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COVID-19: intensive care units, mechanical ventilators, and latent mortality profiles associated with case-fatality in Brazil

COVID-19: unidades de terapia intensiva, ventiladores mecânicos e perfis latentes de mortalidade associados à letalidade no Brasil

COVID-19: unidades de cuidados intensivos, ventiladores mecánicos y perfiles latentes de mortalidad asociados a la letalidad en Brasil

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Abstract

In response to the accelerated increase in the number of COVID-19 cases, countries must increase their supply of beds in intensive care units (ICUs). Respiratory diseases, neoplasms, cardiopathies and hypertension, and diabetes are associated with higher COVID-19 case-fatality. The study aimed to identify the regions of Brazil with higher specific mortality rates from these comorbidities and the regions with the greatest shortage of ICU beds and mechanical ventilators. A cross-sectional ecological study was performed in which the units of analysis were the country's Health Regions. Data were obtained from Brazilian Health Informatics Department – DATASUS (National Registry of Healthcare Establishments – 2019, Mortality Information Systems – 2017, and Population Projections – 2017). We calculated the disease group-specific mortality rates for hypertension, neoplasms, diabetes, cardiac diseases, respiratory diseases and the rates of total ICU beds, private ICU beds, ICU beds in the Brazilian Unified National Health System (SUS), and ventilators in the SUS, per 100,000 inhabitants. The mortality profile was determined by latent profiles analysis, and the cluster analysis of ICU beds and ventilators used the spatial scan method. Kernel maps were constructed for the data's visualization. Level of significance was set at 5%. Four latent mortality profiles were observed. The Health Regions with the highest mean mortality rates were located in regions with shortages of ICU beds and ventilators, especially in parts of the Northeast, Southeast, and South of Brazil. The spatial localization of regions with both the highest mortality and shortages of ICU beds/ventilators requires attention by policymakers and public planners to deal efficiently and fairly with the COVID-19 epidemic in Brazil.

COVID-19; Intensive Care Units; Mechanical Ventilators; Latent Class Analysis; Mortality

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Introduction

The outbreak of infection with the novel coronavirus SARS-CoV-2, called coronavirus disease 2019 (COVID-19), was first reported in December 2019 in Wuhan, China [1,2]. The disease appeared with severe forms of pneumonia and rapid human spread. Patient signs and symptoms include dry cough, headache, hypoxia, fever, and shortness of breath. The deaths occur due to progressive respiratory failure caused by pulmonary damage [3,4,5]. Severe cases thus require treatment in intensive care units (ICUs) [6].

The rapid increase in the numbers of cases and deaths in China led the World Health Organization (WHO) to declare an International Public Health Emergency of International Concern on January 30, 2020 [7]. From that point on, a series of health measures were announced by the WHO, culminating in the declaration of a global pandemic on March 11, 2020 [8].

The spatial distribution of COVID-19 crossed various national borders, leading different countries to declare health emergencies and states of public calamity. The COVID-19 epicenter shifted from China to Europe, especially Italy and Spain. In March 2020, the United States also began to experience a rapidly growing number of COVID-19 cases and deaths.

The first case in Brazil was identified on February 26, 2020, in the State of São Paulo, and the first death occurred on March 17 in that same state. Estimates of the epidemic's progression indicate exponential growth (Ministério da Saúde. Painel coronavirus. https://covid.saude.gov.br/, accessed on 12/Apr/2019). Measures to contain the epidemic's spread include hygiene, testing more cases, and social isolation [9], since COVID-19 is not symptomatic in all infected individuals [10,11,12].

All the measures taken thus far aim to avoid exhausting health systems' capacity to treat the population that evolves to the more severe forms of the disease. These situations require admission to intensive care units (ICUs) and the use of mechanical ventilators for respiratory support in severe cases [13]. Since the beginning of the epidemic in China, countries have mobilized to provide their health systems with the maximum capacity to treat patients with respiratory complications. However, the more severe cases have tended to present in older patients with certain comorbidities, especially respiratory and cardiac diseases, hypertension, and diabetes [14]. This association with comorbidities also means that the younger population with these conditions are at increased risk.

Since Brazil does not have a database of persons with these comorbidities (which would involve considerable underreporting), the use of mortality from these causes could help identify areas where these diseases are more prevalent, thereby providing more trustworthy data. The current epidemiological study thus aimed to identify the Health Regions of Brazil with the highest mortality rates from diseases associated with the severe forms of COVID-19 and the spatial distribution of ICU coverage (ICU beds and mechanical ventilators) for the national response to the pandemic.

Methodology

This was a cross-sectional spatial ecological study in which the analytical units were Brazil's Health Regions. The Brazilian Ministry of Health defines a Health Region as a continuous geographic space formed by the combination of adjacent municipalities with cultural, economic, and social similarities. The definition also considers shared communications networks and transportation infrastructure with the aim of integrating the organization, planning, and execution of health activities and services [15]. The study included all the 450 Health Regions of Brazil.

Two blocks of variables were used, disease-specific mortality variables and intensive care variables. In the block of mortality variables, the principal causes of mortality related to the severe forms of COVID-19 were selected. Four sets of disease-specific mortality rates per 100,000 inhabitants were calculated for the year 2017, which was the most recent period with data available on the Brazilian Health Informatics Department website (DATASUS. http://www.datasus.gov.br). The analysis used deaths by place of residence and the population estimates for the same year according to the Federal Accounts Court (TCU). This allowed calculating the mortality rates for the group of neoplasms (ICD-10, Chapter 2), respiratory diseases (ICD-10, Chapter 10), diabetes (ICD-10, Chapter 4, E10-E14), and hypertension and cardiac diseases (ICD-10, Chapter 9, I10-I15, I20-I52).

The block of intensive care variables used four population coverage rates (per 100,000 inhabitants): the total number of adult ICU beds divided by the total population, the number of adult ICU beds in the Brazilian Unified National Health System (SUS) divided by the SUS-dependent population (population not covered by private health insurance), number of adult ICU beds in the private sector divided by the non-SUS-dependent population, and the number of SUS ventilators divided by the SUS-dependent population. The data are from January 2020, available in the Brazilian National Registry of Healthcare Establishments (CNES). All the data for this block of variables were made publicly available by the Institute of Health Policy Studies in Technical Note n. 3 of 2020 [13].

The data were analyzed in three blocks. In the first block, the mortality profile was constructed according to the four groups of causes. Thus, latent profiles analysis (LPA) was performed [16,17,18], a statistical method that aims to group the set of data (qualitative or quantitative) according to similarities in the response profile. The search is for intra-group homogeneity and inter-group heterogeneity. The latent variable is a variable that is not observed directly, but indirectly, based on variables that can be observed directly (indicator variables). Since there is not only a single disease condition that predisposes individuals to the severe form of COVID-19, using the main mortality groups, a single latent variable was constructed that simultaneously encompassed these four groups.

Latent profiles analysis aims to classify individuals from a heterogeneous population into smaller and more homogeneous subgroups based on the individuals' values in continuous variables. Importantly, LPA is not limited to continuous variables, but can include combinations of continuous, discrete, and categorical variables as indicator variables of latent classes [19]. Although this option differs from latent class analysis (LCA), which only considers categorical indicator variables, both analyses generate categorical latent classes (in the case of LCA) and latent profiles (in the case of LPA) [20].

In the construction of our latent variable, models with different numbers of latent profiles (categories) were created and tested until an ideal model was found to describe this variable. In the choice of the best statistical model for the latent variable, the following criteria were used: Akaike information criterion (AIC), Bayesian information criterion (BIC), and adjusted Bayesian criterion (adjusted BIC), in all cases observing the lowest values when comparing the current model with the previous model. The highest entropy value was also considered [21]. In addition to these criteria, three other statistical tests were performed (Vuong-Lo-Mendell-Rubin, Lo-Mendell-Rubin, parametric bootstrapped) to verify whether the chosen number of profiles was the best in terms of the model's fit, when compared to the number of profiles in the previous model. This analysis used the Mplus 6.12 software (https://www.statmodel.com/version6.12.shtml).

Analysis of intensive care coverage used the spatial scan test in the identification of spatial clusters. The four coverage rates were recalculated to construct the expected rates according to the exposed population and its neighboring matrix, according to a given spatial scan ratio (spatial window). Having calculated the expected rates, coverage ratios were calculated between the observed (real) rate and the expected rate in each Health Region. Values greater than 1 indicate clusters where the coverage rate is greater than expected, while values below 1 indicate clusters where the observed rates are lower than expected.

This analysis used the SaTScan 9.6 (https://www.satscan.org/) program with a Poisson probability model [22] for the detection of high and low-risk clusters and a circular spatial window with 15% of the exposed population at risk. This percentage considered the fact that not all individuals with COVID-19 infection require admission to intensive care, rather approximately 15%, who present the severe forms of the disease [14]. Maximum likelihood test was used to identify clusters. The alternative hypothesis is that there is a high value inside the window compared to outside it. Monte Carlo simulations were considered (999 permutations) to obtain p-values [22]. Level of significance was 5%.

After analysis of the two blocks, Kernel maps were constructed for spatial visualization of the Health Regions according to the mortality profile and intensive care coverage. Kernel maps or Kernel estimators are a set of nonparametric statistical procedures for smoothing points on a geographic surface according to the points' density [23]. This is the adjustment of a 2D function that counts all the points within an area of influence (grid), weighting them by the distance from each point to the location of interest. The degree of smoothing used an adaptative radius, varying according to the density of points and quartic function. The points were generated from the Health Regions' centroids. Spatial analysis was performed with TerraView 4.2.2 (http://www.dpi.inpe.br/terraview). This statistical technique produces a density surface where it is possible to observe the concentration of phenomena indicating a spatial cluster [24]. In all the analytical blocks, significance for the statistical inferences was set at 5%.

Since these data are publicly available on the internet and have no individual form or identification, rather aggregated by Health Regions, the study did not require submission to the respective Institutional Review Board.

Results

Table 1 shows the results of the LPA. According to the target parameters, the best model was the one with four latent mortality profiles. Although this model did not present the highest entropy, it was the one with the lowest AIC, BIC, and adjusted BIC values, with statistical significance in all three tests. These three tests indicate that the model with four profiles is superior to the previous three-profile model. Table 1 also shows the typology of the mortality profile generated by LPA according to the mean cause-specific mortality rates in each profile. We observed an ordinal qualitative variable in which we found the lowest rates in profile 1 and the highest rates in profile 4.

Table 1 also presents the diagonal probabilities for each profile. This information refers to the probability that individuals classified in their profile actually belong to that profile. A perfect classification would show a probability of 100%. Still, the main contribution by this analysis is to come as close as possible to a pattern that enables the highest possible classificatory agreement. The analysis provides an alternative to the traditional cutoff points that always penalize the borderline values. In this sense, the diagonal probability produces this information, in which the classifications are not perfect but indicate the probability of correct classification in their intergroup discrimination. In this way, each profile means a block of Health Regions with similarities in the disease-specific mortality rates for the four major mortality groups (neoplasms, respiratory diseases, diabetes, hypertension/cardiac diseases). The profile is analyzed by the mean of each mortality coefficient in each of the four latent profiles. The mortality profile was thus defined as an ordinal qualitative variable. Profile 1 was the set of Health Regions with low coefficients, profile 2 with medium values, profile 3 with high coefficients, and profile 4 with very high coefficients.

In relation to the total number of ICU beds, Brazil had 29,891 beds, of which 14,094 were in the SUS and 15,797 were private ICU beds. The SUS had 40,508 mechanical ventilators. Of the 450 Health Regions, 126 had no ICU beds (either SUS or private), and 44.4% of these Health Regions where in the Northeast of Brazil. Another 145 Health Regions had no ICU beds in the SUS, and they were also predominantly in the Northeast (45.5%). There were 188 Health Regions with no private ICU beds, 42% of which in the Northeast.

Table 1 also shows the Health Regions classified in the worst mortality profile (profile 4), where 42.9% and 36.7%, respectively, showed total and private ICU bed rates below the expected levels.

Table 2 shows the results of the clusters with statistical significance referring to intensive care coverage (ICU beds and ventilators). Northeast Brazil stood out, where 70% of the Health Regions showed total ICU rates below the expected levels. The result was similar for public (SUS) ICU beds, with more than half of the Health Regions (55.6%) below the expected number of beds. However, considering private ICU beds, the Northeast showed 27.1% of its Health Regions with rates higher than expected. As for mechanical ventilators in the public system (SUS), although practically all of the regions have ventilators, rates below the expected levels were found in 93.3% of the Health Regions in the North of Brazil and 81.2% in the Northeast. Note that the values without statistical significance (Tables 1 and 2) refer to the Health Regions where the ratios between the observed and expected rates were not significant according to the scan parameters executed in the spatial window used here.

Figure 1 shows the Kernel maps of Health Regions according to the mortality profile category estimated by the LPA. Profile 1 is concentrated in the entire North and Northeast, especially the northern parts of the states of Maranhão, Bahia, and Pará and northwestern Mato Grosso. Southeast Brazil showed high density in regions in a large part of the State of Minas Gerais. Profile 2 was heavily concentrated in the eastern part of the states of Paraíba, Pernambuco, and Alagoas, reaching a large part of other states in the Northeast. Higher density was also observed in the state of Tocantins and

Table 1

Classification of mortality profiles according to latent profiles and spatial clusters of values below and above expected intensive care rates (total ICU beds, SUS ICU beds, private ICU beds, and mechanical ventilators in the SUS). Brazil, 2020.

Mortality profile	**Latent profiles analysis**				**Total**
	Profile 1	**Profile 2**	**Profile 3**	**Profile 4**	
Classification of mortality	Low	Medium	High	Very high	
Number of observations (Health Regions)	90	86	176	98	450
	Mean (SD)	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**	**Mean (SD)**
Mean coefficient per 100,000 inhabitants					
Neoplasms	61.2 (17.9)	77.0 (14.2)	113.1 (20.1)	138.5 (28.4)	101.6 (35.3)
Respiratory diseases	44.4 (13.8)	55.4 (12.2)	87.3 (16.4)	103.6 (17.0)	76.3 (27.3)
Diabetes	22.5 (6.7)	43.3 (9.0)	28.0 (7.0)	41.1 (9.6)	32.9 (11.8)
Hypertension and cardiovascular diseases	71.3 (17.3)	116.9 (18.7)	116.3 (17.5)	151.6 (21.1)	115.6 (32.4)
Diagonal probabilities	0.92	0.89	0.88	0.90	-
	n (%)	**n (%)**	**n (%)**	**n (%)**	**n (%)**
Intensive care clusters					
Clusters of total ICU beds below expected	37 (41.1)	55 (64.0)	79 (44.9)	42 (42.8)	213 (47.3)
Clusters of total ICU beds above expected	2 (2.2)	1 (1.1)	11 (6.2)	9 (9.2)	23 (5.1)
Without statistical significance, total ICU beds	51 (56.7)	30 (34.9)	86 (48.9)	47 (48.0)	214 (47.6)
Clusters of SUS ICU beds below expected	21 (23.3)	48 (55.8)	13 (7.4)	10 (10.2)	92 (20.4)
Clusters of SUS ICU beds above expected	1 (1.1)	4 (4.7)	26 (14.8)	9 (9.2)	40 (8.9)
Without statistical significance, SUS ICU beds	68 (75.6)	34 (39.5)	137 (77.8)	79 (80.6)	318 (70.7)
Clusters of private ICU beds below expected	12 (13.3)	13 (15.1)	66 (37.5)	36 (36.7)	127 (28.2)
Clusters of private ICU beds above expected	10 (11.1)	16 (18.6)	12 (6.8)	8 (8.2)	46 (10.2)
Without statistical significance, private ICU beds	68 (75.6)	57 (66.3)	98 (55.7)	54 (55.1)	277 (61.6)
Clusters of SUS ventilators below expected	71 (78.9)	67 (77.9)	40 (22.7)	17 (17.3)	195 (43.3)
Clusters of SUS ventilators above expected	3 (3.3)	1 (1.2)	39 (22.2)	12 (12.2)	55 (12.2)
Without statistical significance, SUS ventilators	16 (17.8)	18 (20.9)	97 (55.1)	69 (70.4)	200 (44.5)

ICU: intensive care units; SD: standard deviation; SUS: Brazilian Unified National Health System.

southwestern Mato Grosso. Profiles 3 and 4 showed a similar pattern, with strong densities in various states of the Northeast, Southeast, and South of Brazil. The worst profile (profile 4) was in the northwest of the State of São Paulo and central-north of the State of Rio Grande do Sul.

Figure 2 shows the Kernel maps locating the regions in which the intensive care coverage rates were below the expected levels. The North and Central were the regions of Brazil with large numbers of Health Regions in which significant clusters were not found. Considering the regions with significant clusters of ICU beds and mechanical ventilators in the SUS, the scenario shows the principal Health Regions where the shortage of intensive care infrastructure overlaps with the severity of the mortality profile from diseases associated with higher COVID-19 case-fatality. Considering the shortage of total ICU beds and public ICU beds, a large part of the Northeast, Southeast, and South suffer this shortage at the same time as they concentrate various regions classified as profiles 3 and 4 (the worst mortality scenarios, as shown in Figure 1).

Interestingly, a large part of the North of Brazil was classified as mortality profile 1 (Figure 1). In addition, this region did not show significant clusters of shortage of ICU beds, except for clusters of ventilators in the SUS. Note however the size of the exposed population according to the spatial scan window in this region. Due to the low population density in the North of Brazil, the low observed values are within the expected levels, due to a radius that requires a larger diameter in order to reach 15% of the exposed population.

Table 2

Distribution of spatial clusters of intensive care values (total ICU beds, SUS ICU beds, private ICU beds, and mechanical ventilators in the SUS) below and above expected levels according to major geographic regions. Brazil, 2020.

	North n (%)	Northeast n (%)	Southeast n (%)	South n (%)	Central n (%)	Total n (%)
Number of health regions	45	133	165	68	39	450
Clusters of total ICU beds below expected	14 (31.1)	94 (70.7)	59 (35.8)	43 (63.2)	3 (7.7)	213 (47.3)
Clusters of total ICU beds above expected	0 (0.0)	0 (0.0)	13 (7.9)	6 (8.8)	4 (10.2)	23 (5.1)
Without statistical significance, total ICU beds	31 (68.9)	39 (29.3)	93 (56.4)	19 (28.0)	32 (82.1)	214 (47.6)
Clusters of SUS ICU beds below expected	9 (20.0)	74 (55.6)	4 (2.4)	0 (0.0)	5 (12.8)	92 (20.4)
Clusters of SUS ICU beds above expected	0 (0.0)	1 (0.8)	34 (20.6)	3 (4.4)	2 (5.1)	40 (8.9)
Without statistical significance, SUS ICU beds	36 (80.0)	58 (43.6)	127 (77.0)	65 (95.6)	32 (82.1)	318 (70.7)
Clusters of private ICU beds below expected	0 (0.0)	18 (13.5)	66 (40.0)	43 (63.2)	0 (0.0)	127 (28.2)
Clusters of private ICU beds above expected	2 (4.4)	36 (27.1)	7 (4.2)	0 (0.0)	1 (2.6)	46 (10.2)
Without statistical significance, private ICU beds	43 (95.6)	79 (59.4)	92 (55.8)	25 (36.8)	38 (97.4)	277 (61.6)
Clusters of SUS ventilators below expected	42 (93.3)	108 (81.2)	28 (17.0)	0 (0.0)	17 (43.6)	195 (43.3)
Clusters of SUS ventilators above expected	0 (0.0)	1 (0.8)	50 (30.3)	2 (2.9)	2 (5.1)	55 (12.2)
Without statistical significance, SUS ventilators	3 (6.7)	24 (18.0)	87 (52.7)	66 (97.1)	20 (51.3)	200 (44.5)

ICU: intensive care units; SUS: Brazilian Unified National Health System.

Discussion

Latent profiles analysis identified Health Regions in Brazil in which the principal causes of mortality associated with higher COVID-19 case-fatality are located. In the first epicenter of the COVID-19 epidemic, in Hubei, China, a study [25] showed that the mean age of patients admitted to ICU was 66 years, with a predominance of males and 58% with chronic health conditions, including hypertension, diabetes, cardiovascular diseases, and renal failure. According to the study, these individuals present higher probability of evolving to severe forms of the disease. As reported by Wu & McGoogan [14], the case-fatality rates were high: 10.5% in patients with cardiovascular diseases, 7.3% with diabetes, 6.3% with chronic respiratory diseases, and 6% with hypertension.

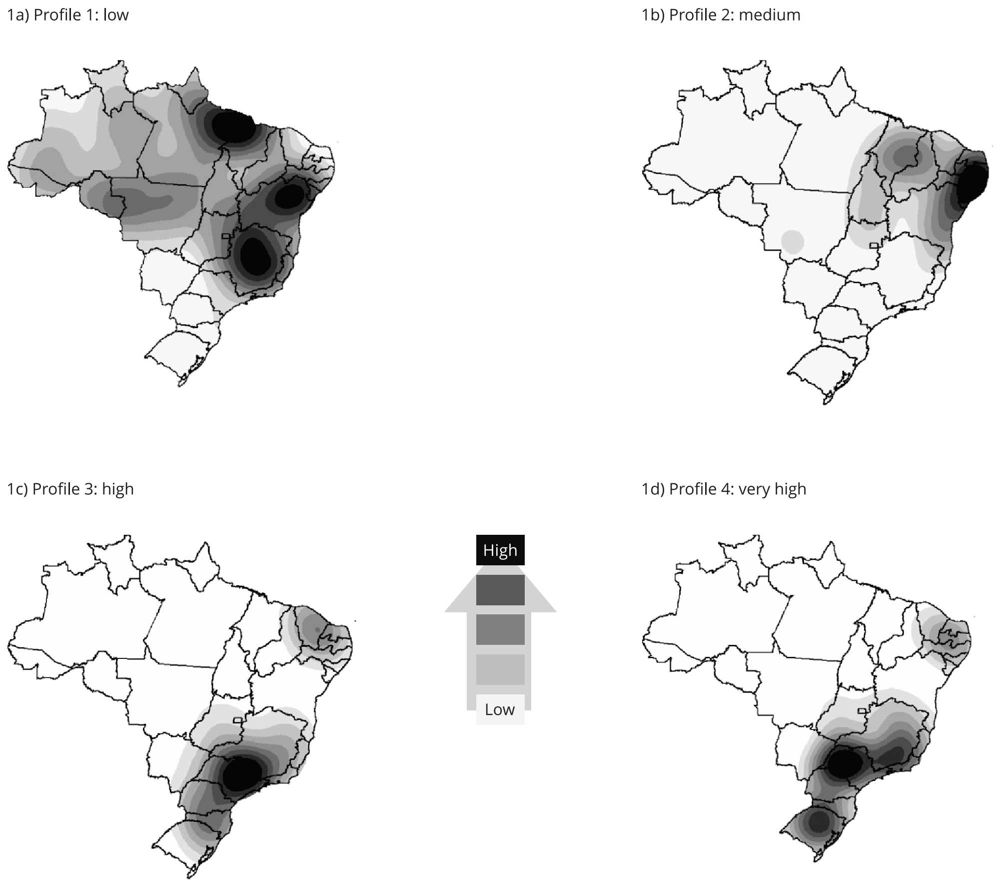
It is highly useful to spatially identify regions with the simultaneous presence of the four groups of specific causes of mortality. LPA allowed locating regions where the mortality rates were similar. Meanwhile, the Kernel map allowed spatial visualization of the place where these profiles occur. Geographic space is thus a key focus in epidemiology, since it allows not only producing knowledge of the place where health events occur, but also establishing the role of geographic space in generating these events. Knowledge of who experiences the events and where they experience them produces the principal variables, both in establishing causal relations and in defining the appropriate public health responses.

As for the spatial distribution of intensive care coverage rates, it is important to address some relevant issues for dealing with the pandemic. Different parts of the world population have already experienced similar situations with the pandemic, and the preventive measures adopted thus far still appear to be the principal weapons in this struggle. Interestingly, even with all the world's important technological and scientific progress, we are still adopting basic measures in hygiene, quarantining, isolation, and social distancing, historically recommended in past epidemics [26]. There are also measures that will determine the exact number of persons with severe symptoms of the disease [27], which in turn will determine the demand for mechanical ventilators and ICU beds.

Given the finite amounts of intensive care resources, including both physical and human resources, questions emerge concerning their fair allocation and use. Previous proposals for resource allocation in pandemics and other situations of absolute shortage coincide on four fundamental values: maxi-

Figure 1

Kernel maps of Health Regions according to latent mortality profiles of diseases associated with higher COVID-19 case-fatality. Brazil, 2020.



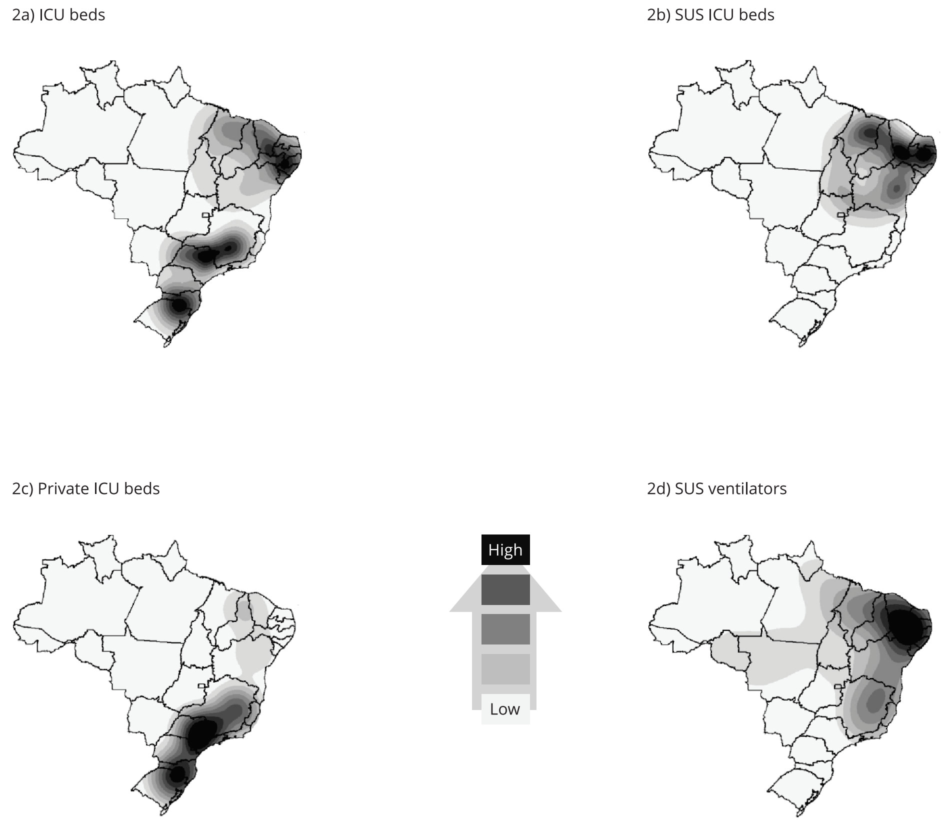
ICU: intensive care units; SUS: Brazilian Unified National Health System.

mizing the benefits produced by scarce resources, treating persons fairly, promoting and rewarding instrumental value, and assigning priority to the worst moment in the disease. There is consensus that a person's social class should not determine who lives or dies. Although medical treatment in the United States outside of pandemic contexts is frequently limited to those who can pay, no proposal considers the ability to pay as the proper criterion during a pandemic [27].

Critical interventions such as testing, personal protective equipment (PPE), ICU beds, ventilators, treatments, and vaccines should be allocated first to frontline health workers and others who care for sick patients and who keep the critical infrastructure operating. In particular, workers that face high risk of infection and whose level of training makes their replacement difficult should be prioritized. These workers should have priority not because they are worthier in any way, but because of their instrumental value: they are essential in the response to the pandemic [28,29]. However, the fact that they work on the frontline considerably increases their risk of infection, especially in the absence of PPE and an adequate work protocol [30]. The need to balance multiple ethical values for various interventions and in different circumstances will probably lead to different judgments on the weight assigned to each value in specific cases. This highlights the need for fair and consistent allocation procedures

Figure 2

Kernel maps of clusters of rates per 100,000 inhabitants, for total ICU beds, SUS ICU beds, private ICU beds, and SUS ventilators below expected levels. Brazil, 2020.



ICU: intensive care units; SUS: Brazilian Unified National Health System.

that include the affected parties. Such procedures should be transparent in order to guarantee the public trust in their fairness [27].

As for priorities in the occupation of Brazil's ICU beds in general, the Federal Board of Medicine (CFM) drafted resolution 2156/2016, in which the criteria for ICU admission are critical instability, the need for life support interventions, absence of limitation of therapeutic support, and high likelihood of recovery. The resolution defined five levels of priority, ranging from maximum priority for patients that require life support interventions, with high likelihood of recovery and with no limitation on therapeutic support, to the last priority for terminal or dying patients, with no possibility of recovery [31].

However, the above-mentioned criteria were not defined for a pandemic situation like the one we are experiencing with COVID-19, with situations in which numerous patients are in the maximum-priority category. Social criteria can lead to diverse interpretations, generating prejudices, with the exception of health professionals, for the reasons cited above. Wang & de Lucca-Silveira [31] discuss some alternatives, one of which would be to change the criteria for ICU discharge, discharging patients earlier in order to allow greater turnover of the ICU beds. Importantly, other conditions may be present that require intensive care, i.e., routine situations not involving COVID-19. It is also true that primary and secondary care systems should act effectively to avoid referrals to intensive care.

Finally, although each hospital sets its own criteria for distributing ICU beds, in a time of tragedy and shortage of resources, centralization of the decisions on the use of ICU beds may be a logistically valid alternative. Considering the existence of private ICU beds, which could generate a social decision on the availability of these beds, their administration at the federal level, whether collaborative or compulsory, may facilitate the harmonization of criteria and the equitable distribution of beds.

The fact that the North of Brazil and part of the Central region did not present significant clusters of intensive care coverage below the expected levels does not necessarily mean the presence of better intensive care infrastructure. The large geographic dimensions and low population density in these two geographic regions of Brazil may explain the lack of formation of clusters, as discussed in the *Results* section. Thus, Health Regions where there are no ICU beds and ventilators may fall within the expected levels, according to the spatial scan pattern. These two regions also presented better mortality profiles, which shows a different epidemiological scenario in relation to chronic noncommunicable diseases. An analysis focusing on the large metropolitan areas in these two regions of Brazil could provide a more accurate assessment of the shortage of healthcare resources, independently of their epidemiological mortality profile. The most important factor in the intensive care supply for confronting COVID-19 is to understand the accelerated infection rate in the absence of social isolation measures.

Although it is not a limitation to this study, the ecological design does not allow inferences at the individual level. Another important factor is that the study's cross-sectional design does not allow testing causal relations; however, the objective was not to establish causal relations, but associations and a prognosis of the intensive care situation. Spatial knowledge of mortality and intensive care coverage can reveal places in which interventions are necessary to keep the mass spread of COVID-19 from collapsing the SUS.

Conclusion

In the COVID-19 pandemic, knowledge of Brazil's intensive care capacity is essential for the rational use of ICU beds and mechanical ventilators. Associated with the regions with higher probability of demand, determined by the disease-specific mortality profile that increases the case-fatality of the novel coronavirus infection, we observed a worrisome situation in the health services' response. Even with all the measures to prevent the spread of COVID-19, this study reveals where the public health authority should act to increase intensive care coverage with strategies for rationing ICU beds and ventilators and transparent and fair criteria for their allocation. The spatial analysis of the two dimensions investigated here can thus be useful for decisions by public health officials in coordinated actions according to scale economy and equitable distribution.

Additional information

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Resumo

O acelerado aumento do número de casos de doença pelo novo coronavírus (COVID-19) exige que os países aumentem as vagas nas unidades de terapia intensiva (UTI). Doenças respiratórias, neoplasias, cardiopatias, hipertensão e diabetes aumentam sua letalidade. O estudo objetivou identificar tanto as regiões com as maiores taxas de mortalidade específica por essas doenças quanto as com maior escassez de UTI e ventiladores pulmonares. Foi realizado um estudo ecológico transversal, as unidades de análise foram as Regiões de Saúde no Brasil. A fonte de dados foi o Departamento de Informática do SUS – DATASUS (Cadastro Nacional de Estabelecimentos de Saúde – 2019, Sistemas de Informação de Mortalidade – 2017 e Projeções Populacionais – 2017). Foram calculadas as taxas por 100 mil habitantes de mortalidade específica para hipertensão, neoplasias, diabetes, doenças cardíacas e respiratórias, leitos de UTI total, leitos de UTI privados, leitos de UTI do Sistema Único de Saúde (SUS) e ventiladores do SUS. O perfil de mortalidade foi determinado pela análise de perfis latentes, e a análise de clusters *dos leitos e ventiladores foi feita pelo método de varredura espacial. Mapas de Kernel foram construídos para a visualização dos dados. O nível de significância foi de 5%. Observou-se quatro perfis latentes de mortalidade. As regiões de saúde com as maiores médias na mortalidade estão localizadas em regiões cuja escassez de leitos de UTI e de ventiladores foi visualizada, especialmente, em partes das regiões Nordeste, Sudeste e Sul. A localização espacial das regiões com maior mortalidade e com escassez de leitos de UTI/ventiladores requer a atenção dos gestores e planejadores públicos, para o enfrentamento eficiente e equânime da epidemia no Brasil.*

COVID-19; Unidades de Terapia Intensiva; Ventiladores Mecânicos; Análise de Classes Latentes; Mortalidade

Resumen

El acelerado aumento en el número de casos de la enfermedad por el nuevo coronavirus (COVID-19) exige que los países aumenten sus plazas en las unidades de cuidados intensivos (UCI). Enfermedades respiratorias, neoplasias, cardiopatías, hipertensión y diabetes aumentan su letalidad. El estudio tuvo como objetivo identificar tanto las regiones con mayores tasas de mortalidad específica por estas enfermedades, como las que tenían mayor escasez de UCI y ventiladores pulmonares. Se realizó un estudio ecológico transversal, la unidad de análisis fueron las regiones de salud en Brasil. La fuente de datos fue el Departamento de Informática del SUS – DATASUS (Registro Nacional de Establecimientos de Salud – 2019, Sistemas de Información de Mortalidad – 2017 y Proyecciones Poblacionales – 2017). Se calcularon las tasas por 100 mil habitantes de mortalidad específica para hipertensión, neoplasias, diabetes, enfermedades cardíacas y respiratorias, camas de UCI total, camas de UCI privadas, camas de UCI del Sistema Único de Salud (SUS) y ventiladores del SUS. El perfil de mortalidad se determinó por el análisis de perfiles latentes y el análisis de clústeres de las camas y ventiladores fue realizado por el método de análisis espacial. Se construyeron mapas de Kernel para la visualización de los datos. El nivel de significancia fue de un 5%. Se observaron 4 perfiles latentes de mortalidad. Las regiones de salud con las mayores medias en la mortalidad se localizaron en regiones cuya escasez de camas de UCI y ventiladores se visualizó, especialmente en partes de las regiones Nordeste, Sudeste y Sur. La localización espacial de las regiones con mayor mortalidad y con escasez de camas de UCI/ventiladores requiere la atención de los gestores y planificadores públicos para el combate eficiente y ecuánime de la epidemia en Brasil.

COVID-19; Unidades de Cuidados Intensivos; Ventiladores Mecánicos; Análisis de Clases Latentes; Mortalidad

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