REVISTA DE NUTRIÇÃO
Brazilian Journal of Nutrition

ORIGINAL
ORIGINAL

Collective Health
Saúde Coletiva

Editor
Luciana Bertoldi Nucci

Conflict of interest
The authors declare they have no conflict of interest.

Received
February 13, 2023

Final version
May 19, 2023

Approved
September 4, 2023

Geographical distribution of nutritional status of adolescents in a Brazilian city in the early years of the pandemic

Distribuição espacial do estado nutricional de adolescentes de um município brasileiro nos anos iniciais da pandemia

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How to cite this article: Gomes TG, Bicalho JMF, Coelho KR. Geographical distribution of nutritional status of adolescents in a Brazilian city in the early years of the pandemic. Rev Nutr. 2023;36:e230030. https://doi.org/10.1590/1678-9865202336e230030

ABSTRACT

Objective

This study aims to build geographic models related to the nutritional status of adolescents and describe territories regarding the prevalence of malnutrition, overweight, and obesity, in order to spatially represent how the nutritional status of adolescents is distributed in the city.

Methods

Using geocoding techniques, graphic models were built using data from the SISVAN platform, as well as the addresses and nutritional status of adolescents aged 10 to 19 years in the municipality of Divinópolis, in the state of Minas Gerais (Brazil), between 2020 and 2021.

Results

There was a prevalence of 34% of obesity and overweight in the 2020 and 2021 samples. The graphical models showed that there is no specific pattern of points for the spread of nutritional diagnoses, but it was possible to identify areas of heat and places with a higher concentration of overweight. Underweight had a homogeneous spread and did not stand out in the formation of profiles.

Conclusion

Geographic tools with the adolescents' nutritional profile were successfully modeled, which have the potential to contribute to better health indicator management in the assessed territory, even with the limitations of the study.

Keywords: Geographic mapping. Malnutrition. Obesity. Overweight. Primary health care. Spatial analysis.

RESUMO

Objetivo

Este trabalho tem como objetivo construir modelos geográficos relativos ao perfil nutricional de adolescentes e descrever territórios quanto à prevalência de déficit de peso e excesso de peso, de modo a representar espacialmente como o diagnóstico nutricional de adolescentes está distribuído na área estudada.

Métodos

Através da técnica de geocodificação foram construídos modelos gráficos utilizando a plataforma SISVAN, os endereços e o estado nutricional de adolescentes de 10 a 19 anos do município de Divinópolis, Minas Gerais, nos anos de 2020 e 2021.

Resultados

Houve prevalência de 34% de excesso de peso na amostra de 2020 e 2021. Os modelos gráficos mostraram que não há um padrão específico de pontos de propagação dos diagnósticos nutricionais, porém foi possível identificar áreas de calor e locais de maior concentração de excesso de peso. O déficit de peso teve um espalhamento homogêneo e não se destacou na formação de perfis.

Conclusão

Foi possível modelar ferramentas geográficas com o perfil nutricional dos adolescentes, as quais têm potencial de contribuir para a melhor gestão de indicadores de saúde no território avaliado, mesmo com as limitações do estudo.

Palavras-chave: *Mapeamento geográfico. Desnutrição. Obesidade. Sobrepeso. Atenção Primária à Saúde. Análise espacial.*

INTRODUCTION

Geoprocessing technologies have been assisting in data collection, processing, and understanding in environmental assessment, urban planning, and other sciences. In the field of health, data requires epidemiological surveillance or well-structured surveys for information collection; thus, health data georeferencing is a complex task, but one that is becoming increasingly necessary for Brazilian municipalities [1].

According to Malta et al. [2] Brazil has some epidemiological surveillance systems known as *Sistemas de Informação em Saúde* (SIS, Health Information Systems). Due to survey designs, these data are not always used for spatial analysis or represented in cartographic models, resulting in a limited perspective of data collected by Health Surveillance policies [2]. In this context, geographical information systems, combined with population data collection, provide ideal and effective tools, according to the Pan American Health Organization, for decision-making and territorialization in health systems [3].

The *Sistema de Vigilância Alimentar e Nutricional* (SISVAN, Food and Nutritional Surveillance System) is the most important system for collecting nutritional status data and food consumption markers in Brazil, converging information to the *Sistema Único de Saúde* (SUS, Unified Health System) [4]. Coverage of adolescent Food and Nutritional Surveillance is a challenge. In the city of Divinópolis, in the state of Minas Gerais (Brazil), there was a slight increase in coverage from 2020 to 2021, with the percentage rising from 5.5% (1892 adolescents) to 6.3% (2163 adolescents). This fact reflects the existing concern about the epidemiological profile of children and adolescents in Brazil, which still has low coverage in some health regions [5].

According to the most recent National Health Survey, the average overweight rate among adolescents aged 11 to 19 years was over 22% in Brazil in 2015 [6]. In the state of Minas Gerais, out of 428,700 assessments conducted in 2020, about 21% of the sample had excess weight, 11% were obese, and 3% had severe obesity, according to SISVAN data [7].

In 2020, the World Health Organization declared the onset of the COVID-19 pandemic. COVID-19 is an acute respiratory syndrome caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) that spread to almost every country in the world [8].

As the virus spread, sanitary measures forced countries to impose social isolation, school closures, and various levels of restrictions on social interactions, resulting in many consequences, including impacts on the teaching-learning process [9].

This pandemic posed challenges for all age groups, as access to primary health care and contact with health services underwent significant changes [10]. Adolescents' isolation from school, which is a promoter of food and nutritional security, along with increased screen time due to virtual learning models and more time at home, are among the factors that have the potential to exacerbate the already rising trend of excess weight in this population [11]. Research conducted with students in the city of Divinópolis in March 2021 already showed a prevalence of 32.2% of overweight, as well as a decrease in parameters related to quality of life [12].

Based on these facts, a panorama of public health is outlined, where knowledge of additional factors associated with primary outcomes can provide greater capacity for planning and intervention by public authorities and health teams. Considering the challenges of accessing the adolescent population, the importance of understanding the territory and the geographic peculiarities of the region becomes crucial to investigate potential geographical patterns in the studied municipality, suggesting influences of determinants and conditions in the physical space. Thus, the significance of this study lies in transforming already collected health data into analytical tools, enabling critical discussions and supporting local policies for health protection and promotion, as well as food and nutritional security.

The objective of this study was to construct geographical models related to adolescents' nutritional profiles and describe territories regarding the prevalence of excess weight (overweight, obesity, and severe obesity) and weight deficit (underweight and severe underweight), spatially representing how the nutritional diagnosis of adolescents is distributed in the studied area during two years of the COVID-19 pandemic.

METHODS

This is a descriptive, retrospective study with a quantitative approach aimed at constructing geographical profiles using population data. The spatial distribution of nutritional status observations of adolescents in the municipality of Divinópolis, located in the mid-western region of the state of Minas Gerais (Brazil), was performed. Geocoding was conducted using tools for processing data collected by the health care network without prior georeferencing.

The first stage of the study involved obtaining data from the SISVAN database, specifically the nutritional status reports [7]. These data, originating from primary health care, include the address of each sample.

To create the sample, retrieved through the SISVANWEB platform, the age range between 10 and 19 years old was used, corresponding to adolescence according to the World Health Organization. The selected observation period covered the complete years of 2020 and 2021, which respectively marked the initial and intermediate stages of the COVID-19 pandemic. The spatial scope was defined by the addresses associated with the observations, respecting the political boundaries of the reference municipality for this study (Municipal Master Plan of Divinópolis, Complementary

Law nº 169/2014), and using data from all health establishments that collected anthropometric data for this age group [13].

The second stage involved data tabulation and database treatments, with access to two databases. The raw data for the year 2020 comprised 2,204 observations, and for the year 2021, 2,880 observations. The samples were classified according to Body Mass Index by age (BMIxAge) and stratified into Severe Thinness, Thinness, Eutrophy, Overweight, Obesity, and Severe Obesity (according to z-scores). Absolute and relative frequencies of the adolescents' nutritional status were calculated based on this stratification. During data processing for map creation, the authors chose to unify the strata into three classifications for ease of visual interpretation on maps: "Excess Weight" (overweight, obesity, and severe obesity), Eutrophy, and "Weight Deficit" (thinness and severe thinness).

In the data treatment stage, the 2020 and 2021 databases included repeated assessment of the same adolescent, incomplete data, and information that could not be utilized, including address information, which was removed. For the continuation of this study, three databases were used: the consolidated 2020 database with a 19% loss (1,789 samples included); the consolidated 2021 database with a 23% loss (2,220 samples included); and a compiled database representing the 2020-2021 biennium, without duplicates or erroneous data, considering the most recent assessment for each individual. This third database had 1,680 included observations.

The third stage involved constructing geographical models using the free platform GoogleMyMaps® and the ArcGIS® software. These platforms were used to convert obtained addresses into geolocated points containing information about the nutritional diagnosis, following the technique defined by Eichelberger [14]. To construct polygons, the authors visually delineated them according to the clustering trend displayed on the GoogleMyMaps® platform and confirmed by the heat map generated in the ArcGIS® software.

This project was approved by the Research Ethics Committee of the Universidade Federal de São João Del Rei – Campus Centro Oeste (Federal University of São João Del Rei - Central West Campus) under protocol nº 5.446.343.

RESULTS

Access to the data available on the SISVAN platform allowed for a general description of the nutritional status panorama in the city of Divinópolis. Table 1 presents absolute values (n) and relative (%) values of the nutritional status of adolescents for the years 2020 and 2021. The table was formulated prior to data treatment and, therefore, does not account for the losses during the geocoding/georeferencing stage.

One standout data point is the percentage of adolescents with obesity and severe obesity in both years, approximately 10% and 3% respectively. When combined, overweight, obesity, and

Table 1 – Nutritional diagnosis based on Body Mass Index by Age for adolescents aged 10 to 19 years in Divinópolis (Brazil) between 2020 and 2021.

Year	Severe thinness		Thinness		Eutrophy		Overweight		Obesity		Severe besity		Total	Adolescents
	n	%	n	%	n	%	n	%	n	%	n	%	n	%
2020	18	0.82	65	2.95	1.361	61.75	466	21.14	233	10.57	61	2.77	2.204	6.36
2021	51	1.77	98	3.40	1.767	61.35	577	20.03	276	9.58	111	3.85	2.880	8.32

Source: SISVAN [7].

severe obesity in both 2020 and 2021 contribute to a prevalence of around 34% of excess weight (considering the BMIxAge diagnosis). Regarding weight deficit, there is a 0.45% increase in prevalence from 2020 to 2021 (Table 1).

Concerning the locations of the surveyed adolescents' residences, Figure 1 shows the gray area labeled "urban area," corresponding to the urbanized zone and consequently where the points are concentrated. The sample distribution covers the entire urban extent of the city, with exceptions for some points not represented due to sample losses caused by geographic inconsistencies or unregistered data. Most of these areas without points are preservation areas, parks, and/or non-residential areas. Notably, addresses located in rural areas mostly had inconsistencies for the related database (GoogleMyMaps®) (Figure 1).

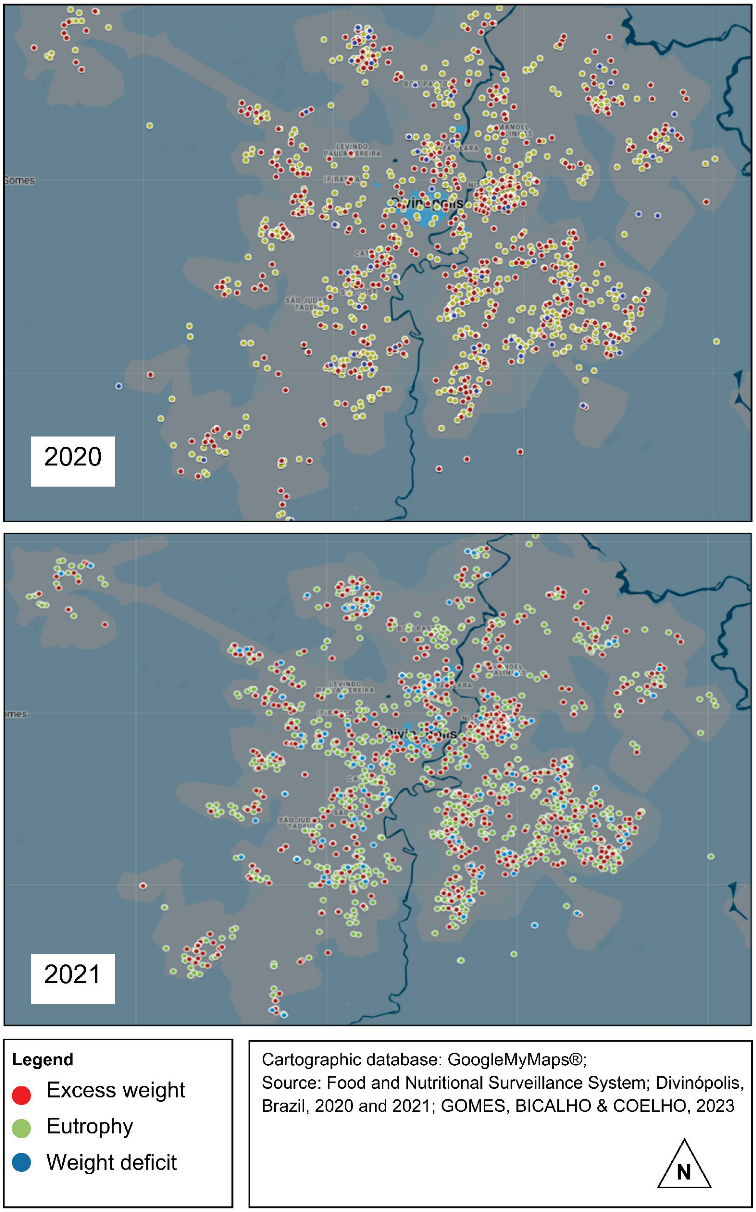

Figure 1 – Distribution of nutritional diagnoses among adolescents in the city of Divinópolis (MG), Brazil, between 2020 and 2021.
Source: SISVAN [7].

The visualization of excess weight distribution indicates that the same establishments identifying eutrophic nutritional states also identified excess weight. Figures 1 and 2 also reveal that certain locations had higher sample clustering.

According to Figure 2, for the year 2020, in polygons 1, 2, 3, 4, and 5, the groupings are more discrete, with polygon 3 representing the most distinct clustering profile. In the same figure, concerning the year 2021, two polygons exhibited greater expressiveness. The area of polygon 7, roughly corresponding to the same area of polygon 3, demonstrated significant clustering in terms of urban density. Polygon 8 showed a considerable sample clustering, and the space lacks limiting factors like rivers and uninhabited areas. This area corresponds to an extensive and more peripheral territorial zone. The same region in 2020, while similar, displayed more discreet observations (Figure 2).

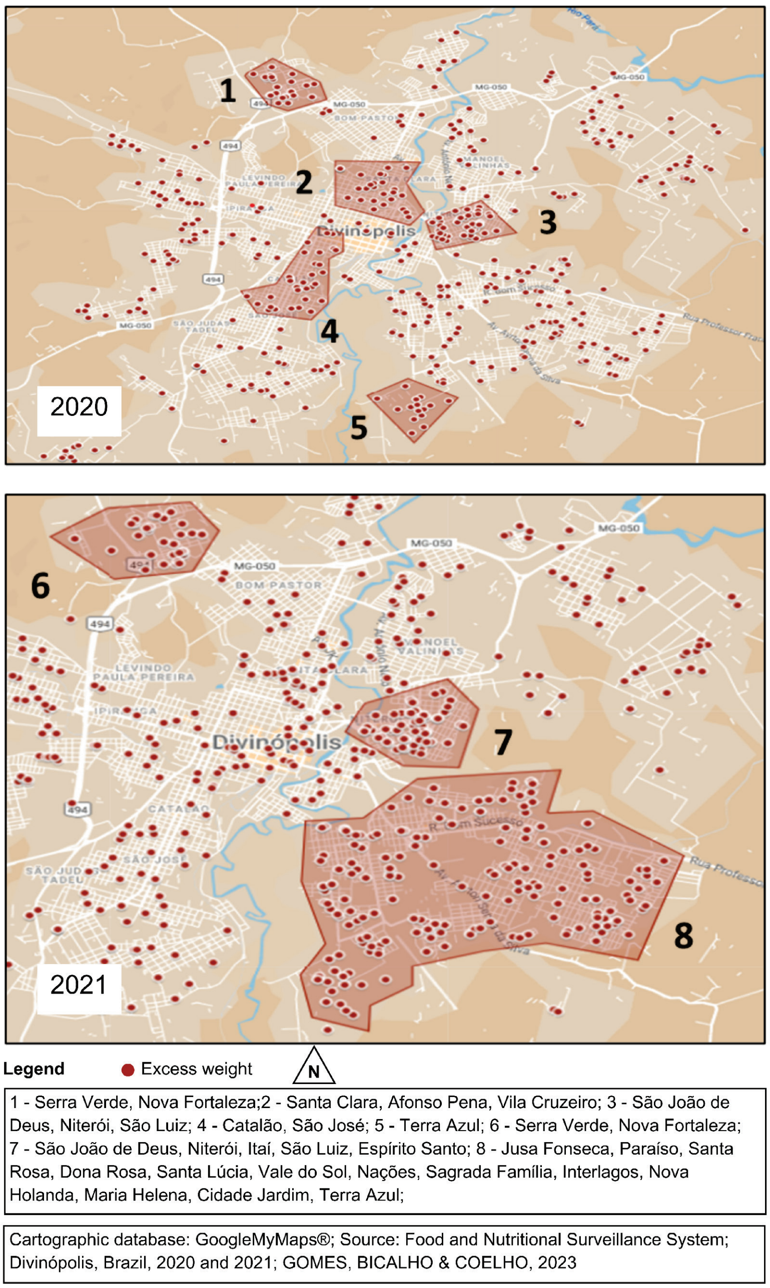

Figure 2 – Distribution of excess weight in adolescents in the city of Divinópolis (MG), Brazil, between 2020 and 2021.
Source: SISVAN [7].

Regarding weight deficit, the points did not suggest specific or expressive profiles; the spread demonstrated a trend similar to the total sample, with a few points lacking observations. As such, the data is numerically represented in Table 1 as "thinness" and "severe thinness."

For comparison purposes, a heat map was created using the ArcGIS® platform based on the 2020-2021 biennium database, as described in the method section. The maps can be observed in Figure 3 and demonstrate similarities between the overall distribution profile and that of excess weight alone. The central region and the Niterói district and its surroundings had more pronounced observations in this heat map, similar to polygons 2 and 3 in Figure 2. Another noteworthy region on the heat map was related to polygon 1 and part of polygon 8.

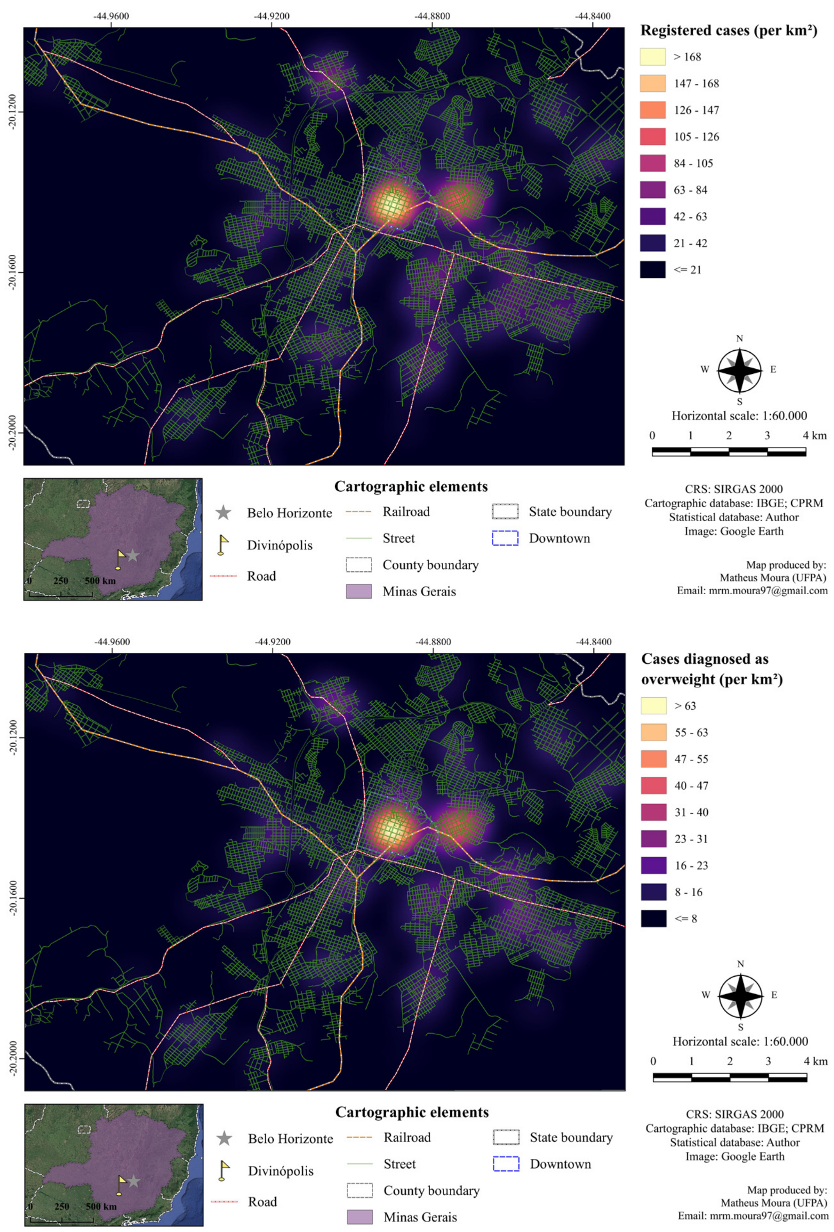

Figure 3 – Heat map of the distributions of nutritional diagnosis and excess weight in adolescents for the 2020-2021 biennium in the city of Divinópolis (MG), Brazil.

Source: SISVAN [7].

DISCUSSION

The present study revealed a significant percentage of overweight and obesity among the studied adolescent population, which aligns with the current national scenario. In Brazil, the nutritional transition accompanies the demographic and epidemiological transition of the population, resulting in increased obesity levels and the development of chronic diseases [15]. Adolescents are following the same trend due to increased sedentary lifestyles, social changes, technological access, and a shift in dietary patterns towards high consumption of ultra-processed and energy-dense foods [16,17].

The comparison between 2020 and 2021 highlighted an increase in the percentage of thinness and severe thinness in the city where this study was conducted. These numbers may be related to the "dual burden." Despite being a discreet increase, it is important to contextualize that the COVID-19 pandemic placed many Brazilians in situations of food insecurity and socio-economic vulnerability, contributing to record levels of poverty affecting 62.5 million people in Brazil, the highest level since 2012 [18].

Regarding the geographical profiles of adolescents' nutritional status in the years 2020 and 2021, it was observed that excess weight was more clustered. The geographical profiles followed the trend of the original dispersion, meaning they maintained similar proportions between the two studied years [19]. An increase in the number of assessed adolescents in the municipality can be observed; however, these numbers indicate a low coverage when compared to the total adolescent population of the municipality, as described in Table 1.

In addition to their limited expressiveness, scientific findings on georeferencing do not always aim to create detailed graphical models and territorial maps of a specific health issue or situation. When it comes to studies related to nutritional status, initiatives usually seek to portray broader territories, such as countries, rather than states, municipalities, and health territories [1]. An example is the Behavioral Risk Factor Surveillance System, a telephone survey similar to Brazil's Vigitel (a telephone survey system for surveillance of risk and protection factors for chronic diseases). The American research gathers data on risk factors for overweight, obesity, and chronic diseases, and one of the ways to disseminate data to the population is through graphical tools and cartographic models, highlighting states with higher incidence of excess weight, obesity, chronic diseases, metabolic syndrome, and others [20].

On smaller territorial scales and using similar techniques, Calistro identified points of social vulnerability within the territory of a Family Health Strategy by combining geographic data with family risk information. The maps allowed for increased information granularity and health territorialization by identifying additional information such as clinical conditions and present risks like alcohol users (14.97%), hypertensive patients (13.90%), and diabetes mellitus patients (4.38%) [21]. In monitoring infectious diseases, georeferencing plays a crucial role in identifying risk areas for infection and transmission. Studies conducted with tuberculosis patients were able to highlight clinical and epidemiological aspects in a specific territory in the state of Paraná. Using notification forms, Thomé et al. [22] described three districts where approximately 55% of disease notifications were concentrated, identifying a higher prevalence among white males up to elementary school [22].

Not all experiences with georeferencing and geocoding yield analytically potential results. For instance, with COVID-19 pandemic data, the distribution of cases in slum areas in the city of Rio de Janeiro was observed. However, using only ZIP codes, Izaga et al. [23] noted a significant number of errors and inconsistencies in the sample due to low data availability. Nevertheless, many other studies indicate that geocoding techniques can achieve over 80% accuracy in correctly identifying addresses when the data is more robust [24].

Regarding the profiles depicted in the maps, the polygons did not indicate a specific trend of moving away from or towards the city center. However, except for numbers 2 and 4, all the others have more than two primary care establishments in the dashed area. It is important to consider that the territory in question features geographical barriers (rivers and state highways). Spatial segregation caused by these factors directly influences issues such as dietary patterns, leisure, access to healthcare services, and work, as observed in areas with similar urban layouts, which are determinant factors in the development of various health issues [25,26].

The increase in SISVAN coverage in the city of Divinópolis from 2019 to 2021, as demonstrated in the SISVAN assessments, was surprising given the priority of healthcare during the historical period experienced. The pandemic hindered the population's access to healthcare services for various demands as COVID-19 became the priority for healthcare services. However, the population's need to maintain government assistance programs may have incentivized the continued data collection during this period, with the B*olsa Família/Auxílio Brasil* (Family Allowance/ Brazil Assistance) program being a significant data contributor to SISVAN [5,10,27].

In the heat map, the geocoding technique was employed using the combined database of 2020 and 2021. However, it is noticeable that the central region of the city was one of the areas where excess weight was more frequent in terms of the proportion per square meter. These data differ from the other maps and are not confirmed in the biennial database. This study demonstrated a concentration of excess weight in the central region of the studied municipality on this heat map. This occurrence can be attributed to the tendency of inconsistent data to be directed to this region, meaning there was an overestimation of data in this location due to the primary address data not being sufficient to accurately reference its location. Following the region around the city's downtown, the second most prevalent area (in the heat map) was around the neighborhoods where polygons 3 and 7 were drawn. These areas encompass two significant healthcare units of the municipality (called "Itaí" and "Niterói"), highlighting the importance of the strategic location of primary care facilities.

Older studies described by Barcelos et al. in Brazilian capitals faced the same problem of data inconsistency, with efficiency in some cases as low as 40% of the total sample [1]. In more recent studies, these data were preprocessed to improve the data recovery rate in databases, excluding spelling errors and other limitations. After this step, addresses that still contained errors were manually worked on once again, which took around four months in the abovementioned study. Frequently, research projects used multiple platforms to work around data loss, and inconsistent data were treated as losses, meaning they did not make it into cartographic expressions [28,29].

The spatial distribution of data samples from population databases through geocoding differs from the traditional georeferencing process, where the data is collected along with spatial referencing. In geocoding, the referencing is done based on the nominal relationship of these addresses with data libraries [30].

In this context, it is worth noting that despite the study's limitations, regarding the availability to manually correct incorrectly recorded addresses and the use of only one data library (Google Maps®), it still provides an important contribution to healthcare managers and professionals, particularly in the context of primary healthcare. This study demonstrates the need to combine Geographic Information System tools with food and health surveillance, as well as the continuation of this type of monitoring over the years, with a vision towards clearer data and greater potential for the implementation of public policies.

CONCLUSION

The study demonstrated an increase in the coverage of food surveillance from 2020 to 2021, as well as in the prevalence of excess weight and underweight in the studied sample. It was possible to create geographic tools and maps that described the nutritional profile of adolescents, especially the distribution of excess weight. This investigation enabled the spatial visualization of the nutritional profile of adolescents in the studied municipality and provided insights that can contribute to the reflection and discussion of strategies for better access to adolescents within the territories, particularly those with nutritional issues. Furthermore, this proposal suggests the development of tools that enhance health surveillance through territorialization within the framework of primary healthcare under the SUS system.

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CONTRIBUTORS

All authors are responsible for the reported research and have made substantial contributions to the study design, data analysis, and writing of the manuscript, and have approved the manuscript as submitted.