Overweight and Obesity in Adults: Contributions from a Geospatial Analysis

Sobrepeso y obesidad en adultos: aportes de un análisis geoespacial

Sobrepeso e obesidade em adultos: contribuições de uma análise geoespacial

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Abstract

Objective. To perform a geospatial analysis of overweight and obesity behavior based on the 2015 "National Nutritional Situation Survey". **Methods.** A cross-sectional spatial distribution geospatial analysis model was applied from the Survey at departmental scale. To achieve it, the prevalence of overweight, class I, II and III obesity was calculated according to the body mass index and abdominal obesity in women and men according with waist circumference. Geographic information systems tools were used, like the Global Moran's I, the local index of spatial autocorrelation (LISA) and the Getis-Ord Gi*, to determine the patterns of high and low grouping prevalence. **Results.** Local conglomerates illustrated in the maps show that their residuals are normally distributed in space. Randomness is observed in the spatial autocorrelation model. The high-high LISA groupings appear in 10 departments with these conditions (La Guajira, Magdalena, Atlántico, Sucre, Cesar, Norte de Santander, Córdoba, Antioquia, Chocó, and Cundinamarca). According to the body mass index, 38.5 in every 100 inhabitants are overweight; 20.9 in every 100 inhabitants are obese and, according to waist circumference, 53.2 in every 100 inhabitants has abdominal obesity. **Conclusions. T**he overweight and obesity spatial distribution may be conditioned with sociodemographic variables treated in the study. The country has the challenge to continue implementing population actions in public health to diminish these conditions.

----------*Keywords:* adults, non-communicable diseases, geospatial model, obesity, geographic information system, overweight

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Resumen

Objetivo: Realizar un análisis geoespacial del comportamiento de sobrepeso y obesidad basado en la "Encuesta Nacional de Situación Nutricional" de 2015. **Metodología:** Se aplica un modelo de análisis geoespacial de distribución espacial trasversal a partir de la Encuesta, a escala departamental. Para lograrlo, se calculan las prevalencias de sobrepeso, obesidad clase I, II y III según el índice de masa corporal y la obesidad abdominal en mujeres y hombres de acuerdo con la circunferencia de cintura. Se utilizan herramientas de sistemas de información geográfica, como el índice de Moran Global, el índice local de autocorrelación espacial (LISA) y el G* Getis Ord, para determinar los patrones de agrupaciones altas y bajas prevalencias. **Resultados:** Los conglomerados locales ilustrados en los mapas demuestran que sus residuales están distribuidos normalmente en el espacio. Se observa una aleatoriedad en el modelo de la autocorrelación espacial. Las agrupaciones de LISA alta-alta se presentan en diez departamentos con estas condiciones (La Guajira, Magdalena, Atlántico, Sucre, Cesar, Norte de Santander, Córdoba, Antioquia, Chocó y Cundinamarca). Según el índice de masa corporal, el 38,5 por cada 100 habitantes tienen sobrepeso; el 20,9 por cada 100 habitantes presenta obesidad, y según la circunferencia de cintura, 53,2 por cada 100 habitantes tiene obesidad abdominal. **Conclusiones:** La distribución espacial del sobrepeso y la obesidad puede estar condicionada con variables sociodemográficas tratadas en el estudio. El país tiene el reto de continuar implementando acciones poblacionales en salud pública para disminuir estas condiciones.

----------*Palabras clave:* adultos, enfermedades no transmisibles, modelo geoespacial, obesidad, sistema de información geográfica, sobrepeso

Resumo

Objetivo: Realizar uma análise geoespacial do comportamento do sobrepeso e da obesidade com base na "Pesquisa Nacional de Situação Nutricional" de 2015. **Metodologia:** Aplica-se um modelo de análise geoespacial de distribuição espacial transversal da Pesquisa, em escala departamental. Para isso, calcula-se a prevalência de sobrepeso, obesidade graus I, II e III segundo o índice de massa corporal e obesidade abdominal em mulheres e homens segundo a circunferência da cintura. As ferramentas do sistema de informações geográficas, como o Índice de Moran Global, o Índice de Autocorrelação Espacial Local (Smooth) e o G* Getis Ord, são usadas para determinar padrões de alto agrupamento e baixa prevalência. **Resultados:** Os clusters locais ilustrados nos mapas demonstram que seus resíduos são normalmente distribuídos no espaço. Uma aleatoriedade é observada no modelo de autocorrelação espacial. Grupos de tainhas alto-alto ocorrem em dez departamentos com essas condições (La Guajira, Magdalena, Atlântico, Sucre, Cesar, Norte de Santander, Córdoba, Antioquia, Chocó e Cundinamarca). De acordo com o índice de massa corporal, 38,5 por 100 habitantes estão acima do peso; 20,9 por 100 habitantes são obesos e, segundo a circunferência da cintura, 53,2 por 100 habitantes têm obesidade abdominal. **Conclusões:** A distribuição espacial do sobrepeso e da obesidade pode estar condicionada pelas variáveis sociodemográficas tratadas no estudo. O país tem o desafio de continuar implementando ações populacionais em saúde pública para reduzir esses agravos.

----------Palavras-chave: adultos, doenças não transmissíveis, modelo geoespacial, obesidade, sistema de informação geográfica, excesso de peso

Introduction

Overweight and obesity are due to an "abnormal or excessive accumulation of fat that can be harmful to health" and, in turn, occurs as risk for non-communicable diseases (NCD) [1]. In recent years [2], these conditions continue increasing and, according to the World Health Organization (WHO) [3], NCD cause 41-million deaths each year, turning into a public health problem that threatens with hindering economic and social development globally [4].

This public health problem is a research topic. Undoubtedly, these conditions are risk factors the world is trying to "control" [5], which has allowed generating contributions, like the "National Nutritional Situation Survey" (ENSIN, for the term in Spanish) [6] that reviews the health status of populations of interest in Colombia with data collected every five years. So far, the Survey has three versions: 2005, 2010 and 2015 [7]. From the ENSIN data, studies have been made, such as associating the disease with the number of meals/day or the socioeconomic level [5,8]. However, other studies seek answers by linking these conditions with other comorbidities, for example, with hypertension and metabolic syndrome [9], and with stroke, type-2 diabetes, and cardiovascular disease [10,11]. Nevertheless, few authors use spatial analyses in public health.

Despite the low use of said instruments, geographic information systems (GIS) and spatial epidemiology have been fundamental tools [12,13] to determine the variation and neighboring behaviors at spatial level in diseases [14]. Kang-Tsung [15], Maheswaran and Craglia [16], Chrisman [17] and Goodchild and Haining [18,19] define GIS as an information system with stages from the acquisition to the presentation of geographic information [20]; in addition to being a "response to human needs for information management and analysis" [21]. Likewise, Anselin and Getis [20], Goodchild [22] and Maguire [23] mention that the importance of the GIS are the spatial models and statistical methods that permit creating scenarios from the information [24] and integration of plans, maps, and drawings in the same scale [25]. It should be highlighted that application of the GIS has increased in recent years [25], where important authors, like Roger Tomlinson (father of the GIS) [25,26] and John Snow (father of modern epidemiology) [17], have helped to promote and develop the GIS in fields of epidemiology and public health (GIS-EPI) [25].

In a geospatial analysis using GIS tools, the Global Moran's I is important because it measures the global association of the territory; the local Moran's I by Anselin, also known as the Local Indicators of Spatial Association, LISA), used to observe the spatial dependence on the occurrence of the disease and its clustering areas, and the Getis-Ord Gi* to identify the disease's conglomerates at spatial level; on the base of spatial autocorrelation, residuals are used of ordinary least squares (OLS) or the geographically weighted regression. The "Discussion" mentions some spatial analyses conducted in Latin American countries and their results [12,27-29].

Finally, all these contributions by the GIS and spatial epidemiology, in terms of public health, permit elucidating public health problems and issuing responses for decision making. Nonetheless, although prior research lack studies with geospatial analysis, this can be quite useful in cohort and cross-sectional studies and observed geographically, and identify population factors that can serve to make public policies, plans, programs, and projects.

Thus, the aim of this study was to perform a geospatial analysis of overweight and obesity behavior based on the 2015 ENSIN survey.

Methods

This section describes the study area, information sources, population, and variables of interest.

Study area

Colombia is located in South America and has 32 departments and the Archipelago of San Andrés and Providencia. It borders to the north with the Atlantic ocean and the Caribbean sea; to the west, with the Pacific ocean; to the east, with Venezuela; and to the south, with Ecuador, Peru, and Brazil.

The study used the Universal Transverse Mercator (UTM) projected coordinate system (World Geodetic System, WGS) 1984, with southern hemisphere in zone 18.

Source of information

To obtain the data, a secondary data analysis was conducted with the ENSIN database for 2015 [6], in charge of the Colombian Institute of Family Welfare, the Ministry of Health and Social Protection, the Administrative Department for Social Prosperity, the National Health Institute, the Pan-American Health Organization, and the WHO.

Data were taken from the anthropometry and physical activity databases (ENSIN subsample) from adults 18 to 64 years of age and WHO standards to classify overweight and obesity in kg/m^2 according to the body mass index (BMI) [30], where the normal range is 18.50 - 24.99; overweight: 25.00 - 29.99; class I obesity: 30.00 – 34.99; class II obesity: 35.00 - 39.99; class III obesity ≥ 40.00. Also, the work by Ko and Tang [31] was used to classify abdominal obesity in men and women with waist circumference in cm, where abdominal obesity ≥ 90 cm in men and ≥ 80 cm in women, with both references for the study age.

It is necessary to clarify that the BMI variable is taken from the database already calculated and then classified according to the WHO criterion.

Population

The ENSIN anthropometry database has 137,579 people surveyed, of which 73,441 are between 18 and 64 years of age and are not in gestation or postpartum. To achieve this, a data cleaning process was carried out prior to extracting the variables of interest, eliminating atypical data within the natural behavior of each variable. Figure 1 describes the debugging detail and, finally, only the variables of interest are extracted and joined with the variables of interest from the physical activity database.

Variables of interest

The dependent variable represents the number of people with overweight/obesity in each department. The independent variables (called "explanatory variables") are population, sex, age, education level, ethnicity, healthcare insurance regime, compliance with recommendations of physical activity of 150 minutes per week and closeness to parks/recreation centers (Table 1).

Statistical analysis

This was performed by recategorizing the circumference variable and the BMI in the Statistical Package for Social

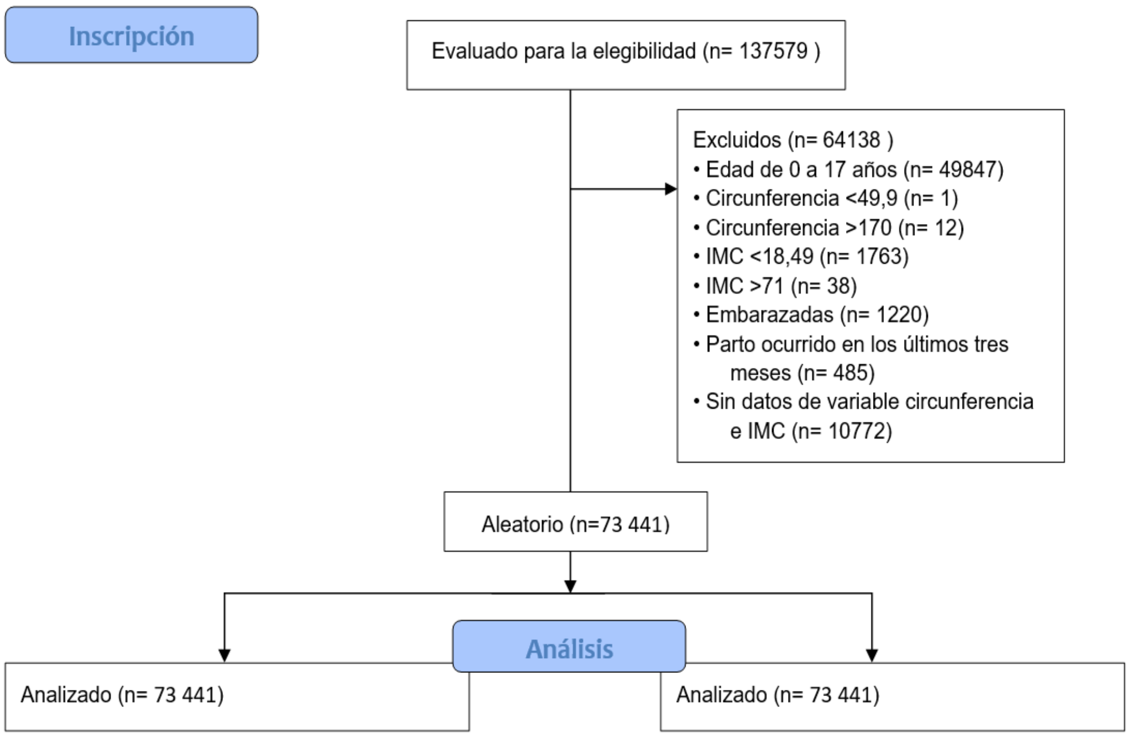

Figure 1. Sample selection criteria.

Note: The figure retains its native language

Table 1. Study variables

Characteristic		Sex				Total	
	Male		Female				
	n	%	n	%	n	%	
Age	Youth (18-26 years)	8,048	24.57	9161	22.52	17,209	23,43
	Adulthood (27-64 years)	24,705	75.43	31 527	77.48	56,232	76,57
Total		32,753	100,00	40 688	100,00	73,441	100,00
Abdominal obesity	Yes	13,362	40.80	25 689	63.14	39,051	53,17
	No	19,247	58.76	14,689	36.10	33,936	46.21
	Without data*	144	0.44	310	0.76	454	0.62
Total		32,753	100,00	40,688	100,00	73,441	100,00
BMI	Class I	4,067	12.42	7,205	17.71	11,272	15.35
	Class II	785	2.40	2,307	5.67	3,092	4.21
	Class III	197	0.60	778	1.91	975	1.33
	Normal	14,790	45.16	14,831	36.45	29,621	40.33
	Overweight	12,848	39.23	15,398	37.84	28,246	38.46
	Without data*	66	0.20	169	0.42	235	0.32
Total		32,753	100,00	40,688	100,00	73,441	100,00

Ethnicity	Indigenous	2,615	7.98	3,171	7.79	5,786	7.88
	Black / *Mulato* / Afro-Colombian / Afro-descendent / *Palenquero* from San Basilio	3,057	9.33	3,754	9.23	6,811	9.27
	No ethnicity	26,776	81.75	33,359	81.99	60,135	81.88
	Without data*	305	0.93	404	0.99	709	0.97
Total		32,753	100,00	40,688	100,00	73,441	100,00
Schooling	Between complete primary and incomplete secondary (5-10 years)	10,116	30.89	12,262	30.14	22,378	30.47
	Between complete secondary and incomplete higher education (11-15 years)	13,675	41.75	17,820	43.80	31,495	42.88
	Less than complete primary (0-4 years)	6,618	20.21	7,403	18.19	14,021	19.09
	Complete higher education and more (16-24 years)	2,151	6.57	3,079	7.57	5,230	7.12
	Without data*	193	0.59	124	0.30	317	0.43
Total		32,753	100,00	40,688	100,00	73,441	100,00
Health insurance	Not affiliated	2,477	7.56	1,507	3.70	3,984	5.42
	Contributive or special regime	12,772	38.99	16,055	39.46	28,827	39.25
	Subsidized regime	17,280	52.76	23,011	56.55	40,291	54.86
	Without data*	224	0.68	115	0.28	339	0.46
Total		32,753	100,00	40,688	100,00	73,441	100,00
Nearby Parks	No	3,137	9.58	3,655	8.98	6,792	9.25
	Yes	4,644	14.18	4,844	11.91	9,488	12.92
	Without data*	5	0.02	5	0.01	10	0.01
	Not surveyed**	24,967	76.23	32,184	79.10	57,151	77.82
Total		32,753	100,00	40,688	100,00	73,441	100,00
Physical activity 150 minutes per week	No	2,977	9.09	4,963	12.20	7,940	10.81
	Yes	4,804	14.67	3,536	8.69	8,340	11.36
	Without data*	5	0.02	5	0.01	10	0.01
	Not surveyed**	24,967	76.23	32,184	79.10	57,151	77.83
Total		32,753	100,00	40,688	100.00	73,441	100,00

* Percentage of data lost = 0.26%.

** The ENSIN physical activity database is a subsample, the study found 57,151 people who were not surveyed and were not considered for the results.

Source: Author's elaboration, from data taken from ENSIN [7].

Sciences by International Business Machine (IBM® SPSS®) version 25, licensed to Universidad de Antioquia. The descriptive analysis calculated the overweight and obesity prevalence in each department and graphics were made. The formula is as follows [32]:

$$p = \frac{\textit{número total de individuos con sobrepeso u obesidad}}{\textit{número total de la población estudiada}} \times 100$$

Note: The formula retains its native language

Spatial analysis

The geospatial analysis used the ArcGIS software version 10.8, licensed to Universidad San Buenaventura. The layer of the political-administrative division of Colombia was uploaded to the Geodatabase and the geo-data were added using the ArcToolbox for the layer of departments, with the attributes analyzed and the table with debugged and recategorized data with the absolute values of the 32 departments.

To achieve such, the study began an exploratory analysis with all the variables to identify if the data have normal distribution and the OLS geo-process was conducted with its formula [33]. Thereafter, a test was made (performance criterion and absence of redundancy criterion) to determine which model adjusted to the significant variables, where independent variables were permuted 999 times, until finding the best adjusted coefficient of determination (adjR^2) (> 0.5) and the lowest corrected Akaike information criterion (AICc).

These last tools are used to comply with the performance criterion, which identifies if the explanatory variables account for the variation of the dependent variable. Similarly, the criterion of absence of redundancy or multicollinearity must be met with the variance inflation factor (VIF) to determine if the explanatory variables are independent from each other; if not, these must be removed because multicollinearity exists and this value must always be < 7.50.

The test mentioned is performed to select the best autocorrelation spatial model to guarantee the linear relation between these variables and the response variable.

Then, Global Moran's I was applied with the OLS residuals with its formula [34, p. 52], where the interpretation is similar to the *r* correlation coefficient, where if the value is close to 0, no spatial correlation exists and its distribution is random. Values range between +1 and –1, that is, the result is a perfect positive autocorrelation that indicates spatial dependence and a perfect negative autocorrelation, respectively, which indicates geographic distinction in its units.

Geo-processes were run, using spatial techniques, like LISA with its formula [34, p. 58; 35, p. 192], which is the count of its neighboring departments (in a geographic observation), and the Getis-Ord Gi* [36], to analyze how spatially correlated the data are.

First, it should be clarified that all these indicators are in the ArcGIS software through the ArcMap (data mining tool) and can be executed from a table of georeferenced data; and second, that the study did not consider the frequencies of variables without data, whether lost or measurements not evaluated (not interviewed by the ENSIN) [7].

The geo-data geo-storage structure was divided into two parts: the first ("Results", Figure 3) is the LISA result and the second (Figure 4) is the Getis-Ord Gi*. In Figure 3, white is used for insignificant geo-data; dark gray (color with 70%) for departments with frequencies above the average (*High-High*); light gray (color with 10%) for departments with frequencies below the average (*Low-Low*); light gray (color with 50%) for departments with high frequencies and surrounded by departments with low to average frequencies (*High-Low*), and light gray (color with 30%) for departments with low frequencies and surrounded by departments with high frequencies to the average (*Low-High*).

In Figure 4 (also shown in the "Results"), the Getis-Ord Gi* geo-visualization was represented with four gradient colors from light gray (color with 30%) to dark gray (color with 70%) for high frequencies, called "hots pots", and gradient colors from light blue (color with 30%) to dark blue (color with 70%) for low frequencies, called "cold spots". These cold and hot spots are clustered with statistical significance with 95% confidence interval.

Ethical considerations

This study complies with the criteria set forth in the "Ethical Principles for Medical Research in Human Beings," set forth by the World Medical Association in the "Declaration of Helsinki" [37], and with that determined in Resolution 8430 of 1993 [38], with minimum risk due to working with anonymous secondary data by the ENSIN.

The study did not need approval by the Ethics Committee at Universidad San Buenaventura due to working with secondary data that does not affect confidentiality of private information of individuals.

Results

Table 2 shows that the conditions studied were significant (< 0.001); overweight prevalence is at 38.6 (28,246 / 73,206) for every 100 inhabitants, and abdominal obesity prevails in 53.5 (39,051 / 72,987) for every 100 inhabitants. Women prevail 22.6 points above obesity in men.

Results of the spatial analysis

Table 3 presents the dependent variables associated with the best model obtained by OLS and Global Moran's I, with significance of *p* values. *T*he models are considered good for the spatial analysis, given that the residuals are normally distributed.

Regarding the *p* value, the models differ among abdominal obesity and class II and class III obesity; however, for overweight and class I obesity, it is significant with $p < 0.05$; however, overweight is –0.72, that is, negative autocorrelation, where its spatial location is dissimilar between its neighbors.

Table 2. Prevalence according to BMI and waist circumference by sex.

Characteristic	Male		Female		Total		p**
	n	Prevalence*	n	Prevalence*	n	Prevalence (Global)*	
Abdominal obesity* **							
Yes	13,362	41.0	25,689	63.6	39,051	53.5	< 0.001
No	19,247	59.0	14,689	36.4	33,936	46.5	
Total	*32,609*	*100*	*40,378*	*100*	*72,987*	*100*	
Data according to BMI							
Normal weight	14,790	45.2	14,831	36.6	29,621	40.5	< 0.001
Overweight	12,848	39.3	15,398	38.0	28,246	38.6	
Class I obesity	4,067	12.4	7,205	17.8	11,272	15.4	
Class II obesity	785	2.4	2,307	5.7	3,092	4.2	
Class III obesity	197	0.6	778	1.9	975	1.3	
Total	*32,687*	*100*	*40,519*	*100*	*73,206*	*100*	

BMI: body mass index.

* To calculate prevalence, only valid data were taken.

** The chi-square statistic is significant at 0.05 level.

*** data according to waist circumference.

Source: Author's elaboration, from data taken from ENSIN [7].

Table 3. Results of spatial autocorrelation

Dependent variable	OLS				Global Moran's I (residuals)		
	AdjR2	AICc	VIF	Model	p value	Z score	Result
Abdominal obesity in women	0.97	365.70	3.54	Less than primary Secondary Not affiliated	0.964080	0.045034	–0.029530 No clusters
Abdominal obesity in men	0.91	365.34	6.50	Afro-Colombians Formal occupation Subsidized Not affiliated No physical activity	0.519512	0.598491	–0.008045 No clusters
Overweight	0.99	333.43	5.14	Informal occupation Contributive Not affiliated Does not have parks	0.467835	–0.726007	–0.059174 No clusters
Class I obesity	0.93	336.98	6.87	Primary Secondary Afro-Colombians Has parks	0.390352	0.858979	0.001753 No clusters
Class II obesity	0.81	295.40	6.80	Afro-Colombians Informal occupation Contributive No physical activity	0.758963	0.306843	–0.019403 No clusters

Class III obesity	0.52	256.56	6.72	Primary Higher education No ethnicity	0.828672	0.216406	–0.022937 No clusters

adjR2: Adjusted determination coefficient; AICc: Corrected Akaike information criterion; OLS: Ordinary least squares; VIF: Variance inflation factor.

Women with abdominal obesity with Global Moran's I of 0.45 ($p = 0.964$) and 0.59 ($p = 0.519$) in the prevalence of abdominal obesity in men; this indicates existence of positive autocorrelation and spatial randomization in both sexes.

Obesity according to BMI in class I, with Global Moran's I of 0.85 ($p = 0.390$); class II, 0.30 ($p = 0.758$); and class III, 0.21 ($p = 0.828$), indicating randomization, its residuals are distributed normally in space and has a positive spatial autocorrelation, that is, the random variable has a tendency to cluster in space.

Due to the foregoing, the Global Moran's I values range between 0.8 and −0.7 in the study's six dependent variables, accepting the null hypothesis, that is, the spatial configuration is random.

Further, the result of the spatial autocorrelation model is reported (Table 2). The independent variables mentioned in Table 1 are the factors to keep in mind to implement actions and increase population strategies to diminish the prevalence of these health conditions.

Figure 2 presents the prevalence map. It is interesting that Vichada, after the Archipelago of San Andrés, has greater prevalence of abdominal obesity, overweight, and class I obesity. Overweight is observed in the south of Colombia and abdominal obesity in the north of the country, coastal zone.

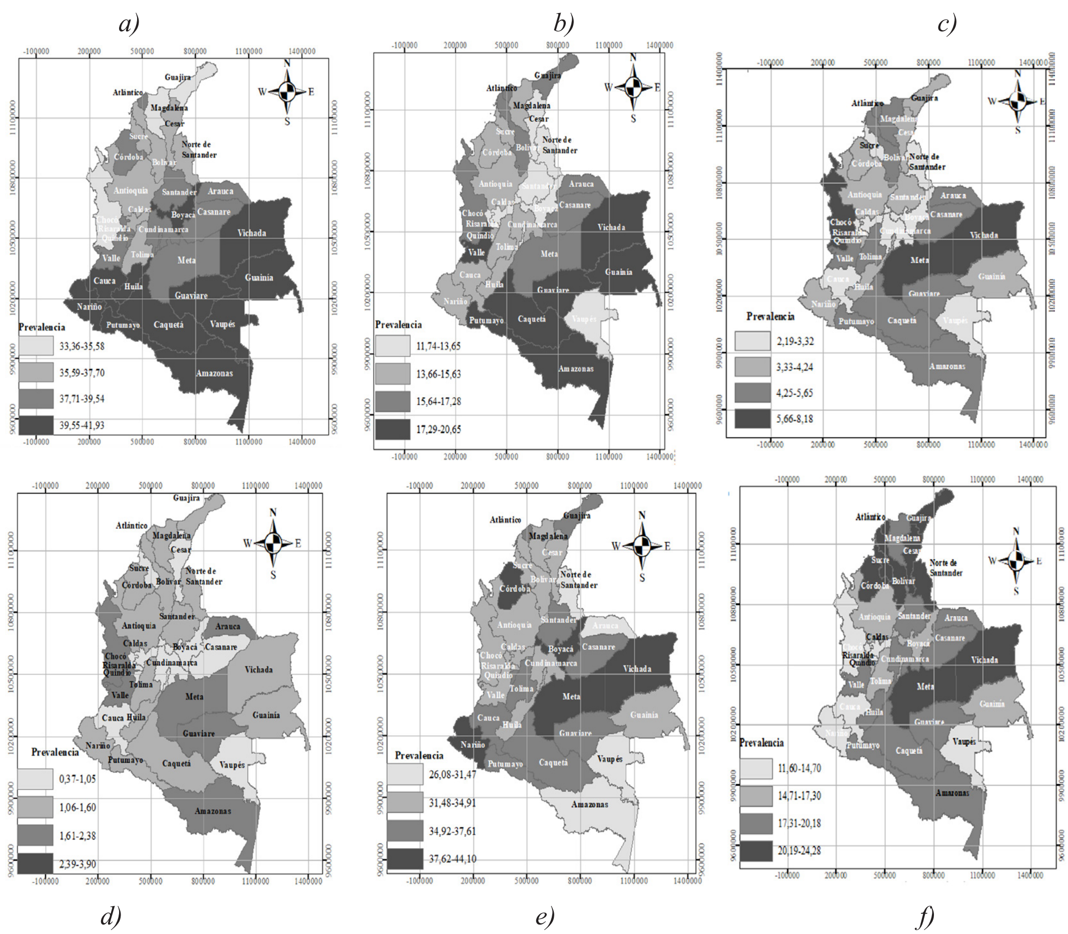

Figure 2. Spatial distribution of overweight and obesity prevalence. *a*. overweight prevalence; *b*. class I obesity prevalence; *c*. class II obesity prevalence; *d*. class III obesity prevalence; *e*. abdominal obesity prevalence in women; *f*. abdominal obesity prevalence in men.

Figure 3 shows the map of local Moran's I by Anselin, which presents clusters. "High-high" departments, like Antioquia, Córdoba, Bolívar, Sucre, Cesar, and Magdalena, have greater risk, independent of their neighboring departments, of having abdominal obesity in women and men. In six 'high-high" departments for abdominal obesity in women and nine "high-high" departments for abdominal obesity in men, these were 18.7% (6/32) and 28.1% (9/32), respectively.

Moreover, a "high-high" cluster appears in class I obesity (Chocó, Antioquia, Córdoba, Bolívar, Sucre, Magdalena, and Cesar) and in overweight at 21.8% (7/32) (Antioquia, Córdoba, Bolívar, Sucre, Magdalena, Cundinamarca, and Norte de Santander). Lastly, in class II it is 9,09% (3/33), with no conglomerates in class III.

In Figure 4, the map of the Getis-Ord Gi* indicator shows a concentration of the departments. This is evident in dark gray zones, that is, a conglomerate exists with respect to departments neighboring Córdoba, of abdominal obesity in women at 12.5% (4/32), and in men, at 15.6% (5/32). In obesity according to BMI, there is 99% *HotSpot* (hot spots), that is, disease conglomerate exists, in class I, at 18.7% (6/32); in class II, at 12.5% (4/32), and in class III no relation exists with its neighboring departments and no significance exists with respect to the departments. In overweight there is 99% *HotSpot* autocorrelation of coincidence with 9.37% (3/32). In conclusion, for abdominal obesity and overweight in women and men, hotspots were detected, with 99% coincidence in the departments of Córdoba, Sucre, and Magdalena.

It should be clarified (Figures 3 and 4) that overweight and obesity are clustered in northwestern Colombia, highlighting an increase in the Atlantic coast.

Figure 3. The Anselin spatial clustering analysis. *a*. Class I obesity map; *b.* class II obesity map; *c.* class III obesity map; *d.* overweight map in Colombia; *e.* map of abdominal obesity in women; *f.* map of abdominal obesity in men.

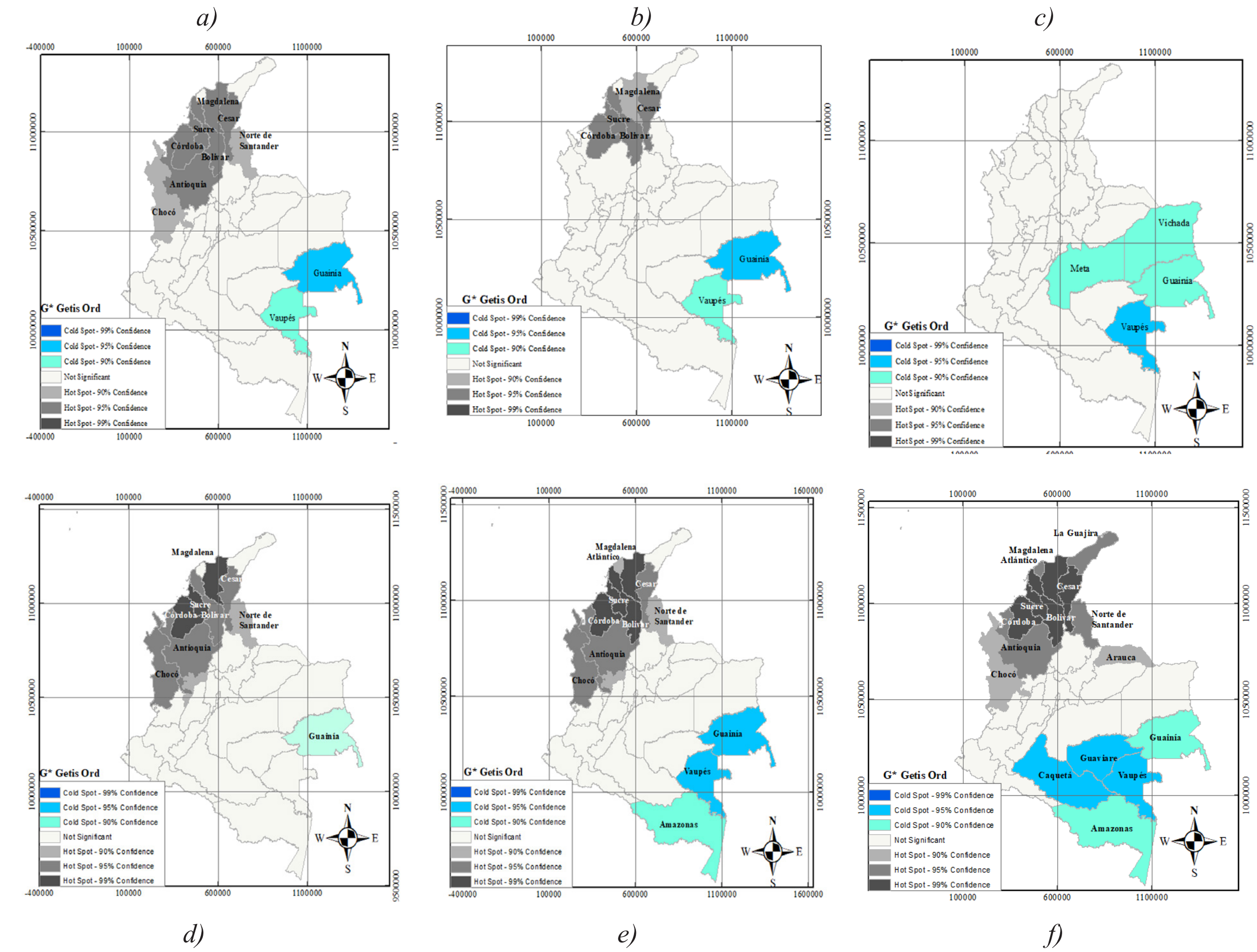

Figure 4. Getis-Ord Gi* spatial clustering analysis. *a*. class I obesity map; *b*. class II obesity map; *c*. class III obesity map; *d*. map of overweight in Colombia; *e*. map of abdominal obesity in women; *f*. map of abdominal obesity in men.

Discussion

The study demonstrates, by using Global Moran's I, clusters, LISA, and Getis-Ord Gi* tools, that the dependent variables analyzed have randomization, calling for the need for public health strategies in the departments of the northwest with hotspots mentioned in the study. A finding in this study is the prediction of high prevalence in coastal zones, like the Archipelago of San Andrés and La Guajira, which proposes the need to develop public health programs to improve health conditions in this population.

It should be highlighted that these coastal zones are also marked with these conditions in Latin American studies, like that by Hernández-Vásquez *et al.*, [28] which show greater obesity and overweight prevalence in coastal zones of the Tacna, Moquegua, Callao, Lima and Ica regions in Peru. Additionally, it is observed that prevalence is higher in the urban zone with respect to overweight in 199 districts, where 126 are urban (63%) and 73 rural (37%).

In turn, Hernández-Vásquez *et al.*, [29] report similar results of higher prevalence in coastal urban zones, which coincides with the higher wealth index compared to jungle and mountain zones.

Unlike the last two articles referenced, this study has no differentiated urban and rural data, but this raises the need to carry out a spatial analysis from this point of view.

Besides, this study found spatial dependence in overweight-obesity occurrence, a similar situation as the article published in 2023 by Muñoz *et al.*, [39] where the dietary pattern is observed as a key factor by departments, according to socioeconomic level in Colombia.

Another finding is the similar high prevalence of excess weight in women from Colombia and many studies [8,27,40-42] that demonstrate the formulation of the urgency required in public health. This high prevalence traces the need to carry out continuous surveillance of the BMI and waist circumference, and execute health policies for prevention, treatment, and rehabilitation of these health conditions among Colombians.

Upon comparing prevalence for 2020, a study [43] conducted in five principal cities of Colombia (Bogotá, Medellín, Cali, Barranquilla, and Bucaramanga) found 57.5% prevalence of excess body weight (36.2% overweight, 21.3% obesity) and 34.4% abdominal obesity, while in this study the overweight-obesity prevalence is two points above these results from 2020.

Limitations

The results have limitations because they can be biased by not having information at detailed but global scales, that is, at departmental scale. However, this study has been the only one to perform a spatial analysis with these secondary data

Another limitation that arises is when the principle of completeness in secondary data is not met because the results may be biased. Likewise, although it is the most-recent ENSIN version, many years have passed and data is not updated to know precisely the health conditions.

Conclusions

In the geospatial analysis of prevalence, it may be concluded that high prevalence existed of the conditions studied in two departments, the Archipelago of San Andrés and Providencia, and Vichada. In turn, the health conditions studied with BMI prevail in departments of southern Colombia, while the conditions studied with waist circumference prevail in north of the country. Additionally, regarding sex, high prevalence of obesity was evidenced in women.

Moreover, the prediction made with the indices shows high prevalence, in coastal zones, of the conditions studied, both with BMI and with waist circumference.

In addition, the non-systematic review found no studies that have used the three prediction indices; however, from the results of the spatial autocorrelation, the spatial model suitable to reduce abdominal obesity in women is to implement education strategies in primary and secondary, and in their affiliation to the Colombian health system, while abdominal obesity in men may be conditioned to being Afro-Colombians, having a formal occupation, being subsidized, not being affiliated to the health system, and not conducting 150 minutes of physical activity during the week.

Likewise, although the study was conducted with data from 2015, studies found demonstrate that this public health problem still warrants identification of risks and the implementation and attention in the country's public health policies.

Recommendations

This methodology is recommended, firstly, because executing a geospatial analysis of prevalence using the Global Moran's I, local Moran's I by Anselin, and the Getis-Ord Gi* permit knowing the overweight and obesity behavior preferably at smaller scales. Secondly, having updated anthropometric information permits performing spatial analyses to identify the zones that require prioritizing public health actions and intervene in a timely manner, given that with the autocorrelation results, factors that influence on the disease can be identified.

In terms of public health, the maps obtained can also be used to propose new study hypotheses, like, for example, elucidating the reasons for the high prevalence in women and in coastal zones, and revising at smaller scales (municipalities, townships, neighborhoods), and implementing strategies that diminish these health conditions.

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Conflict of interest

The author states not having any potential conflict of interest.

Declaration of responsibility

The author declares having responsibility in all results and the manuscript.

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