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RESEARCH ARTICLE

Analysis of the Association between Excess Weight in Schoolchildren in Costa Rica and the Food Environment using Collaborative Mapping

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ABSTRACT

This study explored the relationship between excess weight in schoolchildren and the local food environment in Costa Rica through the lens of Health Geography and collaborative mapping. Using data from the 2016 School Weight/Height Census, OpenStreetMap, Google Maps, and official demographic records, this study examined 62 statistically representative districts classified by degree of urbanization. Spearman correlation analyses revealed a moderately positive association between the density of food establishments and the prevalence of excess weight, particularly in rural and predominantly rural districts. No significant correlations were found in the urban areas. Spatial analyses also highlighted significant geographic disparities, with the highest obesity rates being concentrated in urban and transitional rural districts. Collaborative mapping has proven to be an effective, low-cost method for analyzing food environments, demonstrating its potential as a tool for public health planning and policy-making. These findings underscore the complex interplay between urbanization, food access, and childhood obesity, suggesting the need for integrated geographic and social approaches to address nutritional challenges in school populations.

Keywords: Childhood obesity, food environment, health geography, public health.

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1. Introduction

This research is framed within the field of Health Geography and uses collaborative mapping as a valuable resource for understanding the food environment, which is defined by the Food and Agriculture Organization of the United Nations (FAO) as the set of all types of food that people have access to in their daily lives through supermarkets, small stores, markets, street vendors, cafeterias, school dining rooms, restaurants, and other locations where people purchase and consume food [1]. Children refer to all accessible places where food and beverages can be acquired in areas near their homes or schools. This study aimed to support decision-making processes by government agencies responsible for preventing obesity, particularly in school-aged children.

García-Araque [2] defines collaborative mapping as the creation of maps that require citizen participation, involving individuals who are not professional cartographers and who may or may not reside in the area being represented.

This analysis is based on the results of the latest National Weight and Height Census in Costa Rica, which found that the prevalence of overweight and obesity, measured using Body Mass Index (BMI), among children and adolescents aged 5–12 years was 34%. The census included 347,379 students (178,417 boys and 168,962 girls), achieving a coverage rate of 90.9% and an omission rate of 22% (response rate of 77.9%), and was statistically representative at the national level. The malnutrition in Costa Rica did not exceed 2.5%, with an estimated average of 1.8%. Overweight and obesity rates by sex show a higher prevalence among girls [3].

Geographically, the highest prevalence was observed in urban areas (34.9%) compared to rural areas (31.4%), with a difference of 3.5%. Overnutrition was recorded throughout Costa Rica, with the highest prevalence in the Greater Metropolitan Area, particularly in the Heredia and San José provinces. At the canton and district levels, the prevalence varied significantly; for instance, the canton of Atenas had a rate of 40%, while San José registered 37.4% [3]. Studies such as that by DuBreck *et al*. [4] highlight the importance of considering the degree of urbanization when examining children's food environments.

In Costa Rica, obesity and socioeconomic status have two associations in the school population [3]:

- A direct association exists, in which individuals with a higher socioeconomic status generally have a higher prevalence of obesity.
- An inverse association exists, in which individuals with lower socioeconomic status generally have a higher prevalence of obesity.

Similar studies have shown that, as excess weight increases, the distance children travel to food acquisition points decreases, emphasizing the geographic importance of food environments [5].

Another relevant reason for this study lies in the acquisition of high-calorie foods, particularly from fast food chains. According to Gómez *et al*. [6], despite the 2008–2009 economic crisis, this situation did not threaten fast-food chains, but rather became an opportunity for transnational franchises to attract new customers through services such as home delivery. The opening of new restaurants and price wars aimed at maintaining and attracting clients has led to aggressive competition among franchises in recent years.

The general objective of this research was to explain how collaborative mapping can contribute to understanding the association between excess weight in schoolchildren in Costa Rica and the food environment. Accordingly, this is an exploratory study of the food environment in districts with the highest and lowest prevalence of childhood obesity in Costa Rica, based on the urbanization degree classification by the National Institute of Statistics and Censuses (INEC) and using collaborative mapping data extracted from OpenStreetMap via QGIS and Google Maps.

2. Materials and Methods

2.1. Data

The data used in this research came from various sources, each with a different nature. Below is a detailed description of each type and source of the data used.

- **Costa Rica 2016 School Weight/Height Census:** This census aimed to establish a baseline of anthropometric indicators (weight and height) for the school population aged 6–12 years to provide updated information on nutritional status. These data can support decision-making processes that affect children's nutrition and health. The census data are available at the different levels of the political-administrative division; for this study, the smallest unit, districts, was used. Specifically, the data used referred to obesity prevalence and were processed in. xlsx format.
- **OpenStreetMap and Google Maps:** Both geographic tools were used to obtain the food acquisition points. For OpenStreetMap, the Quick OSM tool in QGIS was employed to obtain the locations of establishments in ESRI shapefile (point) format. In the case of Google Maps, data were extracted directly from the app using KML files, which were then converted into ESRI shape files for format consistency.
- **District vector layer:** This information was obtained from the National Territorial Information System (SNIT) of the National Geographic Institute (IGN), updated in 2023, in the ESRI shapefile (polygon) format.
- **Degree of urbanization:** An important variable collected is the degree of urbanization, classified by INEC into four categories (Table I):

2.2. Phases and Processes

The following steps were carried out in this stage:

- **Classification by degree of urbanization:** All 172 districts included in the census were categorized according to their degree of urbanization: 14 urban districts, 49 predominantly urban, 28 rural, and 81 predominantly rural.
- **Sample selection by urbanization category:** As this is an exploratory study, a sample larger than 30 observations was used, as recommended for correlation processes. A total of 62 districts across the country were selected. The number of sampled districts per category was proportional to the total number of districts in each category (Table II).

The sample size was calculated using the following formula for a finite population [8], with the following parameters:

$$n = \frac{\left(N * Z_a^2 * p * q\right)}{\left(e^2 * (N-1) + Z_a^2 * p * q\right)}$$

$n = 172$ (total districts), $Z_a^2 = 1.96$ (95% confidence level), $e = 0.1$ (maximum estimation error), $p = 0.5$ (probability of occurrence), and $q = (1 - p)$.

The resulting sample size was 61.86, rounded to 62 districts). Given the four categories (urban, predominantly urban, rural, and predominantly rural), stratified sampling

TABLE I: Coding of Urbanization Degree per District [7]

Urbanization degree	Code
Urban	1
Predominantly urban	2
Rural	3
Predominantly rural	4

TABLE II: District Sample Representation by Urbanization Degree

Urbanization degree	Total districts	Percentage	Sampled districts	Sample percentage
Urban	14	8.14	5	8.07%
Rural	28	16.28	10	16.13%
Predominantly urban	49	28.49	18	29.03%
Predominantly rural	81	47.09	29	46.77%
Total	**172**	**100**	**62**	**100%**

was used. Proportions were calculated using the following distribution:

$$ncategory = \left(\frac{NC}{N}\right) * n$$

where *ncategory* is the number of districts sampled per category, *NC* is the number of districts in each category within the population, *N* is the total population size, and *n* is the sample size. For example, for predominantly rural districts:

$$npredominantlyrural = \left(\frac{81}{172}\right) * 62 = 29$$

The number of sampled districts per category was determined using proportional allocation and was selected randomly.

- **Food establishment data collection:** Locations were obtained from OpenStreetMap using Quick OSM in the shapefile format. KML files were used for Google Maps. The data reflect 2024 conditions and underwent manual validation for completeness in each district.
- **Density calculations:** Population and area data were obtained from INEC and SNIT, respectively.
- **Association analysis:** Data were processed using JASP (a free statistical software). Key variables included obesity prevalence (the sum of overweight and obesity) and establishment density. Spearman's correlation was used because of the non-parametric nature of the data and the presence of outliers, as it is more robust than Pearson's correlation.

3. Results

3.1. Spatial Behavior and Food Environment of the Studied Districts

The selected districts vary significantly in terms of characteristics, such as area in square kilometers. For example, the district of Tres Ríos in the canton of La Unión covers only 2.28 km^2 and is classified as highly urbanized according to INEC. In contrast, Chánguena is a rural district with an area of 273.04 km^2, which includes several indigenous territories. Valle La Estrella, in the canton of Limón, has an area of 1238.42 km^2 and is predominantly rural.

This variability was also reflected in the obesity prevalence values (the sum of overweight and obesity) from the Costa Rica 2016 School Weight/Height Census. As shown in Table III, on average, urban and predominantly urban districts reported a higher prevalence of obesity compared to rural and predominantly rural districts. The data also indicate that, in some cases, rural districts reached maximum obesity prevalence levels of up to 55%, in contrast to other districts where prevalence levels were approximately 42%. In relation to this, the highest minimum values were observed in urban districts, with 28% of the student population affected by obesity prevalence, compared to the remaining districts, which maintained levels between 16% and 21%.

To analyze this, a non-parametric Kruskal-Wallis ANOVA test was performed on the full sample of 172 districts. The sample was then subdivided into rural, predominantly rural, urban, and predominantly urban districts, according to the classification defined by INEC. This non-parametric test was used instead of the standard ANOVA because the data were heteroscedastic (according to Levene's test) and included outliers in the prevalence variable.

The results from the Kruskal-Walli's test χ^2 (3) = 26.7, p 0.001, $\varepsilon^2 = 0.156$ indicated statistically significant differences in obesity prevalence among urban, predominantly urban, rural, and predominantly rural districts. Further post-hoc tests using the Dwass-Steel-Critchlow-Fligner (DSCF) method showed the following:

- Urban districts had a significantly higher obesity prevalence than rural districts ($p = 0.008$) and predominantly rural districts ($p = 0.011$) (see Table IV).
- Predominantly, urban districts also had a higher prevalence than rural ($p = 0.001$) and predominantly rural districts ($p = 0.003$) (Table IV).
- There was no significant difference between the rural and predominantly rural districts ($p = 0.091$) (see Table IV).

Therefore, it can be concluded that the prevalence of obesity is significantly higher in urban and predominantly urban districts than in rural and predominantly rural districts.

3.2. Spatial Analysis

This study analyzed selected districts across the country based on their obesity prevalence and degree of urbanization, with the goal of ensuring statistical representativeness; that is, the 62 sampled districts reflected the same characteristics or properties as the total population of 172 districts. For this purpose, data from the National Institute of Statistics and Censuses [7] were used along with aggregated variables such as total population, population density, and area in km^2, among others. Using Geographic Information Systems (GIS), additional variables were included, such as the number of establishments and the density of establishments per district (see Fig. 2).

TABLE III: Descriptive Data on Obesity Prevalence in Schoolchildren by District Category

	Urbanization degree	N	Mean	Median	SD	Min	Max
Obesity prevalence	Predominantly rural	81	31	30.8	4.26	20	42
	Predominantly urban	49	33.6	34.1	4.26	21.3	42.2
	Rural	28	29	27.9	8	16.2	55.5
	Urban	14	34.8	35.5	3.59	28.3	42.1

TABLE IV: Pairwise Comparisons with p-Values from the DSCF Test

Comparison	p-value
Urban vs. Predominantly urban	0.773
Urban vs. Rural	0.008
Urban vs. Predominantly rural	0.011
Predominantly urban vs. Rural	0.001
Predominantly urban vs. Pred. Rural	0.003
Rural vs. Predominantly rural	0.091

Among the 62 districts analyzed, 22 were located in Alajuela, 14 in Limón, 12 in Cartago, 9 in Puntarenas, 4 in San José, and 1 in Guanacaste (see Map 1). Some districts cover extensive areas, such as Valle La Estrella (1238.42 km^2) and Chirripó (940.90 km^2), while others are much smaller, such as Tres Ríos and Concepción in Cartago (2.28 and 3.79 km^2, respectively), making them more difficult to visualize on large-scale.

In Fig. 1, a categorization was made using INEC's urbanization index. As shown, most of the districts classified as urban or predominantly urban are located in the provinces of Alajuela and Cartago, near the Greater Metropolitan Area (GAM)—17 districts fall under these categories. The other six were distributed as follows: three in Limón, two in San José, and one in Puntarenas. In contrast, the Southern Zone and Caribbean region have a greater presence of rural and predominantly rural districts, totaling 21. The remaining 18 rural-type districts are located across Alajuela, Guanacaste, and Cartago, mostly in peripheral areas.

Fig. 2 shows a categorization based on the number of food sales establishments per district. This data collection, covering 62 districts, was enabled using collaborative cartography from OpenStreetMap. Value ranges were established to meaningfully group districts.

46 districts have between 2 and 50 food establishments, 34 are rural or predominantly rural, 12 are predominantly urban. Among the remaining 16 districts, 8 districts have

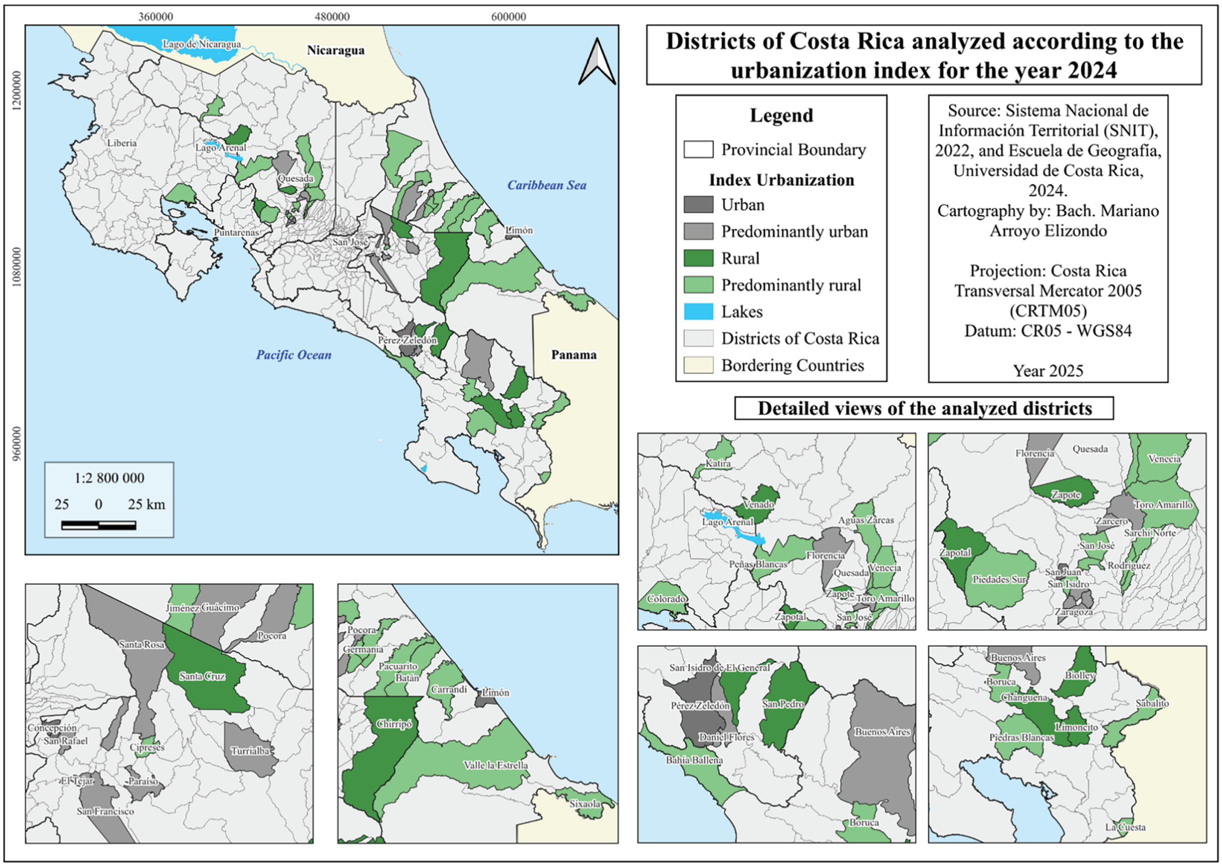

Fig. 1. Districts map according to the urbanization index.

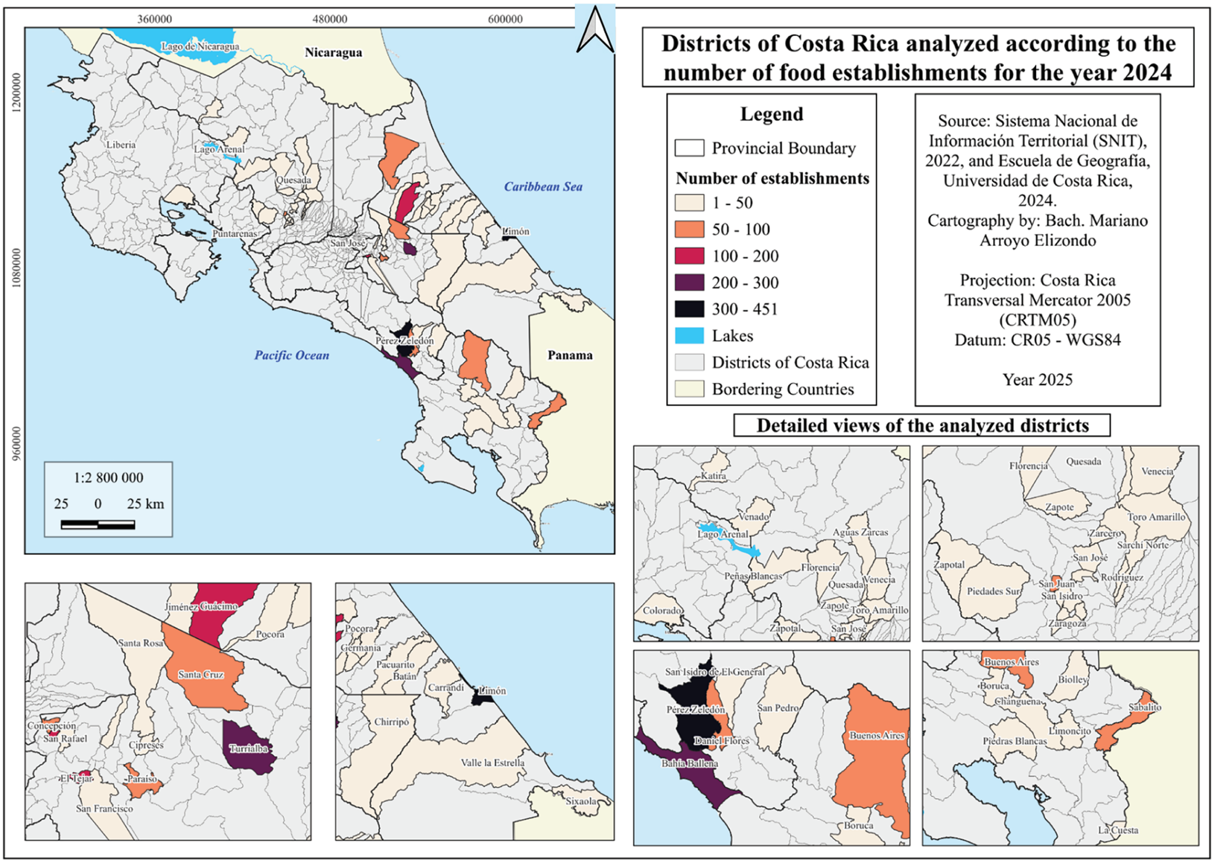

Fig. 2. Districts map according to the number of food establishments.

between 50 and 100 establishments (2 urban, 3 predominantly urban, 1 rural, 2 predominantly rural), 3 districts have between 100 and 200 establishments, 2 districts have between 200 and 300. The districts with the highest values were Limón (430 establishments) and San Isidro del General (451 establishments).

Of the top seven districts, six belong to the urban or predominantly urban category, indicating a clear correlation between urbanization and the number of food establishments.

It is important to note that data on food establishments were collected using OpenStreetMap and Google Maps, with a detailed manual review of each district's area to locate all existing establishments. However, the data are subject to updates and accuracy on these platforms, and depend on whether businesses are properly registered by their owners in geolocation databases. Therefore, the numbers are not exact or definitive.

3.3. Establishing Relationships between Excess Weight and the Food Environment According to a Degree of Urbanization

Once the districts under study were selected, several correlation tests were conducted to explore the relationships between key variables. These included the prevalence of excess weight (combining overweight and obesity), obesity, density of food establishments, total number of establishments, area of each district in square kilometers, total population per district, and population density. During each test, possible outliers were identified and a margin of error of 5% was accepted.

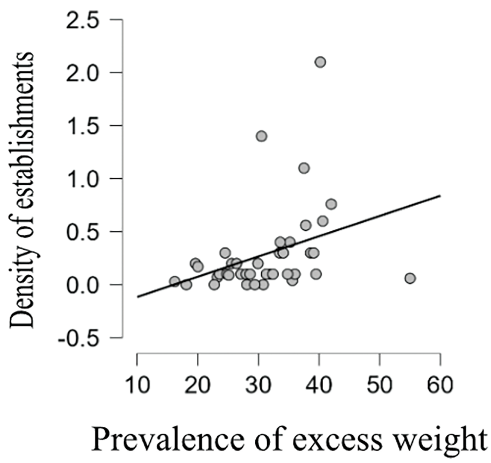

Fig. 3. Spearman correlation scatterplot between establishment density and excess weight prevalence.

Several Spearman's correlation tests were conducted to reveal the key patterns in the data. A positive correlation was found between the prevalence of excess weight and density of food establishments in rural and predominantly rural districts ($r_s(37) = 0.46$, $p = 0.003$) (see Fig. 3). When all district types—rural, predominantly rural, urban, and predominantly urban—were analyzed together, a similar positive correlation was observed ($r_s(60) = 0.43$, $p < 0.001$). (see Fig. 4). However, no significant correlation was identified between urban and predominantly urban districts ($r_s(21) = 0.293$, $p = 0.175$).

Among the selected districts, higher prevalence rates were observed in Zapotal, Tierra Blanca, Santa Rosa, La

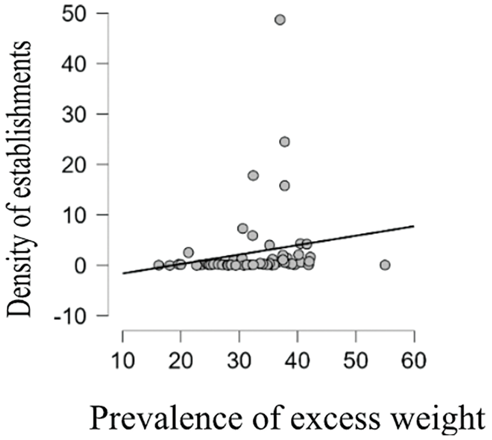

Fig. 4. Spearman correlation scatterplot between establishment density and excess weight prevalence (all types of districts combined).

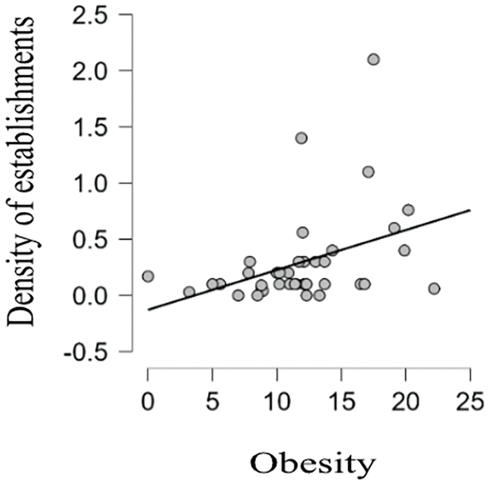

Fig. 5. Spearman correlation scatterplot between establishment density and obesity (Rural and Predominantly Rural Districts).

Cuesta, Turrialba, Santa Cruz, La Granja and Cipreses. These districts showed average prevalence rates ranging from 40.2% in the case of Cipreses to 55% in the district of Zapotal.

Spearman correlation tests were also conducted between obesity (excluding overweight) and the density of food establishments. In rural and predominantly rural districts, a moderate positive correlation was found (r_s (37) = 0.43, p = 0.005) (see Fig. 5). In contrast, no significant correlation was observed between the urban and predominantly urban districts (r_s (21) = 0.261, p = 0.229). However, when all districts were included in the analysis, the correlation between obesity and establishment density remained moderately positive (r_s (60) = 0.45, $p < 0.001$) (see Fig. 6).

Among the selected districts, those with the highest obesity rates were Zapotal, La Cuesta, Rodríguez, Santa Rosa, Turrialba, Santa Cruz, La Granja, and Tierra Blanca districts. These districts show average obesity rates ranging from 17.20% in Tierra Blanca to 22.20% in Zapotal.

4. Discussion

The results of the coefficient of determination calculations indicate that the density of food establishments

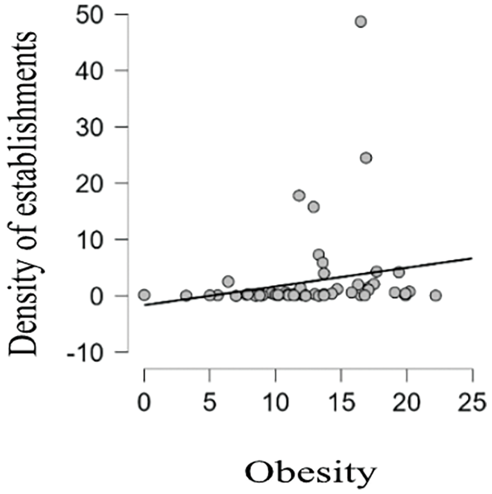

Fig. 6. Spearman correlation scatterplot between establishments density and obesity (All districts combined).

explained 21% of the variability in prevalence rates within rural and predominantly rural districts. When considering all district types together urban, predominantly urban, rural, and predominantly rural, this factor explained 18% of the variability in excess weight prevalence. Similarly, 21% of the variability in establishment density within rural and predominantly rural districts was associated with obesity levels, comparable to the 20% variability observed across all district types.

It is also important to note that the temporal mismatch between district level food establishment data and census data from earlier years may have influenced the correlation results obtained. However, in Costa Rica, official records on the number and type of establishments by district and by year are not publicly available, making such information difficult to access. This limitation highlights the importance of open-access platforms such as OpenStreetMap and Google Maps, which provide territorial information on establishments in countries where such data are not available through official local government sources.

At the regional level, studies in Central America have documented a steady rise in childhood overweight and obesity since the 1990s, with Costa Rica, Panama, and Guatemala reporting the highest levels in the region [9], [10]. In Costa Rica, prevalence among children aged 2 to 4 years increased from 22% in 1990 to approximately 40% by 2020, a trend associated with poor diet, sedentary behavior, excessive consumption of processed foods, increased screen time, and reduced physical activity [9]. These patterns raise concern, as early childhood weight gain is linked to long-term health risks, including dyslipidemia, certain cancers, hypertension, and coronary heart disease [9].

Another important aspect to consider is district level variability in social development. The Social Development Index (IDS), which integrates economic, educational, health, security, and electoral participation indicators [11], reveals marked inequalities across the country. Urban and predominantly urban districts, such as Pérez Zeledón, Turrialba, and Tres Ríos, are concentrated in the higher quintiles of social development, while rural and predominantly rural districts, including Batán, Sixaola, Biolley, and Boruca, among others, are disproportionately found in the lower quintiles [11]. This variability may partly explain differences in obesity prevalence and access to food establishments, underscoring the importance of interpreting correlations within a broader socioeconomic context.

Taken together, these results suggest that multiple factors contribute to the rise in excess weight among schoolchildren, highlighting the need for interdisciplinary approaches that combine geography with fields such as public health, nutrition, and education.

5. Conclusions

Understanding the food environment is crucial, as it can affect not only health but also the environment, the local economy, cultural connections, and the ability to address social issues related to food. As highlighted by Troncoso-Pantoja *et al*. [12], understanding these environments helps achieve healthy eating and food security by identifying both healthy and unhealthy environments and recognizing the factors that influence their development.

This study demonstrates the importance of spatial analysis for gaining a comprehensive understanding of the food environment. It also underscores the value of collaborative mapping tools such as OpenStreetMap for conducting spatial analyses on this topic. These tools allow for the mapping of a large amount of information across many districts from a computer, which would otherwise require high economic costs and significant time if done through fieldwork.

Among the main findings of this study, we can highlight:

- The large geographical differences among the analyzed districts, such as the disparity in size, some barely exceed one square kilometer. These smaller districts tend to be urban or predominantly urban and also show a high density of food outlets.
- On the other hand, rural and predominantly rural districts often present greater complexity because of their large size and the presence of indigenous territories, where food establishments are scarce and information is outdated (e.g., the district of Chánguena). However, some smaller rural districts show a high number of food outlets, exceeding 50 establishments, likely due to ongoing urbanization processes.

Medina-Medina *et al*. [13] found that differences in children's food environments are related to the socioeconomic and educational conditions of their families, while Horner and Wood [14] emphasized the importance of variables such as distance and travel time to food sources. In this context, Collaborative Mapping has emerged as an important tool for monitoring food environments.

Conflict of Interest

The authors declare that they do not have any conflict of interest.

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