data was extracted from the Brazilian Institute of Geography and Statistics (IBGE) (https://sidra.ibge.gov.br/home/pms/brasil).

The following equations were used to calculate the indicators:

a) COVID-19 incidence rate

$$Incidence\ rate = \frac{Number\ of\ COVID-19\ cases}{Resident\ population\ in\ the\ year\ 2020} \times 100{,}000$$

b) Mortality rate due to COVID-19

$$Mortality\ rate = \frac{Number\ of\ deaths\ due\ to\ COVID-19}{Resident\ population\ in\ the\ year\ 2020} \times 100{,}000$$

c) Case fatality rate

$$Case\ fatality\ rate = \frac{Number\ of\ deaths\ due\ to\ COVID-19}{Number\ of\ confirmed\ cases} \times 100$$

The second group of variables was composed by 12 social indicators that describe the population's living conditions. The following indicators were taken from the 2010 IBGE demographic census:

1. Literacy rate of people ≥ 10 years of age (%);
2. Average nominal monthly income of people ≥ 10 years of age (BRL);
3. Average number of residents in permanent private housing units (number of people);
4. Neighborhood Area (km²);
5. Total resident population in the neighborhood (number of people);
6. Demographic density (hab/km²);
7. Households with more than four residents (%);
8. Extension of subnormal agglomerates (%);
9. Population ≥ 60 years of age (%);
10. Percentage of population with income below minimum wage (%);
11. Percentage of population with lack of access to piped water (%);
12. Proportion of resident brown population (%).

The statistical analysis was carried out in two stages

<u>Spatial analysis and identification of risk areas</u>

This analysis was divided into two stages: i) global and local Moran's statistics; and ii) purely spatial scanning statistics.

Initially, spatial autocorrelation was calculated using the Moran global index (IM Global). The index provides a general measure of the spatial association, and considers the proximity matrix of order 1 for calculation. The index varies between -1 and +1, where the values equal to zero indicate the absence of spatial autocorrelation and the values close to +1 and -1 indicate the existence of positive or negative spatial autocorrelation [8].

Once the global dependence was verified, the Local Moran Index (LISA) was calculated. The municipalities are positioned in the quadrants of the Moran scattering diagram based on the LISA: Q1 (High-High) - municipalities where the attribute value and the average value of the neighbors are above the average of the set and, therefore, the municipalities are considered highest priority for intervention;

Figure 1. Map of the study area.

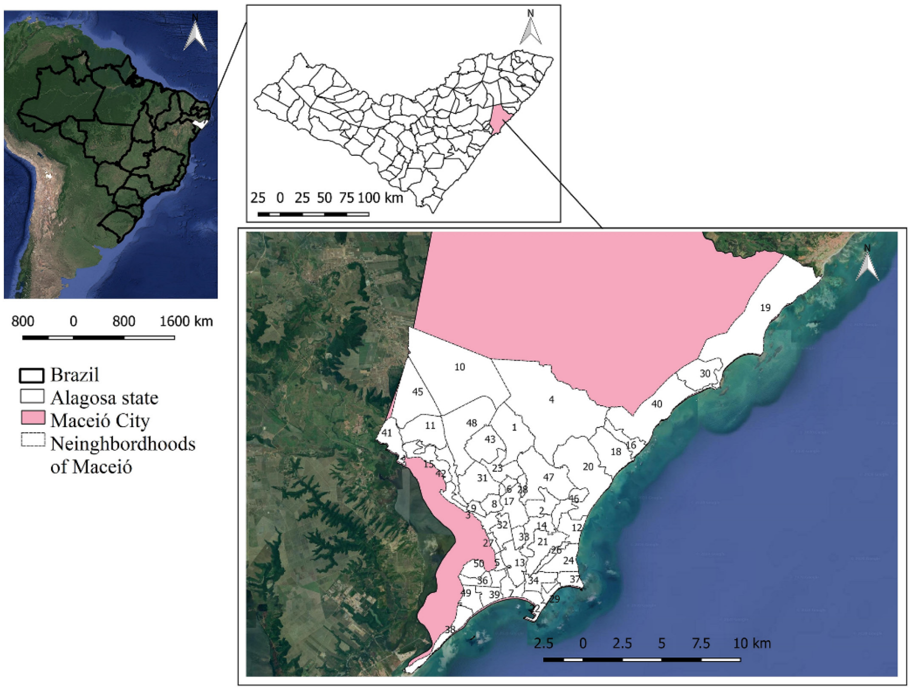
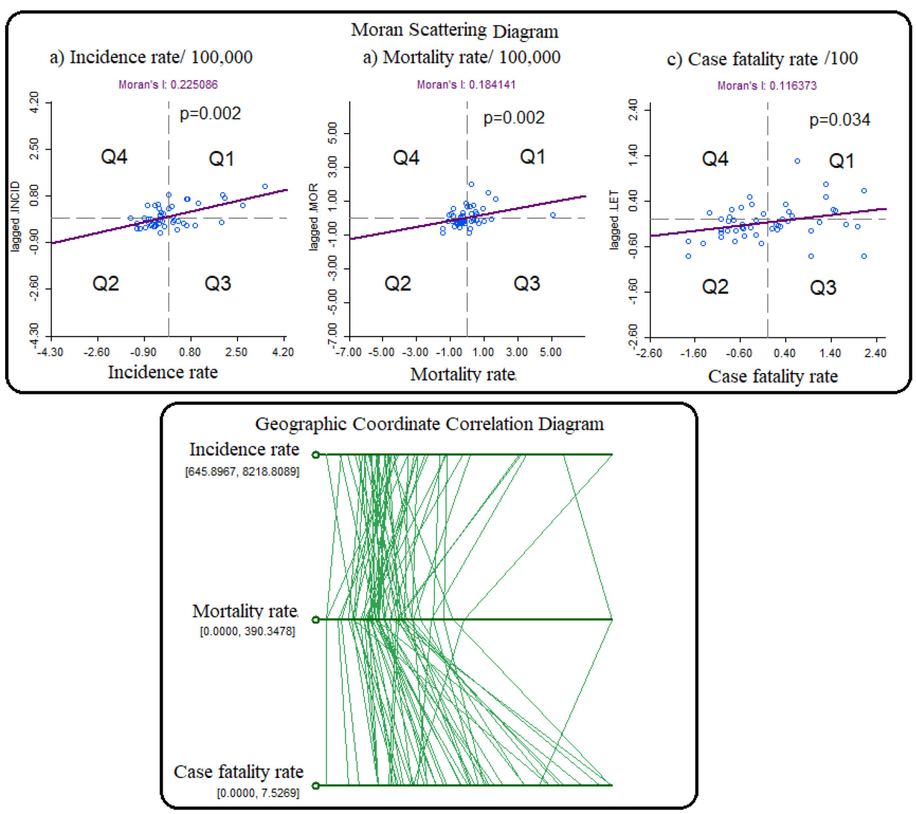


Figure 2. Moran global statistics and geographic coordinate diagram of the epidemiological indicators of COVID-19. Maceió, 2020.



Q2 (Low-Low) - the attribute value and the average of the neighbors are below the average of the set; Q3 (High-Low) - attribute value is greater than that of neighbors and the average of neighbors is less than that of the set; and Q4 (Low-High) - the attribute value is less than that of neighbors and the average of neighbors is greater than the average of the set. The municipalities classified as High-Low and Low-High are those with intermediate priority [8].

The purely spatial scanning statistic was used to detect clusters in municipalities with a high risk of COVID-19 transmission. The statistical tool is based on the Poisson discrete probability model to identify clusters with the maximum likelihood method, whose alternative hypothesis is that there is a high risk inside the window compared to outside [9]. The scan statistic establishes a flexible circular window in the map, positioned on each of the several centroids and whose radius is established in 50% of the total population at risk. The flexibility of the window was justified by not knowing the size of the cluster a priori, since the population at risk is not geographically homogeneous. Monte Carlo simulations (with 999 permutations) were used to obtain p values, and the significance level was determined at $p < 0.05$. Clusters with two or less municipalities were excluded.

The Terra View (version 4.2.2, Brazilian Space Research Institute (INPE), São José dos Campos, SP, Brazil), SatScan (version 9.1, National Cancer Institute, Bethesda, MD, USA) and QGis (version 2.14.11 Open Source Geospatial Foundation (OSGeo), Beaverton, OR, USA) were used for the analyses.

<u>Analysis of the association between epidemiological indicators and neighborhood living conditions</u>

Initially, Spearman's non-parametric correlation was used to identify the independent variables (social indicators) related to the dependent variables (epidemiological indicators). Correlated variables were considered when $p < 0.05$. A multiple linear regression model was used to identify the social indicators that were significantly associated with the epidemiological indicators.

Ethics

This study was approved by the research ethics committee of Centro Universitário Cesmac on October 14, 2020; approval no. 4,338,350s.

Results

Maceió had registered 23,989 cases of COVID-19 (2573.7/100,000 inhabitants) and 778 deaths (83.5/100,000 inhabitants) by August 10, 2020. The case fatality rate was 3.2%. Moran's Global Statistics indicated spatial dependence on three indicators: incidence coefficient (I 0.225086; $p = 0.002$), mortality coefficient (I 0.184141; $p = 0.002$) and case fatality rate (I 0.116373; $p = 0.003$). The geographic coordinate diagram showed that incidence and mortality rates were higher in certain areas, while the case fatality rate was associated with spatial distance (Figure 2).

The neighborhoods Jacintinho (cases = 1747, 2019.3/100,000; and deaths = 62; 71.7/100,000), Benedito Bentes (cases = 1645, 1867.5/100,000; and deaths = 59; 67.0/100,000), Tabuleiro dos Martins (cases = 1527, 2358.1/100,000; and deaths = 40; 61.8/100,000) and Cidade Universitária (cases = 1480, 2071.6/100,000; and deaths = 43, 61.8/100,000) were responsible for 26.7% of all confirmed cases and 26.2% of all deaths in the municipality. The neighborhoods of Ipioca (7.5%), Fernão Velho (7.5%) and Chã da Jaqueira (7.23%) had the highest case fatality rates (Figure 3).

In the case of incidence and mortality, seven neighborhoods were located in quadrant 1 (Q1) of the Moran scattering diagram. The neighborhoods Jatiúca, Farol, Centro, Ponta da Terra, Pajuçara, Mangabeiras and Ponta Verde, were responsible for 4632 (19.3%) confirmed cases. Seven neighborhoods (Ponta Grossa, Jatiúca, Trapiche da barra, Centro, Ponta da Terra, Pajuçara and Mangabeiras) were responsible for 125 (16.1%) of the deaths. The case fatality rates of only three neighborhoods were located in Q1: Trapiche da Barra (4.6%), Fernão Velho (7.5%) and Mutange (5.9%) (Figure 3).

The spatial scan statistics showed the existence of six clusters at high risk for the incidence of COVID-19: cluster 2, with centroid in the Poço neighborhood and eight other neighborhoods with a high relative risk (RR 2.00) and cluster 1 (centroid in Pajuçara, composed of nine neighborhoods and with RR 1.95). Only a large spatial cluster was identified in the case of mortality and this was located in the south of the city and its centroid was located in the neighborhood of Levada. RR of this area with 25 neighborhoods was 1.58. Three risk clusters were identified for the case fatality rate; out of these, the case fatality rate of cluster 3 was 6.6%. This area included three neighborhoods and had an RR equal to 2.01. The neighborhoods Centro, Gruta de Lourdes and Farol were part of clusters for the three indicators analyzed (Figure 4 and Table 1).

Four variables showed a significant correlation with COVID-19 incidence coefficient.

Figure 3. Exploratory spatial analysis of COVID-19. Maceio Alagoas. 2020.

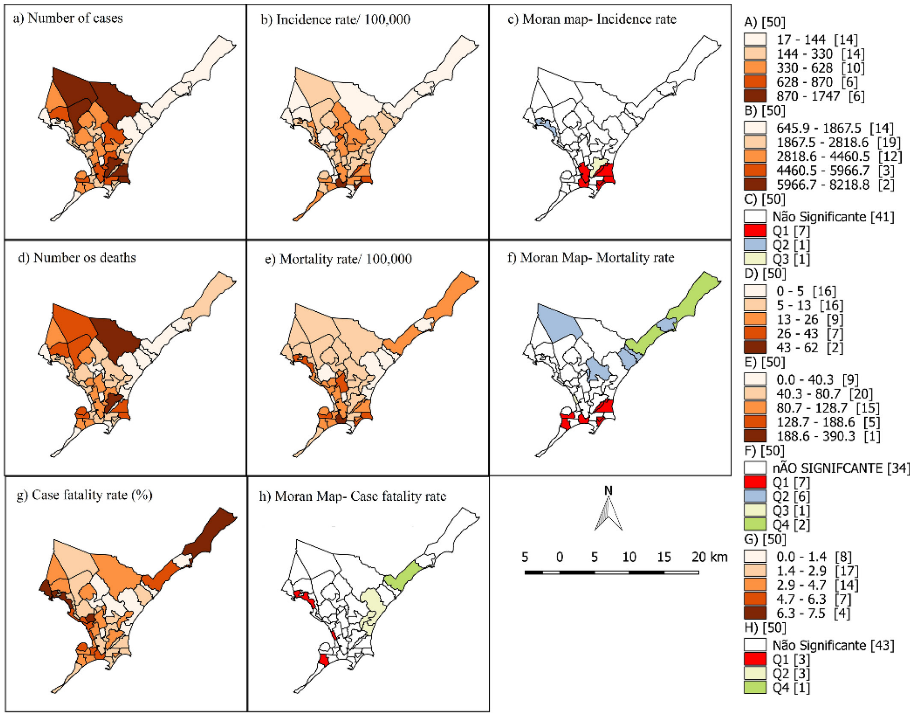


Figure 4. Spatial scan statistics and high-risk areas for COVID-19. Maceió, Alagoas, 2020.

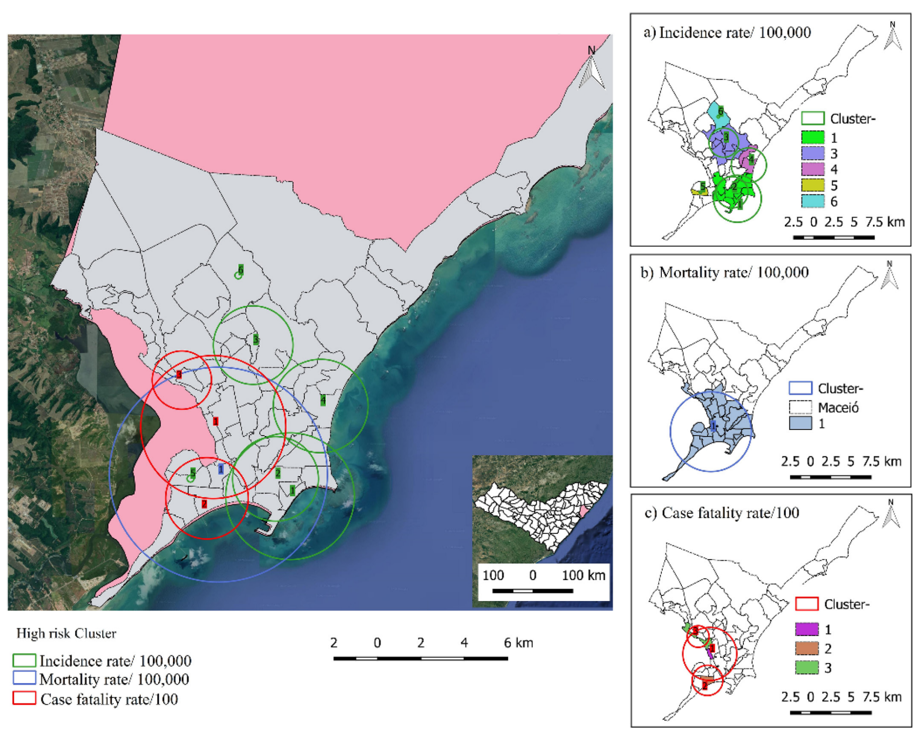


Table 1. Spatial risk clusters for COVID-19, Maceió, Brazil, August 10, 2020.

a) Incidence rate per 100,000 inhabitants

Cluster	Centroid	Radius (km^2)	Locations	No. cases	Incidence/100,000	RR	*p* value
1	29- Pajuçara	2.96	29, 35, 34, 22, 37, 24, 26, 7, 13	5363	4373.4	1.95	< 0.0001
2	34- Poço	1.97	34, 35, 29, 22, 26, 7, 13, 37	3918	4635.5	2.00	< 0.0001
3	28- Ouro Preto	1.83	28, 6, 44, 47, 23, 17, 2	2510	3596.5	1.47	< 0.0001
4	12- Cruz das Almas	2.18	12, 46, 24	1968	3375.6	1.37	< 0.0001
5	36- Ponta Grossa	-	36	839	3841.4	1.54	< 0.0001
6	1- Antares	-	1	577	3354.5	1.34	< 0.0001

b) Mortality rate per 100,000 inhabitants

Cluster	Centroid	Radius (km^2)	Locations	No. deaths	Mortality/100,000	RR	*p* value
1	25- Levada	5.01	25, 5, 7, 39, 36, 13, 50, 49, 27, 34, 22, 33, 32, 35, 29, 21, 26, 14, 24, 37, 9, 17, 3, 8, 38	439	99,6	1.58	< 0.0001

c) Case fatality rate (%)

Cluster	Centroid	Radius (km^2)	Locations	No. deaths	Case fatality (%)	RR	*p* value
1	27- Mutange	3.33	27, 32, 5, 33, 13, 50, 25, 9, 8, 3, 36, 17, 14, 7, 21, 39	310	4.1	1.49	0.0001
2	39- Prado	1.90	39, 49, 36, 25, 7, 50	142	4.8%	1.63	< 0.0001
3	3- Bebedouro	1.36	3, 9, 8	41	6.2	2.01	0.013

Locations: 1: Antares; 2: Barro Duro; 3: Bebedouro; 4: Benedito Bentes; 5: Bom Parto; 6:Canaã; 7: Centro; 8: Cha da Jaqueira; 9: Cha De Bebedouro; 10: Cidade Universitária; 11: Clima Bom; 12: Cruz das Almas; 13: Farol; 14: Feitosa; 15: Fernão Velho; 16: Garca Torta; 17: Gruta De Lourdes; 18: Guaxuma; 19: Ipioca; 20: Jacarecica; 21: Jacintinho; 22: Jaraguá; 23: Jardim Petrópolis; 24: Jatiuca; 25: Levada; 26: Mangabeiras; 27: Mutange; 28: Ouro Preto; 29: Pajucara; 30: Pescaria; 31: Petropolis; 32: Pinheiro; 33: Pitanguinha; 34: Poco; 35: Ponta da Terra; 36: Ponta Grossa; 37: Ponta Verde; 38: Pontal da Barra; 39: Prado; 40: Riacho Doce; 41: Rio Novo; 42: Santa Amelia; 43: Santa Lucia; 44: Santo Amaro; 45: Santos Dumont; 46: São Jorge; 47: Serraria; 48: Tabuleiro dos Martins; 49: Trapiche da Barra; 50: Vergel do Lago.

Two of these variables, literacy rate of people ≥ 10 years (%) and value of the average nominal monthly income of people ≥ 10 years (BRL), were positively correlated. The other two variables, average number of residents in permanent private households (people) and resident brown population (%), were negatively correlated. Five variables showed correlation with case fatality rate; two of these were negatively correlated (literacy rate of people aged ≥ 10 years (%) and value of the average monthly nominal income of people aged ≥ 10 years (BRL)) and three were positively correlated (average number of residents in permanent private housing units (people), households with more than 4 residents (%), and resident brown population (%)). There was no association between the indicators of social vulnerability and mortality rate (Table 2). In the multiple linear regression model, only one variable was associated with the incidence rate (literacy rate of people aged ≥ 10 years (%)) and two variables were associated with the case fatality rate (households with more than four residents (%) and resident brown population (%)) (Table 3).

Discussion

Recommendations for physical distance and hygiene to control the spread of COVID-19 have

Table 2. Spearman's correlation between epidemiological indicators and social vulnerability indicators. Maceió, Brazil, 2020.

Social indicator	Incidence/100,000	Mortality/100,000	Case fatality rate (%)
Literacy rate of people aged ≥ 10 years (%)	0.837 (p < 0.001)	0.141 (p = 0.329)	-0.436 (p = 0.002)
Value of the average nominal monthly income of people aged ≥ 10 years (BRL)	0.762 (p < 0.001)	0.002 (p = 0.987)	-0.529 (p = 0.000)
Average number of residents in permanent private housing units (People)	-0.451 (p = 0.001)	-0.058 (p = 0.690)	0.362 (p = 0.010)
Neighborhood Area (km²)	-0.084 (p = 0.562)	0.147 (p = 0.309)	0.253 (p = 0.076)
Resident population in the neighborhood	-0.016 (p = 0.913)	0.160 (p = 0.266)	0.177 (p = 0.219)
Demographic density (hab/km²)	0.097 (p = 0.504)	-0.108 (p = 0.456)	-0.183 (p = 0.203)
Households with more than four residents (%)	-0.162 (p = 0.261)	0.117 (p = 0.418)	0.287 (p = 0.043)
Extension of subnormal agglomerates (%)	0.031 (p = 0.829)	0.027 (p = 0.853)	-0.048 (p = 0.741)
Population ≥ 60 years old (%)	-0.016 (p = 0.914)	-0.057 (p = 0.696)	-0.049 (p = 0.735)
Income below minimum wage (%)	-0.118 (p = 0.414)	0.063 (p = 0.665)	0.137 (p = 0.341)
Lack of access to piped water (%)	-0.103 (p = 0.475)	0.112 (p = 0.440)	0.154 (p = 0.286)
Resident brown population (%)	-0.636 (p < 0.001)	0.012 (p = 0.935)	0.535 (p < 0.001)

limited effect among the Brazilian population due to social inequalities. The scenario is worse in the slums which are densely populated urban residential areas characterized by lack of public health services and infrastructure. The need for income in the informal sector of the economy, linked to socio-spatial vulnerability, makes it difficult to establish appropriate prophylactic measures in these areas [10]. In this sense, spatial analyses are essential to understand community risk and provide strategic decision making, ranging from social distance measures to resource allocation [11,12].

The first confirmed case of COVID-19 in Maceió occurred 11 days after the first official report of COVID-19 in Brazilian territory, on February 26, 2020. According to the Municipal Health Secretariat, the first reported case of COVID-19 in the capital was a 42 year old man who had recently returned from the most affected region of COVID-19, Lombardy, in northern Italy [13]. The state of Alagoas declared a state of public emergency about a week after the pandemic was announced. Since then, the Municipality and the State Health Secretariat have been publishing daily epidemiological bulletins with information about the spread of the virus in the capital of Alagoas.

In the spatial analysis, it was found that the neighborhood with the highest incidence rate (Pajuçara) had one of the highest per capita incomes in the city. This finding may corroborate the idea of the spillover effect in the dynamics of disease transmission. Initially, cases were concentrated in wealthier neighborhoods and then spread throughout the city. This may be because the more privileged populations have more resources for displacement, favoring the spread of the virus in their places of residence or spreading it to other people outside [14].

The social determinants of health may explain the results obtained in relation to mortality and case fatality rate, since the most affected regions (Levada, Mutange, Prado and Bebedouro) are those with the greater social vulnerability. Access to disease prevention mechanisms is more difficult or nonexistent in the poorest regions [15]. The lack of access to sanitation is also another variable that influences the incidence of the disease in these neighborhoods [16]. This vulnerability has increased the risk of exposure to SARS-CoV-2 [17].

Paradoxically, policies of social distancing may also contribute to the burden of COVID-19 [18]. Since poverty increases the risk of COVID-19, social distancing measures and trade closures accentuate the degree of poverty of the most vulnerable populations, causing an increase in social inequality [19,20]. According to the IBGE, Brazil reached the highest unemployment rate in history during the pandemic [21].

In Maceió, four social indicators showed significant correlation with the COVID-19 incidence coefficient. However, the literacy rate of people ≥ 10 years of age and the average number of residents in permanent private households, showed a positive correlation. The educational level also has a significant impact on the analysis. Areas with higher educational levels had lower case fatality rates. This finding can be justified since the level of education of people directly correlates with the understanding of data and information related to the disease, as well as their socioeconomic conditions [22].

Globally, the areas with the highest population density and internal displacement had the highest levels

Table 3. Multiple linear regression between epidemiological indicators and social vulnerability indicators. Maceió, Brazil, 2020.

Variables	B	Default error	t	*p*	R^2 (*p* value through F test)
a) Incidence coefficient/100 thousand					
(Constant)	-7826.440	6503.856	-1.203	0.235	0.478 (*p* = 0.001)
Literacy rate of people aged ≥ 10 years (%)	155.800	45.206	3.446	0.001	
Value of the average nominal monthly income of people aged ≥ 10 years (BRL)	0.067	0.467	0.143	0.887	
Average number of residents in permanent private housing units (People)	-978.249	968.216	-1.010	0.318	
Resident brown population (%)	0.032	32.566	0.001	0.999	
b) Case fatality rate (%)					
(Constant)	-5.598	9.769	-0.573	0.570	0.361 (*p* = 0.001)
Literacy rate of people aged ≥ 10 years (%)	-0.075	0.065	-1.166	0.250	
Value of the average nominal monthly income of people aged ≥ 10 years (BRL)	0.001	0.001	1.839	0.073	
Average number of residents in permanent private housing units (people)	1.108	1.370	0.808	0.423	
Households with more than four residents (%)	0.080	0.040	2.011	0.045	
Resident brown population (%)	0.142	0.048	2.960	0.005	

of infection in Iran [23]. In Italy, provinces that adopted measures to contain the disease more quickly were not affected by their neighbors [24]. Studies indicated that India had the potential to be the next global epicenter of the disease given the country's socio-demographic characteristics and the environmental factors that spread the disease [25]. On the other hand, in Hubei, the epicenter of the disease in China, the epidemic had centralized characteristic and presented a significant global spatial autocorrelation [26], while the United States had 26 emergent clusters of disease transmission spread across its territory [27].

This study had limitations. Since we analyzed secondary data, it is possible that the number of deaths from COVID-19 have been underreported. Lack of adequate care capacity for initial cases, as well as low testing, may also have contributed to the underreporting of cases early in the pandemic [28,29].

Conclusions

The parts of the city that were affected by the disease included populations that were exposed to intense socioeconomic vulnerability. It is necessary to adopt measures that take into account the social determinants of health to minimize the damage caused by the pandemic. The results presented in this study can serve as a resource to managers and technicians of public administration of essential data and information for sensitive decision making in relation to COVID-19.

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