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How were we before? An analysis of the potential supply and inequality in the geographic access to critical resources for the COVID-19 treatment

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Abstract *The objective was to analyze the situation of the Metropolitan Area of Brasília (AMB) before the onset of the COVID-19 pandemic, focusing on the availability and geographical accessibility of critical resources for the treatment of acute respiratory crises caused by the SARS-CoV-2 virus. Geographic mapping of the population within the territory and geolocation of health facilities and resources, construction of a relationship network between the potential demand simulated to the public health system and the supply of resources available in December 2019. The relationship analysis is based on the theory of complex networks crossing socioeconomic data available in the CENSUS and information from the National Registry of Health Establishments (CNES) and analyzing the micro relationship of census tracts with the stock and availability of health resources concerning Adult ICU Bed Type II/III and Respirators/Ventilators. The Federal District (DF) health facilities concentrate more than 75% of the relationships of potential access to critical resources for the treatment of COVID-19. Although the regions surrounding the DF, belonging to Goiás state, have the greatest relative vulnerability in the studied territory, they are also the most lacking in spatial accessibility and availability of resources, evidencing a care imbalance within the AMB region.*
Key words *COVID-19, Health service access, Public Health, Data science, Complex networks*

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Introduction

On February 26, 2020, when Brazil reported its first case of COVID-19, a race began between the health system's care capacity and the rising curve of new acute respiratory syndrome cases caused by the new coronavirus (SARS-CoV-2), known as COVID-19. Intensive Care Unit (ICU) beds and medical equipment, such as respirators, are crucial resources for treating critically ill patients. The scarcity of these resources has led several countries to experience difficulties addressing the pandemic. Italy was the most extreme example at the onset of the pandemic, where health professionals had to prioritize patients who should have access to proper care during the pandemic's peak in some regions of the country[1,2].

The proportion of the number of patients requiring intensive care in the infected population is an essential indicator of the impact of this viral syndrome. Italy reported 205,700 new infection cases[3] from March 1 to May 1, 2020, while the demand for intensive care was around 9-11% of the total reported cases[4]. In March 2020, the Italian health system already had an occupation of 1,028 intensive care beds for the care of patients with SARS-CoV-2, compared to a total of approximately 5,200 existing beds[4].

The distribution of critical resources for treating severe COVID-19 cases in Brazil has different realities. While dependence on public health care is found in much of the national territory above 80%, the distribution of beds and respirators is uneven, generating different challenges for coping with the pandemic at the local level[5].

As of April 2020, the Federal District had good availability of ICU resources compared to other federative units, with 30 ICU beds and 62 respirators for every 100,000 inhabitants[6]. However, another reality can be perceived when the numbers are analyzed from the perspective of the resources available and offered by the Unified Health System (SUS): that is, respectively, 6 ICU beds and 32 respirators for every 100,000 inhabitants[6]. However, when we say "beds/population" in the Federal District, we do not include the population of almost one million inhabitants of 12 municipalities that make up the Metropolitan Area of Brasília (AMB), in which 86% of the population does not have access to private supplementary health care and, of these, 33% seek health care primarily in the service network of the Federal District[7].

When observing the reality of AMB, the indicators presented by the "Provider-to-Population Ratio" approach, where the availability of a given resource (in this case, beds, and respirators) is calculated per the ratio of this resource with the population within a geographically delimited area. Although this metric is traditionally used for its simplicity and efficiently transmitting information, as explained by Guagliardo[8], it still has recognized limitations, which conceal disparities and veil the recognition of barriers in the access to health, which we can mention as follows:

i) Border transposition between the analyzed spatial section, that is, when considering the resource/population relationship of the Federal District, the surrounding population is disregarded, which, while not belonging to the delimited region, consists of almost 400,000 inhabitants, potential health network users, per the study by the Federal District Planning Company[7] (CODEPLAN);

ii) Disregarding the variations in the availability of resources within the analyzed region; that is, as the Federal District has different characteristics with regions exposed to different social determinants, there is a need to understand the distribution of resources for these different realities;

iii) No explicit incorporation of geographic accessibility indicators. Therefore, inequality in geographic access tends to go unnoticed, not highlighting objectively geographic access barriers between the population and the resource.

It is crucial to analyze the distribution of health resources using metrics that highlight intra-regional inequalities and geographic access barriers to understand decisions on the use of the health system and health care[9,10] and, finally, to support evidence-informed planning in public policies.

This study aimed to analyze the intra-regional distribution of critical resources for treating severe COVID-19 cases, specifically ICU beds and mechanical respirators, within the AMB, using the lowest possible level of aggregation, to highlight aspects related to geographic access and resource availability.

This also aimed to test analysis tools based on the Theory of Complex Networks applied to the COVID-19 context, highlighting areas of greater concentration of resources and inequality between populations, with different levels of social vulnerability within the AMB, offering a complementary and more detailed perspective than the "Provider-to-Population" analyses carried out for the same region[6] and, thus, answering the following question "What would be the arrange-

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ment in terms of availability, geographic access, and potential demand to the public health system if a simulated demand of 1% of the AMB population required critical resources for the treatment of acute respiratory crisis?".

Methods

We performed a cross-sectional analysis on secondary data from the National Registry of Health Establishments[11] (CNES) and aggregated data from the 2010 Census[12]. CNES data referring to December 2019 were used to extract the geolocation of health establishments and the availability of ICU beds and the 'Mechanical Respirator' equipment. We considered establishments of the network linked to the SUS and with resources available to the public health system. The 2010 Census was used as a source for the mesh of aggregate and socioeconomic census tracts referring to the population residing within these spatial sections. Thus, using census tracts within the AMB allowed an intraregional analysis of the population's vulnerability and access to health resources through spatial coordinates provided by the two databases mentioned above.

The Theory of Complex Networks was applied in data analysis based on the modeling described by Costa *et al.*[13], which has a set of metrics based on a model of relationship between census tracts and health establishments, using the concepts of centrality and geographic distance between these entities. This model assessed the importance of specific establishments and types of establishments in covering potential access to health services and resources. Therefore, the model presented here complements these ideas, analyzing the distribution of the stock of resources offered by health facilities to a population that demands potential access to these resources, using the concept of potential access developed by Andersen[9] and the availability of resources described by Penchansky and Thomas[10].

A social vulnerability metric was used to identify and analyze disparities in the distribution of resources to understand the reality of access and availability of resources between different vulnerability conditions. The model created by Drachler *et al.*[14] was employed to calculate the relative social vulnerability within the AMB territory. This index is called IVS-5 and consists of indicators that describe the need of a region in terms of income, sewage infrastructure, access to drinking water, garbage collection service, and population density. The population density component was excluded in this work. This component represents the operational difficulty of health provision in municipalities with low population density. When we evaluated this condition within the intraregional analysis of the AMB, we observed regions of low population density that do not represent conditions of vulnerability, such as that in regions organized in horizontal condominiums.

The first step in calculating the IVS-5 was identifying the deficiency percentage of each indicator. Table 1 reflects the distribution of each indicator by percentiles. Then each census tract was assigned an IVS equivalent to the number of standard deviations in Z-score above and below the mean of the 5,616 tracts used in the study (186 tracts were discarded due to lack of data, corresponding to 3.2% of the total tracts). As the IVS is normalized using the Z-score, the mean and standard deviation of the IVS will be represented, respectively, by 0 and 1. Thus, when normalizing by the standard deviation, the construction of the index is concluded, creating ranges for each vulnerability level applied by census tract, and grouped by AMB municipality in Table 2. We should emphasize that the index addresses relative vulnerability within the territory and, therefore, is not a universal vulnerability index.

We established relationships from the census tracts to the health units, considering a setting where 1% of the tract's population demanded this resource to model geographic access and availability of critical resources. The 1% value represents a simulated demand parameterized in the model so that a proportional portion of all census tracts could participate in the distribution of resources, and this value is not expected to represent the prevalence of acute respiratory crisis within the AMB territory. This research aimed to simulate the application of a model of accessibility and availability of resources. On the other hand, findings in the lack of potential access within a territory could collaborate with micro-regional epidemiological studies guiding the actions of the health service.

The relationship algorithm sought the closest health facilities with the number of resources equivalent to or greater than the potential demand of the tract starting from each census tract. If a census tract had 1,000 residents, it would demand ten units of resources (1% of the population). If three health establishments were found within a radius of 2,500 meters, with Euclidean distances smaller than the search radius and with the sum of the available resources of these establishments greater than or equal to the potential demand of the census tract, we would understand that this demand has been met and the search for the algorithm ends. Also, the algo-

Table 1. Distribution of Indicators and Social Vulnerability Index in the AMB territory.

AMB	(A) % Households with per capita income <0.5 minimum wage				(B) % Households without public water supply				(C) % Households without a sewerage or rainwater network system				(D) % Households without garbage collection				Relative % of the Tract's Social Vulnerability (A + B + C + D) / 4			
	Percentiles																			
	25	50	75	95	25	50	75	95	25	50	75	95	25	50	75	95	25	50	75	95
Brasília	3	13	25	41	0	0	1	88	0	0	2	95	0	0	0	20	1	4	8	46
Luziânia	25	32	40	51	4	45	92	100	64	96	98	100	0	1	5	99	31	38	58	82
Águas Lindas de Goiás	28	34	40	51	1	6	22	92	87	97	99	100	0	2	10	73	31	35	41	72
Valparaiso de Goiás	12	22	30	44	1	16	48	81	1	12	87	99	0	0	0	36	9	20	32	53
Formosa	18	32	46	58	1	3	21	100	35	69	92	98	0	0	13	100	15	27	41	84
Novo Gama	25	33	39	51	0	3	16	93	8	85	96	99	0	0	3	78	12	32	38	72
Planaltina	27	35	44	56	0	2	30	100	74	92	98	99	0	2	25	98	26	34	50	81
Sto. Ant. de Descoberto	28	37	42	51	1	8	95	99	11	68	95	99	0	3	32	99	15	34	59	81
Cidade Ocidental	17	28	36	49	0	3	24	100	1	61	93	99	0	1	10	92	6	26	39	74
Cristalina	22	31	39	54	1	12	100	100	12	81	97	100	0	5	96	100	19	41	72	83
Padre Bernardo	36	42	47	57	2	68	97	100	70	95	99	100	2	45	91	100	36	61	78	85
Alexânia	31	37	44	50	8	19	97	100	86	98	99	99	0	2	43	96	33	38	62	82
Cocalzinho de Goiás	30	36	41	56	1	82	97	100	85	94	98	100	1	3	83	99	32	53	76	83
Total	5	18	30	46	0	0	3	98	0	0	49	99	0	0	0	68	2	6	27	65

Note: Distribution of percentiles for each indicator, for example, for indicator (A), Brasília has 41% of households with per capita income <0.5 minimum wage for the 95th percentile.

Source: Authors, based on data from the 2010 Census (IBGE).

Table 2. Distribution of the social vulnerability index by standard deviation in the AMB census tracts.

AMB	Territory Vulnerability Mean Standard Deviations										
	-1 a -0.51		-0.5 a 0		0.01 a 1		1.01 a 2		>2		Total Tracts
Brasília	2,590	60%	1,018	24%	390	9%	164	4%	131	3%	4,293
Luziânia	11	5%	21	9%	80	33%	68	28%	62	25%	242
Águas Lindas de Goiás	1	1%	18	10%	90	50%	54	30%	16	9%	179
Valparaiso de Goiás	31	18%	41	23%	77	44%	20	12%	6	3%	175
Formosa	7	5%	30	22%	60	44%	9	7%	30	22%	136
Novo Gama	15	12%	23	19%	49	40%	26	22%	9	7%	122
Planaltina	1	1%	13	12%	49	45%	23	21%	22	21%	108
Sto. Ant. de Descoberto	1	1%	20	25%	23	29%	15	19%	21	26%	80
Cidade Ocidental	18	23%	10	13%	28	37%	11	14%	10	13%	77
Cristalina	4	5%	13	17%	19	25%	10	13%	29	40%	75
Padre Bernardo	6	12%	1	2%	9	17%	9	17%	27	52%	52
Alexânia	0	0	3	7%	17	38%	10	23%	14	32%	44
Cocalzinho de Goiás	1	3%	0	0	12	36%	8	24%	12	36%	33
Total	2,686	47%	1,211	22%	903	16%	427	8%	389	7%	5,616

Source: Authors, based on data from the 2010 Census (IBGE).

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rithm admits a 20% distance variation. Thus, if the shortest distance from an establishment to the tract is 1,000 meters, establishments located up to 1,200 meters are admitted as within the search radius (Figure 1).

Thus, the potential demand model of 1% of the population would answer questions about geographic accessibility, that is, where would the closest resources be if 1% of the population in the tract needed them, while availability would describe the proportion of resources available for this potential demand. Then, we formulated a metric that uses the Population-Resources relationship by health establishment and, thus, highlighting the most overloaded establishments and where they are located. Finally, the population served was weighted per its geographic vulnerability, demonstrating the accessibility and availability of resources by the calculated IVS-5 index.

The centrality metric used to establish the importance of health facilities by the relationship between potential demand and resources is based on the *PageRank*[15] metric of network theory. Considering that the network represented nodes of the Census Tract and Health Establishments type, relating by the potential demand for resources, in practical terms, the centrality by PageRank represents the sum of an attribute of the importance of the census tracts (population or population weighted by the vulnerability) that was transmitted in a balanced way (that is, divided by the other health facilities that could potentially offer that resource at similar distances). In turn, "centrality" is an essential analytical tool to determine the structural importance of a node within a network[16]. In this article, it was used to determine which health facilities are vital in meeting the potential demand for resources within the simulated setting.

Within the context of this work, the nodes represent, at the same time, health establishments and census tracts, therefore, a network characterized by the existence of two partitions that relate unidirectionally, starting from the census tract to the health establishment and, thus, establishing a bimodal network structure[17]. Therefore, the centrality of a vertex p_k (a health establishment) or a group of vertices[18] of correlated health establishments (of the same type of establishment) will be calculated with the following formulation:

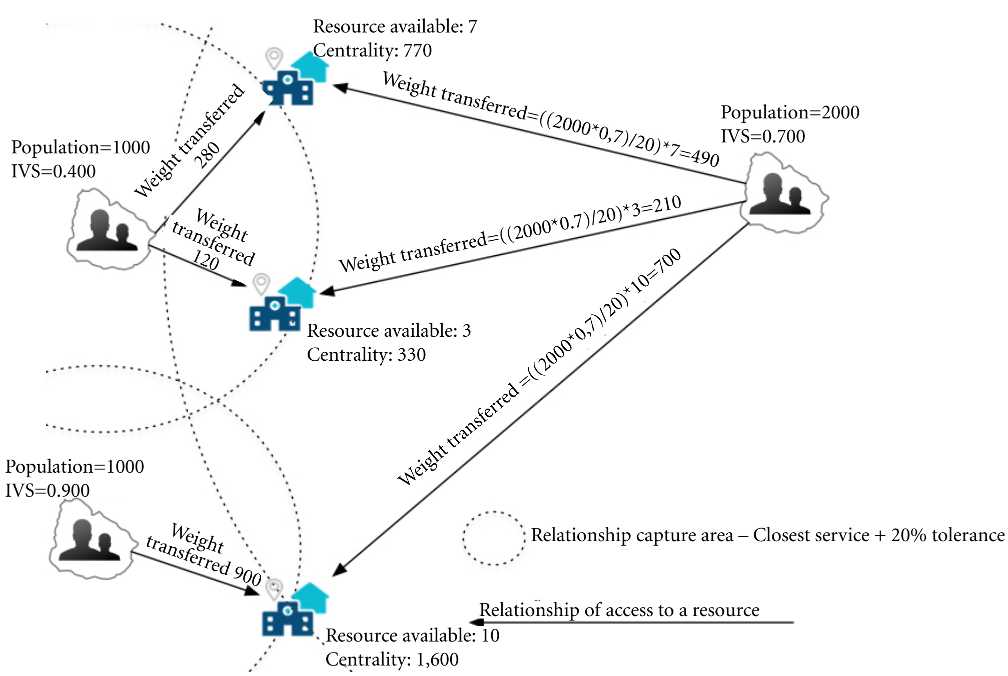


Figure 1. Centrality - Population Weight and Availability.

Source: Authors, 2020.

$$C_{PR}(p_k) = \sum_{i=1}^{n} a(p_i, p_k) \frac{C_{PR}(p_i) + (p_i^{IVS} * p_i^{Pop})}{p_i^S} p^s_k$$

$$p^s_i = \sum_{j=1}^{n} a(p_i, p_j) p^s_j$$

Where $a(p_i, p_k)$ if, and only if p_i vertex (a census tract) shows a relationship with p_k vertex (health establishment or group of vertices under analysis); otherwise, it will be equal to zero, evidencing no relationship between $p_i = p_k$. For each relationship of p_k with p_i (a census tract of the relationship vector), p_i will have the following attributes: p_i^{IVS} = Indicator of Social Vulnerability of the tract p_i, when calculated with this component, we evaluate the importance of the health establishment for the vulnerable population; when we remove it, we consider the total population; p_i^{POP} = Population of Dwellers of tract p_i; p_i^S = Total Resources Available for Tract p_i, i.e., total available resources in all related that originate from census tract p_i to the health establishments and given by the sum function between the function of the relationship between p_i and each tract p_j (where, once more, the result will be zero or 1) and the number of resources p_i^S available in each health establishment.

Finally, the variable p_k^S represents the total number of resources available in the establishment (or group of establishments) p_k under analysis. Therefore, centrality[18] will be calculated by the population ratio of the census tract divided by the total resources available for that tract (within the proximity relationship rule) and multiplied by the number of resources available in the establishment under analysis. On the other hand, component $C_{PR}(p_i)$ represents the centrality of the eigenvector, which operates recursively in the formula, if the census tract has relationships. This component is a constant value equal to zero for this formulation since there are no input relationships in the census tracts. The Gephi[19] tools and the R[20] language were used to prepare the data, apply the calculation to the tables, and analyze and visualize the data.

Finally, the model was applied to the equipment resources '64-RESPIRATOR/VENTILATOR' and the beds' type: '75-ADULT ICU - TYPE II', '76-ADULT ICU - TYPE III'. The following data were obtained for analysis:

i) Mean Euclidean distance between the census tracts and the health units that offer Respirators and Beds.

ii) Distribution of geographic access distance by social vulnerability class for each resource.

iii) Differences in geographic access to resources when considering census tracts, the Federal District, and tracts of surrounding municipalities belonging to the AMB.

iv) Importance of Health Establishments regarding the potential population covered and the resource/population ratio per establishment.

Results and discussion

Two networks were built for analysis, the first based on the search for respirators consisting of 16,884 relationships among 5,616 census tracts with 71 establishments with equipment in use available for the SUS. The second network was based on the availability of Type II and Type III Adult ICU beds, per the criteria used by the IBGE to study the regional availability of these resources[6]. In the bed availability network, 24,617 relationships were formed between 5,616 census tracts and 21 establishments, establishing a network divided into two layers, the first consisting of the search for type II beds and the second for the search for type III beds.

In the network of respirators, the highest concentrations of relationships were observed among the Regional Hospitals of Brasília's administrative regions, emphasizing the Regional Hospital of Santa Maria, with a standardized centrality representing the service of 12% of the possible relationships in this network. The normalized centrality concept determines the relevance of a node within the network structure. An establishment with 100% of the relationships (Normalized Centrality equal to 1) has a relationship with all census tracts and is responsible for the exclusive provision of resources for these tracts. Thus, as we can see in Table 3, 12 health establishments concentrate 75.2% of the normalized centrality of the population in the Federal District and the 12 municipalities in the State of Goiás that belong to the AMB.

The population of the municipalities around Brasília represents 38% of the total AMB population of 3,529,346 (as per the 2010 IBGE Census). Meanwhile, while the health facilities listed in Table 3 are in the Federal District, 22% of the relationships of these establishments are with census tracts located in municipalities around Brasília, thus evidencing the sensitivity of these establishments in covering gaps in the availability of respirators located in the cities of the State of Goiás.

When we look at the relationship network for Adult Type II ICU beds (Table 4), we observe a concentration of 95.8% of all relationships in 11 health facilities, again all located in the Federal District. At the same time, 27.7% of these establishments' relationships originate from census tracts located in the municipalities surrounding Brasília. Relationships based on the demand for Adult Type III ICU beds show even more concentration, with 99.8% of the network served by three health establishments (Table 4), all located in Brasília, with 27% of these relationships deriving from census tracts originating in the surroundings.

From the perspective of the relative vulnerability index (Graph 1), calculated for the AMB region, we observe that the greater the vulnerability condition, the greater the barrier to geographic access to respirators. This vulnerable population is primarily found in Brasília's surroundings (interactive map https://rpubs.com/costa_/heatmapvul01), in municipalities in the State of Goiás, and the health system of the Federal District is the closest option to cover the care gap in these municipalities. While just over 1% of the potential demand originating in the DF needs to travel more than 20 kilometers to access a respirator, this proportion reaches 33% in the surrounding municipalities analyzed. This number is alarming when we see that the total of relationships in the surroundings corresponds to 27.5% of all relationships in the network and, at the same time, concentrates tracts with greater relative vulnerability (Table 2); that is, 71% of the tracts with more than one standard deviation of the mean vulnerability of the territory are found in the AMB region surrounding the DF.

This relationship between mean distance and relative social vulnerability is maintained when we analyze the distribution of Type II and III Adult Beds (Graphs 2 and 3), further increasing the distance between the most vulnerable tracts and the establishments that provide the beds. While the centralization of more complex resources is an expected aspect, it is relevant to observe that even in regions with greater population concentration, such as in Valparaíso de Goiás and Luziânia, the lack of these resources leads to a higher demand for beds in health facilities located on the DF borderline.

The distribution of the centrality of relationships for the three analyzed resources shows that the model captured a strong dependence of the municipalities around the AMB on the DF public health network in the demand for critical resources for the treatment of COVID-19. While surroundings account for 27.5% of the network's relationships, none of the surrounding health establishments had a normalized centrality of at least 3%. Thus, facing an epidemic with the

Table 3. Establishments with Normalized Centrality of up to 3% of the Network.

Establishment	Coverage of Respirators on the Potential Demand of 1% of the Population					
	Distance P50/P75 (KM) (A)	Potential Demand (Centrality) (B)	Demand/ Respirators (C)	Normalized Centrality (D=E+F)	Normalized Centrality DF (E)	Normalized Centrality Surroundings (F)
Hospital Reg. Sta. Maria	5.4/7.9	4,402.87	22.24	0.124	0.037	0.087
Hospital São Francisco (Ceilândia)	5.3/19.6	4,219.40	210.97	0.119	0.091	0.028
Hospital Reg. Samambaia	6.0/7.3	4,043.22	122.52	0.114	0.112	0.002
Hospital Reg. Taguatinga	3.2/5.4	2,196.40	27.80	0.062	0.060	0.002
Hospital Reg. Planaltina	4.7/15.6	2,178.67	217.87	0.062	0.043	0.018
Hospital Reg. Sobradinho	5.2/7.7	1,831.69	32.71	0.051	0.050	0.001
Hospital Reg. Ceilândia	9.0/22.2	1,618.69	43.75	0.045	0.031	0.014
Hospital Reg. Gama	3.1/20.6	1,524.37	56.46	0.043	0.035	0.008
Hospital da Região Leste	7.2/14.4	1,240.52	62.03	0.035	0.034	> 0.001
Hospital DOMED (Ceilândia)	11.1/21.7	1,215.49	63.97	0.034	0.025	0.009
Hospital São Mateus (Cruzeiro)	5.3/6.5	1,193.31	51.88	0.033	0.033	> 0.001
Hospital Reg. Asa Norte	3.7/5.2	1,066.99	62.76	0.030	0.030	> 0.0001

Note: An interactive version of the map with the health facilities and the projected vulnerability in the territory can be accessed at: https://rpubs.com/costa_/heatmapvul02.

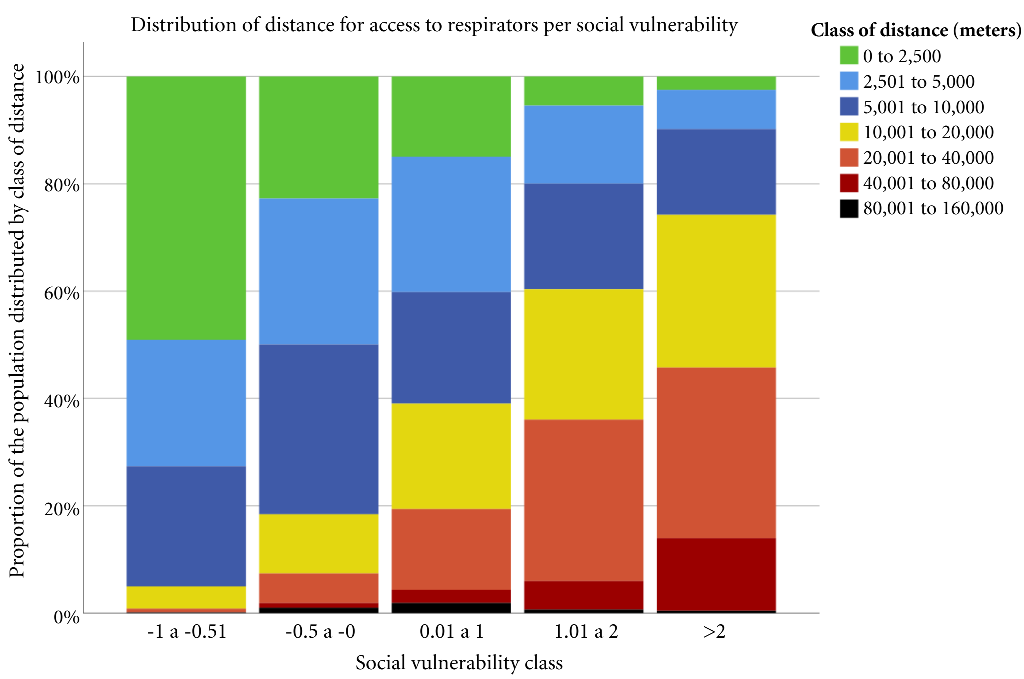
Source: Authors, based on data from the 2010 Census (IBGE) and CNES Dec/2019.

Table 4. Establishments with Normalized Centrality of up to 3% of the Network.

Establishment	Distance P50/P75 (KM) (A)	Potential Demand (Centrality) (B)	Demand/ Beds (C)	Normalized Centrality (D=E+F)	Normalized Centrality DF (E)	Normalized Centrality Surroundings (F)
	Coverage of Type II Adult ICU Beds on the Potential Demand of 1% of the Population					
Hospital Reg. Sta. Maria	10.9/25.2	6,067.66	209.23	0.171	0.038	0.133
Hospital Reg. Samambaia	6.7/19.0	5,664.53	283.23	0.160	0.139	0.021
Hospital DOMED (Ceilândia)	5.1/21.2	4,243.45	326.42	0.120	0.096	0.024
Hospital da Região Leste	21.3/40.7	3,547.63	394.18	0.100	0.074	0.026
Hospital Reg. de Sobradinho	19.8/34.7	3,211.78	535.30	0.091	0.073	0.018
Hospital Reg. Taguatinga	7.9/24.7	2,462.27	410.38	0.069	0.060	0.009
Hospital Reg. Ceilândia	5.2/21.3	2,179.48	363.25	0.061	0.050	0.011
Hospital São Mateus (Cruzeiro)	6.5/8.5	1,881.08	235.14	0.053	0.052	0.001
Hospital da Região do Gama	22.0/29.9	1,772.46	221.56	0.050	0.036	0.014
Hospital Reg. Asa Norte	5.5/6.3	1,673.96	167.40	0.047	0.039	0.008
Hospital Materno Infantil de Brasil.	10.1/17.6	1,301.86	325.47	0.036	0.035	0.001
	Coverage of Type III Adult ICU Beds on the Potential Demand of 1% of the Population					
Inst. De Cardiologia do DF	22.0/34.6	16,465.77	823.29	0.466	0.360	0.106
Hospital de Base do DF	26.9/36.0	11,771.08	588.55	0.333	0.227	0.106
Hospital SARAH Brasília	26.9/36.1	7,056.59	588.05	0.199	0.136	0.063

Note: An interactive version of the map with the health facilities and the projected vulnerability in the territory can be accessed at: https://rpubs.com/costa_/heatmapvul03.

Source: Authors, based on data from the 2010 Census (IBGE) and CNES Dec/2019.



Graph 1. Distribution of distance for access to respirators per social vulnerability.

Source: Authors, based on data from the 2010 Census (IBGE) and CNES Dec/2019.

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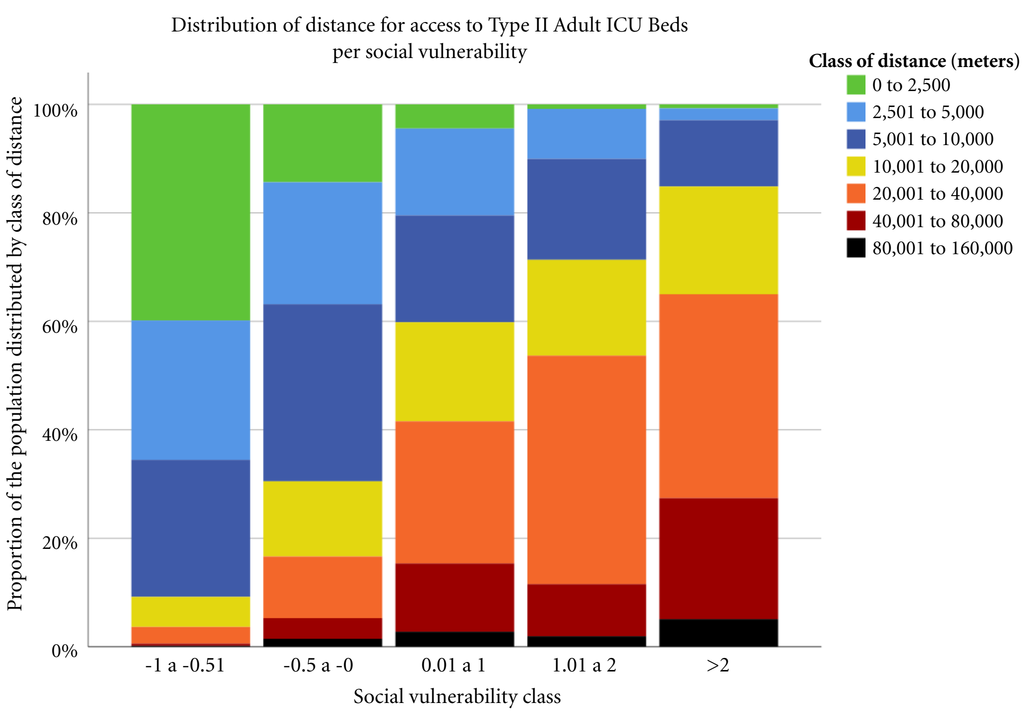
characteristics of COVID-19 in a simulation of demand of 1% of the population could produce an overload in the DF health system not reflected in the traditionally disclosed "resource per population" numbers. Moreover, we should remember that the model included municipalities adjacent to the AMB, belonging to the States of Goiás and Minas Gerais. Although this population was not the object of analysis, health establishments in these regions were used when this was the closest option to an AMB census tract.

Final considerations

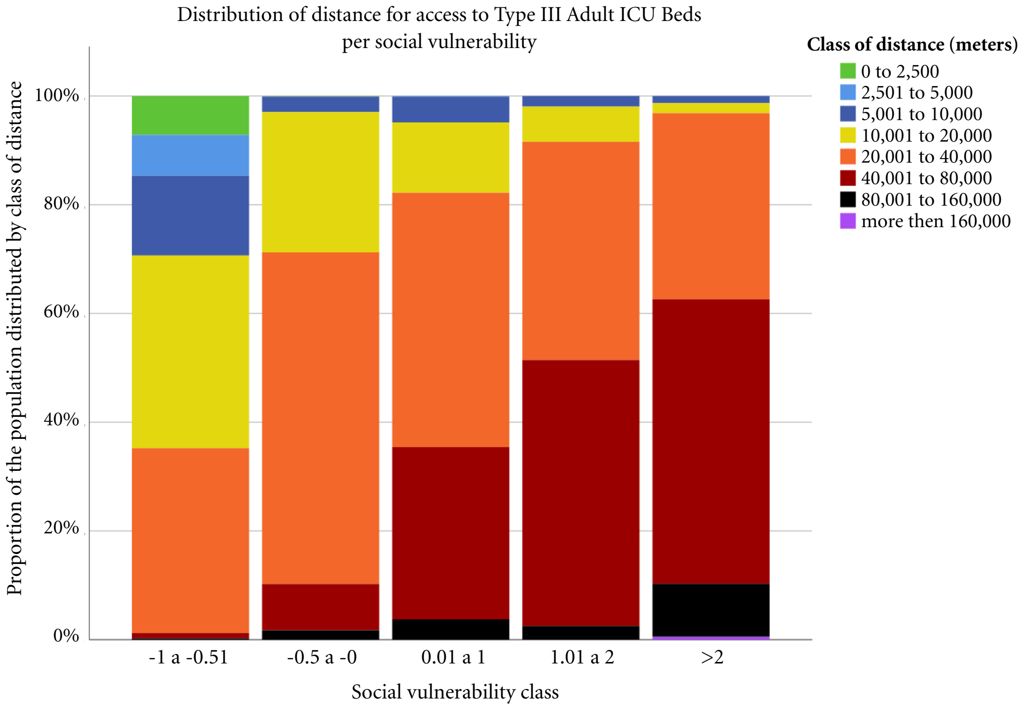
Since the onset of the pandemic, the scarcity of resources for the treatment of acute respiratory crises has already drawn the scientific community's attention. Also, at the time, it was already estimated that 5% of the population could contract the virus within three months, and among these, 20% could demand the use of advanced medical services in the treatment of acute crises[21]. In Brazil, this concern was no different. Works presented by Bezerra *et al.*[22] and a technical note[23] presented by the Institute of Studies for Health Policies (IEPS) translate into a latent concern about the scarcity of resources, especially in a country with imbalanced access to health services infrastructure.

The scarcity of resources and the difficult access imply critical aspects to combat the development of the disease. As it is an acute inflammatory condition, its evolution can lead to heart and kidney injuries and complications in the circulatory system. Except in asymptomatic cases, the disease manifests as an acute respiratory crisis, like a typical viral respiratory infection, leading to up to 14% of the incidence requiring treatment via oxygen therapy[24]. Noteworthy is the role of social determinants such as income and housing density as determining agents of the aggravation and lethality of COVID-19 cases. Therefore, we observe a disease with evident social determination for the increased incidence and the mortality, a condition pointed out by



Graph 2. Distribution of distance for access to Type II Adult ICU Beds per social vulnerability.

Source: Authors, based on data from the 2010 Census (IBGE) and CNES Dec/2019.



Graph 3. Distribution of distance for access to Type III Adult ICU Beds per social vulnerability

Source: Authors, based on data from the 2010 Census (IBGE) and CNES Dec/2019.

Figueiredo *et al.*[24]. Thus, understanding access to critical resources and the population's exposure to social vulnerability conditions are essential dimensions for understanding COVID-19 mortality and severity.

While the results presented here originate from a potential demand simulation process, these results shed light on how metrics and aggregations based on "Provider-to-Population" can lead to superficial interpretations regarding the distribution and access to resources. However, this approach is frequently used by the media, research institutions, and scientific dissemination[6,23,25]. On the other hand, the techniques employed here sought to disaggregate the spatial data into the smallest possible aggregate, exposing the spatial conditions of access more precisely. Although there are different techniques to estimate the accessibility and availability of resources in a territory, models based on the availability of resources and services at the closest provider are used more frequently and can vary regarding the different techniques to measure displacement impedance and distance[8,26,27] and the formulation of availability, which may be based on decay due to distance or competition for resources[28]. This model used modeling that prioritizes the perspective of the health establishment and its positional importance in the network of relationships, assuming simplifications while offering a richer perspective than the use of the proportion between resource and the total population of a territory.

As with any model representing the study object's reality, there are limitations. First, we should consider that access to health services has multidimensional determinants and characteristics, such as those described by Andersen[9] or Penchansky and Thomas[10]. Moreover, the model used Euclidean distances as a determining parameter to decide on the use of one health facility or another, adopting the perspective of geographic accessibility and, therefore, not considering aspects such as the acceptability of the service by the population, for example, which potentially would affect the availability of the service. Although it is a simple concept, the Euclidean distance can be a good model of geographic acces-

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sibility. It is an approximation generally adequate for regions without topographical complexity and with good coverage of the urban network of streets and avenues[27,29,30].

The discrepancy between the public health care infrastructure of the Federal District and the municipalities surrounding Brasília is known, and many factors lead the surrounding population to seek the DF health system. Among them is the referral by PHC units, a perception of the low resolution of the surrounding health network compared to the medium and high-complexity network of the federal capital, and the lack of resources or medium and high-complexity services[27]. This imbalance is expressed in different care realities and cannot be lost in aggregate excerpts of the reality. It must be present and the target of attention in any model that builds evidence for planning actions to face health crises and epidemics, especially when it is about integrated metropolitan regions with high urban mobility.

Although the DF Health Regulatory Complex has an interstate regulation center, this structure operates within highly complex procedures, requiring the development of agreed actions to manage the flow of health care from other levels of care within the metropolitan territory consisting of the Federal District and Goiás[31]. Isolated actions without integrated planning can cause friction between the agents responsible for conducting public policies, especially in a pandemic where there is an imbalance in services' demand and supply structure. An example of this was observed in the AMB when the press reported[32] that the Government of the Federal District would consider, by decree, preventing the access to health of the population residing in Goiás to the public health network of the DF.

Collaborations

DRT Costa worked on the conception and design of the research, writing of the article, analysis and interpretation of data. JOM Barreto worked on the conception and design of the research, critical review and theoretical contributions and approval of the final version. RB Sampaio worked on the critical review and theoretical contributions and approval of the final version.

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