National COVID-19 vaccination plan: using artificial spatial intelligence to overcome challenges in Brazil

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Abstract *This article explores the use of spatial artificial intelligence to estimate the resources needed to implement Brazil's COVID-19 immunization campaign. Using secondary data, we conducted a cross-sectional ecological study adopting a time-series design. The unit of analysis was Brazil's primary care centers (PCCs). A four-step analysis was performed to estimate the population in PCC catchment areas using artificial intelligence algorithms and satellite imagery. We also assessed internet access in each PCC and conducted a space-time cluster analysis of trends in cases of SARS linked to COVID-19 at municipal level. Around 18% of Brazil's elderly population live more than 4 kilometer from a vaccination point. A total of 4,790 municipalities showed an upward trend in SARS cases. The number of PCCs located more than 5 kilometer from cell towers was largest in the North and Northeast regions. Innovative stra tegies are needed to address the challenges posed by the implementation of the country's National COVID-19 Vaccination Plan. The use of spatial artificial intelligence-based methodologies can help improve the country's COVID-19 response.*

Key words *Spatial analysis, Artificial intelligence, Mass vaccination, Immunization programs, Geographic mapping*

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Introduction

The COVID-19 pandemic has rapidly spread to more than 188 countries, affecting more than 106 million people and causing over 2.3 million deaths to date[1]. Against a backdrop of underfunding and overburdened services, the magnitude of the pandemic and fatality rates have led to the adoption of social distancing measures and lockdowns, affecting the global economy[2,3]. Twelve months after the pandemic was declared, there is no evidence of any effective treatment for the disease[4].

At the beginning of 2021, with the development of multiple vaccines with proven efficacy and safety[5], the main challenge related to the COVID-19 response is ensuring timely mass immunization[6]. Up to 7 February 2021, 81 countries had already initiated vaccination campaigns, reaching 99 million people[7].

Health campaigns are one of the main interventions used to control infectious diseases[8]. The challenge of designing effective health campaigns already existed before the pandemic, with vaccines being made available in health services on a regular basis. Even in countries with consolidated health systems, vaccination coverage rarely reaches 100% because it is not possible to locate the entire target population[9,10,11]. Campaign design and management weaknesses hamper the mitigation of the harmful effects of vaccine-preventable diseases, as is the case with measles outbreaks in Brazil[9,10,11]. The drop in the level of vaccination coverage in Brazil in recent years is associated with different factors, including a fall in perceived risk, growing social, political and economic crisis, a rise in vaccine refusal, the spread of negative beliefs and false information about vaccines, logistical problems, and a reduction in the number of people seeking the vaccine in primary care services provided by the country's national health service, the Sistema Único de Saúde (SUS), due to the effects of the pandemic[9,10,11].

One of the challenges of structuring effective health campaigns is defining and identifying the location of the target population. The correct identification of the target audience is essential to estimate necessary resources and health campaign costs. Estimating the target population of a campaign is a challenging task as the main source of data is population censuses and many countries do not have up-to-date census data[12]. In Brazil, the pandemic has severely hampered the 2020 census. As a result, it is likely that primary population data will only be available in the middle of 2024, meaning that the country will be left without an up-to-date overview of its demographic situation for almost 15 years. With regard to the intercensal estimates made by the Brazilian Institute of Geography and Statistics (IBGE), the demographic transition in Brazil has contributed to population growth stagnation in some areas and a fall in growth in others, which can affect the accuracy of estimates made between censuses[13,14]. The lack of reliable estimates of population size and the spatial distribution of populations adversely affects actions based on population denominators.

In light of this challenge, the National COVID-19 Vaccination Plan[15] is likely to face difficulties in implementing its core evaluation components, which require up-to-date information about the distribution of the target population and size of the effort needed to reach the eligible population. Strategies to improve the structure of health campaigns are partially based on microplanning approaches. Campaign microplanning can be understood as a set of strategic actions oriented towards achieving the health campaign's objectives[16]. Microplanning combines local information, logistics analysis, rapid monitoring tools and population databases to create an action plan devoted to promoting the effective implementation of a particular health campaign[17]. However, despite their utility, lack of knowledge of the local situation, absence of up-to-date population estimates, and scarcity of data on the geographic location of health services limit the potential of microplanning solutions.

Microplanning based on inaccurate and outdated population data and wrong information about distances between health facilities and communities can result in inefficient resource allocation, leading to waste of vaccine doses and meaning that it is impossible to reach the target populations in remote areas. One of the numerous innovations adopted to improve health campaign microplanning is the use of geoprocessing solutions (geographic information systems – GIS) as an alternative to the traditional process[16]. GIS-based solutions help identify eligible communities, including those not previously documented. The advantages of this approach include increased capacity to accurately estimate population size and identify location using satellite imagery[18]. The availability of more accurate data during planning phases enables more efficient programming of the resources needed for campaign microplanning.

The National COVID-19 Vaccination Plan mentions the importance of microplanning without going into detail[15]. The use of new technologies to assess vaccination program needs and help ensure the effective implementation of strategies to increase coverage in the face of outdated and incomplete data is therefore essential. Moreover, the use of geographic information systems to support the identification of the location of vulnerable and priority groups for immunization is limited, thus making the use of geospatial artificial intelligence imperative to address the challenges posed by the implementation of the National COVID-19 Vaccination Plan.

Considering the above challenges and gaps in the core components of the National COVID-19 Vaccination Plan, this article seeks to demonstrate how the use of spatial artificial intelligence can be applied to organize information so that health managers are able to better plan local actions to help ensure the effective implementation of the plan.

Methods

Study design and context

Using secondary data, we conducted a cross-sectional ecological study adopting a time-series design. The unit of analysis was primary care centers (PCCs) in Brazil registered in the National Registry of Health Facilities in November 2020 (NRHF).

Data sources

Six secondary data sources were used, as shown in Box 1.

Data analysis

A four-step analysis was performed to explore the ways in which COVID-19 vaccination microplans can benefit from the use of artificial intelligence GIS solutions: 1. Identification of the geographic location of PCCs with functioning vaccination rooms in November 2020; 2. Creation of catchment areas and estimation of the population registered with the vaccination rooms; 3. Estimation of the straight-line distance between PCCs with vaccination rooms and cell towers connected to a mobile data network; and 4. Analysis of spatial and temporal trends in COVID-19 cases based on the *spatial–temporal* clustering of hospitalizations due to Severe Acute Respiratory Syndrome (SARS) linked to Covid-19.

By combining information on the populations within the plan's target age group and their location, COVID-19 situation, and internet access in vaccination rooms, it is possible to identify priority regions in accordance with the criteria defined in the COVID-19 vaccination plan.

Step one - identification of the geographic location of PCCs

The geographic location of the PCCs were identified using two parts of the NRHF. The first part was extracted from the File Transfer Protocol (FTP)[19] of the national health information system (DATASUS), which lists all functioning facilities and their physical infrastructure. A total of 47,543 facilities classified as "clinics" or "health centers/primary care centers" were extracted from an overall total of 330,652 facilities. Of these, 32,226 had at least one registered vaccination room. The FTP details the facilities' physical infrastructure, but does not show their geographic coordinates. This information is contained in another data repository called OpenDatasus[20]. However, this repository uses the wrong decimal separators for the latitude and longitude coordinates. Instead of being expressed as -4,4568898 latitude, for example, the coordinate is presented as the number 44.568.898. This form of file presentation prevents the use of the most recent location data. The coordinate data were therefore processed to correct these errors. For each state, we extracted the geographical limits of the four spatial extremes, using the northernmost, southernmost, easternmost and westernmost coordinates as the boundaries for validating the crude coordinates obtained from OpenDatasus. By validating and correcting the problem crude coordinates, it was possible to reconstruct the data, enabling the identification of the geographic location of 31,727 of the 32,226 PCCs with vaccination rooms. In view of the complexity of this data processing procedure, used to validate the spatial data and ensure the replicability of our findings, the database is available at: https://doi.org/10.6084/m9.figshare.13528421.v1

Step two - definition of the PCC catchment area

The PCCs were then used as the basis to create the catchment areas. The 2017 National Primary Care Policy (NPCP)[21] stipulates that primary care services should be delivered as close as possible to the registered population. PCCs

Chart 1. Secondary data sources.

Database	Purpose	Period/area
National Registry of Health Facilities	Identification of the existence of vaccination rooms in PCCs, their geographic location and status	November 2020/all rooms in the country
OpenStreetMap	Analysis of Brazil's street grid to create catchment areas	April 2020/national territory
WorldPop[19]	Use of dasymetric population data to estimate population and location as at 2020	April 2020/national territory
Mobile phone base stations	Location of cell towers20 to determine internet access (https://doi.org/10.6084/m9.figshare.13528424)	December 2020/national territory
SIVEP-Gripe (Flu Surveillance Information System)	Cases of Severe Acute Respiratory Syndrome (SARS) linked to COVID-19 or unclassified cases to determine hospitalization patterns	All cases recorded up to 07/01/2021, totaling 941,251 cases classified as COVID-19 or pending classification
IBGE population projections	Calculation of the share of the population aged over 60 years using the spatial artificial intelligence approach	Estimate for 2019 by age group21

Source: The authors.

are therefore expected to provide services to the surrounding population. Unfortunately, Brazil does not have a centralized repository that shows the spatial boundaries of PCC catchment areas[22]. PCC catchment areas were therefore created using isodistance polygons demarcating areas with access to a PCC, based on a maximum travelling distance of 4 kilometers, chosen as a proxy for walking for an hour to get to the service. According to the NPCP, distances of more than 4 kilometers are considered a barrier to accessing healthcare. The isodistance polygons were created based on the 2020 street grid obtained from OpenStreetMap[23]. Around 10 million streets were analyzed. Train and boat transport sources were also considered, particularly in the North region. Each resulting polygon was shaped so as not to overlap other polygons, maximizing the area covered by the PCCs.

Step three - allocation of registered populations to catchment areas based on population estimates using geospatial artificial intelligence

In step three, we used the PCC catchment polygons generated in step 2 to calculate the estimated population within the area created.

Dasymetric population is the name given to population estimates obtained from the analysis of data derived from satellite imagery and spatial covariates using artificial intelligence algorithms[24]. The data used for this type of analysis are collected using satellite sensors capable of capturing the presence of *lights* at *night* and the refraction of sunlight by artificial constructions. Based on the analysis of these data, it is possible to make population projections taking into account the rate of population change in each human-modified area. By combining previous census data and analysis of land cover changes, IA algorithms are capable of estimating the number of people in a given human-modified area identified by satellite imagery. Population totals were estimated for local areas down to a scale of 1 square kilometers.

There are various sources of dasymetric population data. For the purposes of this study, we used WorldPop datasets[24], because they allow population estimates to be stratified into age groups. In addition, accuracy analyses show that the estimates obtained using WorldPop datasets show fewer differences with local population estimates than other datasets, thanks to the use of artificial intelligence approaches[25].

The WorldPop raster file containing the distribution of dasymetric population[24] was analyzed using ArcGIS Pro's zonal statistics tool, which calculates the sum of the pixel values corresponding to the population per square kilometers, assigning the resulting value to a PCC catchment area.

The result of this step is the estimated PCC catchment population for each selected age group in April 2020. This data can be used to inform strategic actions to formalize microplans targeting priority pockets of populations and identify areas without health care coverage that may require outreach vaccination programs.

Step four - prioritization of key groups in accordance with the COVID-19 vaccination plan guidelines

The vaccination plan states that the immunization campaign has three core evaluation components: Identification and assessment of existing network structure; Processes; Intervention indicators[15].

The first component refers to the data used to develop indicators for monitoring the implementation of the plan. The second and third components consist of actions developed after beginning vaccination. These components include the monitoring of the following: existing vaccination rooms, admissions due to SARS, definition of target populations, outreach vaccination needs, internet connection in vaccination rooms for the electronic recording of vaccination actions, and the definition of supplies needed to implement the plan. The fourth step therefore characterizes the national territory in relation to the monitoring indicators of the first core component of the plan. The target population (people aged over 60 years) was identified and linked to one of the vaccination rooms defined in steps 1 to 3. In the fourth step, we also analyzed the proximity between the vaccination rooms and cell towers capable of transmitting vaccination data and, finally, spatial and temporal trends in SARS cases, identifying areas that witnessed an increase in severe COVID-19 cases. The spatial and temporal trends analysis was performed by creating space-time cubes using ArcGIS Pro's Emerging Hotspot Analysis Tool[26], where the outcome variable was the SARS linked to COVID-19 incidence rate per 100,000 inhabitants.

The analyses in step 1 were performed using the open-source software R and WOPR packages[27]. The other steps were performed using ArcGIS Pro 2.5.

Results

The first three steps sought to identify PCCs with vaccination rooms and the population aged over 60 years living within a 4 kilometers radius of each facility. Table 1 summarizes the results of the first three steps. The files with the relevant datasets can be found in the following Figshare repository (https://doi.org/10.6084/m9.figshare.13528577.v1). Figure 1 is an illustration of the catchment areas created using the methodological approach proposed in this article. The dotted lines demarcate PCC catchment areas in Belém, the capital of the State of Pará (Figure 1A). Section 1B shows the distribution of the dasymetric population in the same region, where the darker areas are regions with a higher population density (https://doi.org/10.6084/m9.figshare.13528430.v1).

Brazil has 32,474 vaccination rooms distributed across 32,226 PCCs (Table 1). The Northeast region has the largest number of rooms (13,203). Geographic coordinates were obtained for 31,727 of the 32,226 PCCs, for which 23,171 catchment areas were created. The number of catchment areas was less than the number of PCCs due to the following reasons: we were unable to connect 2,308 facilities to the street grid because they were located in zones that had not been mapped by OpenStreetMap; catchment areas were not created for PCCs in close proximity to other facilities and therefore already encompassed by a PCC catchment area. As a result, dasymetric population data was analyzed in 29,419 (or 92.72%) of the 31,727 PCCs with geographic coordinates.

The analysis of the PCCs with geographic coordinates showed that 23,792,907 people aged over 60 years lived within a 4 kilometers radius of a PCC, representing 82% Brazil's elderly population. The remaining 18% of the population need to walk over 4 kilometers to get to a PCC with COVID-19 vaccination rooms. In the South region, 24% of older persons lived more than 4 kilometer from a PCC with a vaccination room. The large proportion of older people facing potential barriers to access to immunization poses an additional challenge to vaccination programs.

A total of 27,388 PCCs were located up to 2.5 kilometers from a cell tower (https://doi.org/10.6084/m9.figshare.13528424.v1). Despite the existence of potential geographical barriers, such as valleys and hills, it is expected that these facilities have access to mobile data networks and are therefore able to transmit vaccination data. The North and Northeast regions had the largest number of PCCs located more than 5 kilometer

Table 1. Characterization of PCCs with vaccination rooms showing the registered population and proximity to a base transceiver station.

Regions states	N vaccination rooms	Dasymetric population registered	Population aged over 60^a years	Total population in 2019 (IBGE)	% share elderly population	% of older persons registered with PCCs	Distance between PCCs with vaccination rooms and the closest cell tower				
							Up to 1km	Between 1 and 2.5 km	Between 2.5 and 5 km	Between 5km and 10 km	More than 10 km
Center-West	2.444	161.1613	1.893.160	16.297.074	12%	85%	1.912	238	44	50	139
Distrito Federal	107	292.762	328.656	3.015.268	11%	89%	95	4	0	1	0
Goiás	1.126	763.783	836.359	7.018.354	12%	91%	920	107	17	17	42
Mato Grosso	769	267.534	375.091	3.484.466	11%	71%	530	87	18	25	86
Mato Grosso do Sul	442	287.534	353.054	2.778.986	13%	81%	367	40	9	7	11
Northeast	13.203	5.759.153	7.030.062	57.068.132	12%	82%	9.245	1.266	653	916	816
Alagoas	783	315.668	370.796	3.337.357	11%	85%	572	54	55	61	24
Bahia	3.358	1.403.404	1.919.291	14.873.064	13%	73%	2.406	339	94	188	269
Ceará	2.072	974.709	1.148.332	9.132.078	13%	85%	1.412	208	158	189	35
Maranhão	1.694	501.333	722.295	7.075.181	10%	69%	962	135	79	142	299
Paraíba	1.054	508.590	546.136	4.014.605	14%	93%	773	131	68	59	12
Pernambuco	2.284	1.127.255	1.213.117	9.557.071	13%	93%	1.772	198	106	126	46
Piauí	880	302.146	411.365	3.273.227	13%	73%	583	78	37	70	92
Rio Grande do Norte	746	413.153	445.618	3.506.853	13%	93%	505	93	38	64	37
Sergipe	332	212.895	253.112	2.298.696	11%	84%	260	30	18	17	2
North	2.566	1.045.259	1.576.099	18.424.440	9%	66%	1.549	183	67	167	515
Acre	186	37.595	68.097	875.395	8%	55%	126	19	10	3	24
Amapá	87	43.235	56.724	845.731	7%	76%	33	8	8	4	29
Amazonas	400	269.814	311.473	4.144.597	8%	87%	286	27	6	19	49
Pará	1.296	452.961	763.716	8.602.865	9%	59%	707	66	30	114	336
Rondônia	162	109.045	169.913	1.777.225	10%	64%	119	23	2	3	14
Roraima	102	5.940	41.240	605.761	7%	14%	25	4	2	11	51
Tocantins	333	126.669	164.936	1.572.866	10%	77%	253	36	9	13	12

it continues

Table 1. Characterization of PCCs with vaccination rooms showing the registered population and proximity to a base transceiver station.

Regions states	N vaccination rooms	Dasymetric population registered	Population aged over 60^a years	Total population in 2019 (IBGE)	% share elderly population	% of older persons registered with PCCs	Distance between PCCs with vaccination rooms and the closest cell tower				
							Up to 1km	Between 1 and 2.5 km	Between 2.5 and 5 km	Between 5km and 10 km	More than 10 km
Southeast	9.243	11.725.059	13.763.522	88.336.847	16%	85%	7.723	871	193	183	63
Espírito Santo	489	399.439	564.777	4.008.094	14%	71%	368	61	24	28	2
Minas Gerais	3.448	2.546.450	3.315.231	21.165.609	16%	77%	2.691	459	73	103	52
Rio de Janeiro	1.449	2.579.116	2.893.098	17.264.943	17%	89%	1.204	108	47	21	4
São Paulo	3.857	6.200.054	6.990.416	45.898.201	15%	89%	3.460	243	49	31	5
South	5.018	3.651.823	4.824.414	29.971.192	16%	76%	3.759	642	180	248	105
Paraná	1.971	1.359.169	1.712.479	11.433.957	15%	79%	1.438	241	84	130	54
Rio Grande do Sul	1.890	1.550.846	2.069.569	11.377.239	18%	75%	1.437	255	43	71	40
Santa Catarina	1.157	741.808	1.042.366	7.159.996	15%	71%	884	146	53	47	11
Brasil	32.474	23.792.907	29.087.257	210.097.685	14%	29.087.257	210.097.685	14%	29.087.257	210.097.685	14%

Source: The authors.

from a base transceiver station. The electronic recording of vaccine doses, and therefore campaign monitoring, will be more difficult in facilities in these areas.

Figure 2 shows the space-time clusters of SARS incidence in 2020 across the country, where warm colors represent an upward trend. Further details on the categories can be found on ESRI's website[28]. SARS incidence increased over the 53 epidemiological weeks in 2020, with a predominance of warm colors on the map.

New hot spots are locations that are categorized as Hot spots in the final time steps and have never been Hot spots before. The incidence of SARS linked to COVID-19 in these locations increased towards the end of 2020, suggesting the potential worsening of cases. The three states in the country's South region were categorized as Oscillating hot spots, which are hot spots in the final time steps that were Cold spots in a prior time step. Oscillating hot spots were found in the states of Minas Gerais, Goiás, Tocantins, Rondônia, Acre and Mato Grosso, and in eastern Pará and on the northeastern coast. Finally, the states of Amazonas, Mato Grosso do Sul, Amapá and southern Roraima were classified as Sporadic hotspots, which are locations that are on-again then off-again hot spots that are not statistically significant. It is important to highlight the situation in the southeast of São Paulo, which was classified as an Intensifying hotspot, which are locations that have been hotspots for 90% of the time-step intervals and where the degree of statistical significance of the clustering is higher in the final time steps.

Table 2 details the distribution of the SARS space-time clusters across 5,561 municipalities. Nine municipalities were excluded due to data inconsistencies. A total of 3,253 municipalities were classified as Oscillating hotspots, 1,102 of which located in the South region. A total of 518 municipalities were categorized as New hot spots in the Northeast, with 28% of cities in this region showing an upward trend in SARS cases at the end of 2020.

Discussion

The objective of this article is to explore how the use of spatial artificial intelligence can provide information to help health managers better plan local actions to help ensure the effective implementation of the National COVID-19 Vaccination Plan.

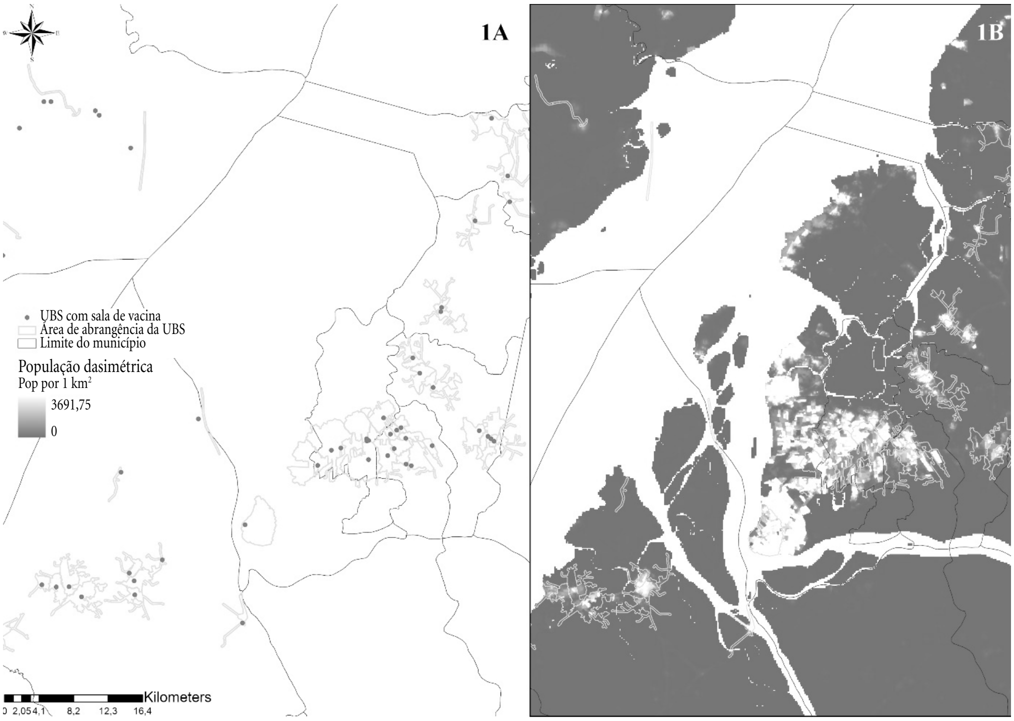


Figure 1. Representation of the coverage areas created and distribution of the dasimetric population to Belém do Pará, 2020.

Source: The authors

Given its magnitude and impact on society, the promotion of actions to mitigate the pandemic in Brazil is imperative. On 7 February 2021, the number of COVID-19 deaths in the country stood at 231,000[29]. Demographic studies show that there were around 234,000 excess deaths in epidemiological week 52 of 2020[30,31], suggesting that up to 34,000 additional deaths may be attributed to COVID-19 after death investigation procedures, just in 2020.

The harmful effects of the COVID-19 pandemic have forced the government to seek solutions to resume economic activities and restore everyday normality. Despite the anxiety permeating society, there are no short cuts to overcoming the challenges posed by the pandemic. In response to the pandemic, the Ministry of Health developed the National COVID-19 Vaccination Plan. This plan has been a target for criticism from the academic community due to the lack of detail on the strategies the government intends to adopt to operationalize the plan.

In view of these shortcomings, this article seeks to present strategies based on geoprocessing and artificial intelligence that can be employed to promote pragmatic actions targeting the most vulnerable populations. The use of remote sensing, satellite imagery and artificial intelligence algorithms to make population projections emerges as a potential path to identify pockets of eligible populations and areas with *difficulties* in *accessing* health services that may require outreach vaccination programs and to estimate the resources needed to implement campaigns in regions hit by disease outbreaks.

In urban areas, the walking distance limit proposed by this study can be overcome with the help of public transport; however, in remote rural areas, distances greater than 4kilometers may pose a barrier to access. The use of this proxy is an interesting alternative given the lack of a national digital repository containing the actual catchment area of the country's PCCs[32]. Although some efforts have been made to address this information gap[22], there is still a long way to go in finding a definitive solution. The approach outlined here is the most effective way to address these challenges and catalyze urgently needed immunization solutions.

The analysis of spatial and temporal trends in SARS cases throughout 2020, the dasymetric population registered at PCCs, share of the population aged over 60 years in the municipalities, and proximity to cell towers connected to a mobile data network provides more concrete data to inform strategies for reaching the priority populations defined in the National COVID-19 Vaccination Plan.

The datasets presented in this article enable health managers to identify their PCCs, obtain an estimate of the eligible population close to the facility, assess internet access in each vaccination room, and compare this information with upward trends in cases in each municipality (https://doi.org/10.6084/m9.figshare.13528577.v1 and https://doi.org/10.6084/m9.figshare.13528430.v1). Managers therefore have access to data to inform the implementation of vaccination microplans, enabling them to estimate population sizes and remote areas potentially without health care coverage. In turn, this data provides state health managers with a macro view of their state, enabling them to select priority areas for vaccine distribution in order to minimize severe cases and ICU bed shortages.

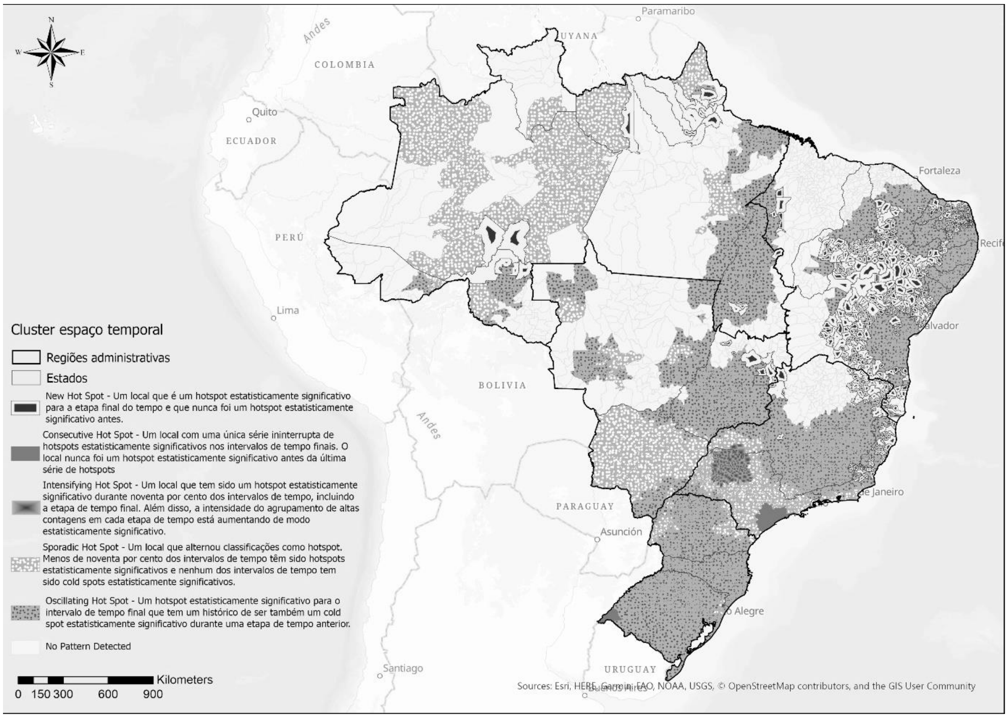
Challenges vary from region to region in Brazil. The national vaccination plan provides that the recording of administered doses should be linked to the *National Healthcare Data Network* (NHDN)[33] and, therefore, the national patient communications hub, Conecte SUS. Given the problems with internet connection in many PCCs, it is likely that the electronic recording of data will pose a challenge in the North and Northeast regions. In this regard, modifications need to be made to the electronic recording of doses to allow for partial offline data collection. In addition, internet connectivity problems mean that follow-up of adverse events and other issues associated with the vaccination process should not be online. Lack of internet access could mean that the monitoring of vaccination campaign problems will be delayed, preventing the adoption of effective protective measures. Our findings provide a room-to-room overview of connectivity to mobile communication networks.

Approximately 5.2 million people live more than 4 kilometers from a PCC, which may suggest a need for outreach vaccination strategies. In the South region, where 24% of older people are in this situation, 93% (n=1,102) of the region's 1,189 municipalities showed and upward trend in SARS cases. Given the characteristics of the facilities and the epidemiological profile of the disease in this region, active search strategies should be stepped up. A total of 4,790 municipalities showed an upward trend in SARS cases during the last epidemiological weeks of 2020, placing large portions of the population in a delicate situation.

One of the difficulties in structuring effective vaccination campaigns is the quality of microplanning strategies developed by municipal governments, which are based on the traditional model adopted by the SUS. Usually, the Ministry of Health defines the campaign guidelines and is responsible for funding, communication, supplies (including vaccines), and logistical support, while the municipal health authority is responsible for executing the program. Brazil is a heterogeneous country with multiple realities that influence capacities for program planning, using data analysis tools, and planning logistics and human resources. While some municipalities will achieve their campaign goals, others will certainly face difficulties. However, it is the Ministry of Health that is ultimately responsible for vaccination coverage. The weak link in the campaign organization chain is precisely the most powerful tool for achieving the desired results: microplanning. The current approach to health campaign organization has resulted in a number of problems over the last five years, including a reduction in coverage[34] and outbreaks of vaccine-preventable diseases[35–37]. This situation means that the problems faced by the COVID-19 campaign extend beyond vaccine and supplies shortages.

The present article combined innovative analytical strategies to address some of the challenges linked to the operationalization of the COVID-19 vaccination campaign, seeking to generate evidence related to indicators in the National COVID-19 Vaccination Plan. All data used in the above analyses and the respective results are available as supplementary material to this article.

Study limitations include the fact that it was not possible to make estimates based on the



Sources: Esri, HERE, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community

Figure 2. Space-time clusters referring to the incidence of SRAG for the year 2020.

Source: The authors

PCCs' actual catchment areas, potential differences between real population figures and estimates made using satellite imagery, and possible inaccuracies in the geographic coordinates of the PCCs obtained from DATASUS. In relation to the trade-off between using 2010 census data and dasymetric population data from 2020, the latter has the advantage of covering the whole national territory, identifying human settlements in areas that are not easily identifiable without the use of satellite data. In addition, WorldPop estimates were adjusted to reflect national estimates. However, these estimates are subject to inaccuracies. Finally, to address possible inaccuracies in the geographic coordinates, we used spatial methods to validate the data, including checking coordinates against the spatial boundaries of each state. However, DATASUS should make improvements to the health facility coordinate dissemination process. An important initiative in this regard, which unfortunately has been discontinued, was the National Program for Improving Access and Quality in Primary Care, under which two-yearly visits were made to all of the country's PCCs, recording the facilities' geographic coordinates on-site using a GPS device[38].

With regard to directions for future research and actions, it is important to highlight two points. First, the creation of a national repository of PCC catchment areas is essential to improve the quality of information analysis linked to primary care services. In this regard, a number of open-source collaborative mapping tools can be used to support a coordinated information generation process. The second point is the need for an in-depth discussion on the use of geoprocessing-based strategies and tools to inform the development of health campaign microplans. In this respect, it is important to stress that the use of geoprocessing-based technologies has the potential to increase the cost-effectiveness and efficacy of COVID-19 vaccination campaign microplanning[16,39]. The approach proposed by the present study can also help improve the equality

Table 2. Distribution of identified clusters by region and state, Brazil 2020.

Regions /states	No pattern detected	Consecutive hot spot	Intensifying hot spot	Oscillating hot spot	Sporadic hot spot	New hot spot	Total region/state
Center-West	121	0	0	273	65	8	467
Distrito Federal	0	0	0	1	0	0	1
Goiás	41	0	0	195	2	8	246
Mato Grosso	80	0	0	51	10	0	141
Mato Grosso do Sul	0	0	0	26	53	0	79
Northeast	403	0	0	872	0	518	1.793
Alagoas	0	0	0	99	0	3	102
Bahia	31	0	0	160	0	226	417
Ceará	76	0	0	84	0	24	184
Maranhão	193	0	0	19	0	5	217
Paraíba	0	0	0	184	0	38	222
Pernambuco	1	0	0	148	0	36	185
Piaui	96	0	0	51	0	77	224
Rio Grande do Norte	6	0	0	62	0	99	167
Sergipe	0	0	0	65	0	10	75
North	154	0	0	214	56	25	449
Acre	14	0	0	3	4	0	21
Amapá	2	0	0	1	3	10	16
Amazonas	24	0	0	0	36	2	62
Pará	48	0	0	84	8	4	144
Rondônia	30	0	0	16	2	4	52
Roraima	12	0	0	0	3	0	15
Tocantins	24	0	0	110	0	5	139
Southeast	93	63	152	792	440	123	1.663
Espírito Santo	1	0	0	35	0	41	77
Minas Gerais	92	0	4	635	51	70	852
Rio de Janeiro	0	0	0	44	36	12	92
São Paulo	0	63	148	78	353	0	642
South	0	3	0	1.102	84	0	1.189
Paraná	0	0	0	324	75	0	399
Rio Grande do Sul	0	3	0	485	9	0	497
Santa Catarina	0	0	0	293	0	0	293
Brazil	771	66	152	3.253	645	674	5.561

Source: The authors.

and universality of health campaigns by enabling the accurate identification of critical regions for the implementation of interventions.

Collaborators

TAH Rocha, GM Boitrago, RB Mônica, DM Silva, DG Almeida, NC Silva, JRN Vissoci, SH Terabe, LA Facchini and C Staton contributed to the conception and development of this article, literature review, drafting the article and revising it critically for important intellectual. All authors approved the final version to be published and declare themselves accountable for all aspects of the work, ensuring accuracy and integrity.

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