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Spatio-temporal patterns of the mortality of diseases associated with malnutrition and their relationship with food establishments in Mexico

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A R T I C L E I N F O

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A B S T R A C T

This study explores the spatio-temporal behavior of mortality due to multiple causes associated with several diseases and their relationship with the physical availability of food. We analyze data for the 2010–2020 period at the municipality level in Mexico. After collecting and standardizing national databases for each disease, we perform SATSCAN temporal and FleXScan spatial cluster analyses. We use the he Kruskal-Wallis test to analyze the differences between municipalities with high relative risk of mortality and their relationship with food retail units and food establishments. We found statistically significant relationships between clusters by disease and the physical availability of food per hundred thousand inhabitants. The main pattern is a higher average density of convenience stores, supermarkets, fast food chains and franchises, and Mexican snack restaurants in high-risk municipalities, while a higher density of grocery stores and inns, cheap kitchens, and menu restaurants exists in the municipalities with low risk. The density of convenience stores, fast food chains and franchises, and Mexican snack restaurants plays a very important role in mortality behavior, so measures must exist to regulate them and encourage and protect convenience stores, grocery stores, and local food preparation units.

1. Introduction

Poor nutrition constitutes one of the greatest global public health challenges (Wells et al., 2020). It is estimated that 2.28 billion children and adults worldwide are overweight and more than 150 million children suffer stunted growth. The majority of them are located in low- and middle-income countries (Popkin et al., 2020). The double burden of poor nutrition, defined as the simultaneous manifestation of malnutrition together with overweight/obesity (Wells et al., 2020), is one of the main factors causing chronic non-communicable diseases (Miller et al., 2022) and other impacts on the health and well-being of people, like effects on physical and cognitive development and livelihoods during a person's life cycle with repercussions for future generations (FAO et al., 2020).

These effects represent a challenge in the health system administration of each country, derived from the number of cases that constitute high incidence and mortality rates and are, at the same time, causes of higher costs related to hospitalizations, medical treatments, and rehabilitation (Serra Valdés et al., 2018). In the recent context of the COVID-19 pandemic, middle-aged patients and those over 60 years of age with chronic diseases, such as type 2 diabetes mellitus, cardiovascular diseases, and arterial hypertension, were particularly susceptible to respiratory failure and have higher risk of complications that can lead to death (Kurtz et al., 2021; Liu et al., 2020). In this sense, the way in which the population is fed becomes relevant in the planning and distribution of a country's resources, and poses variable levels of vulnerability to future epidemiological events.

During the last decades, the influence and power of multinational corporations has led to the industrialization and globalization of the food supply. The dominance of retail sales and the commercialization of ultra-processed foods, rich in refined sugars, saturated fats, and salt, available at lower prices, has also increased (Poti et al., 2015). Rapid changes in the food system, visualized through the commercialization of ultra-processed foods, have delineated a new nutritional reality throughout the world (Popkin, 2017) and have shaped the food environments in which the population develops. Food environments are the set of opportunities, environments, and physical, economic, political, and sociocultural opportunities that frame encase people's decisions regarding food acquisition and consumption (Robitaille et al., 2020; Rosenkranz and Dzewaltowski, 2008).

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Food environments determine food preferences and choices, as well as the nutritional status of individuals (Swinburn et al., 2013). Some of the structural factors of food environments are food retail units, since proximity to food-selling places (physical availability) is a determinant for consumers (Pineda et al., 2021; Reyes-Puente et al., 2022). Food environments in which it is currently easy to offer cheap and ultra-processed food are one of the main triggers of obesity (Atanasova et al., 2022) and of changes in body mass indices (Pineda et al., 2021) in the majority of low- and medium-income countries (Popkin et al., 2020).

Mexico is one of the countries with the highest burden of malnutrition, with an accelerated increase in malnourishment and overweight or obesity (Shamah-Levy et al., 2017). Currently, these diseases represent an important syndemic that threatens the country, since their magnitude is not only related to the number of deaths they cause, but also to the number of years of healthy life lost with important effects on education, environment, and labor productivity (Fernández et al., 2017). According to the results of the 2021 National Health and Nutrition Survey, there is a prevalence of overweight and obesity of 72.4 % in adults over 20 years of age at the national level. This dynamic has a direct implication regarding cases of type 2 diabetes mellitus, given that overweight and obesity are important risk factors for its development and progression. In fact, the prevalence of type 2 diabetes mellitus increased from 13.7 % in 2016 to 15.8 % in 2021 and is the leading underlying cause of death (UC) in Mexico, only surpassed by the group of heart-related diseases (Shamah-Levy et al., 2022). Therefore, the study and mitigation of diseases related to poor nutrition represents a national priority.

Towards the end of the 1990s, technological advances in Geographic Information Systems (GIS) allowed studying the spatial behavior of diseases and their spatial relationships (Thurston et al., 2017). With the incorporation of big data and data mining in geographic studies, the development of statistical methods for public health and epidemiology has been considerably promoted (Davies and Green, 2018). Data mining provides new opportunities and challenges to discover patterns of valuable information from data sets, among which the analysis of spatio-temporal data stands out (Shi and Pun-Cheng, 2019). There are many spatio-temporal approaches used to monitor areas of high epidemiological risk, detect clusters of diseases, and identify determining factors of risk of the disease (Moraga, 2017).

One of the most popular methods is spatio-temporal scan statistics, based on a cylindrical window with a circular geographic base and height corresponding to time (Kulldorff et al., 2005, 1998). One disadvantage of this approach is the use of circles in a study area that presents high spatial heterogeneity, in addition to the fact that it tends to detect larger groupings derived from the incorporation of surrounding regions where there is no high risk (Tango and Takahashi, 2005). To overcome this problem, exploration statistics were proposed in a flexible way (Takahashi et al., 2008). In Mexico, studies of the spatio-temporal patterns of tuberculosis (Zaragoza Bastida et al., 2012), dengue (Hernández-Gaytán et al., 2017), infection patterns in cattle herds (Villa-Mancera et al., 2018; Villa-Mancera and Reynoso-Palomar, 2019), and COVID-19 studies (Mas and Pérez-Vega, 2021) have used these methods based on cylindrical windows or flexible scan statistics.

Recently, Galeana-Pizaña et al. (2022) explored the spatio-temporal behavior of deaths due to UC of diseases associated with poor nutrition, such as type 2 diabetes mellitus, hypertension, ischemic heart disease, cerebrovascular disease, and child undernourishment during 2000–2020 at the municipal level in Mexico based on cylindrical windows. While the spatio-temporal dynamics of mortality by UC has been studied, there are still some limitations associated with the interpretation of a multidimensional phenomenon in a unidimensional fashion. Although UC is an easy-to-understand metric, it is an approach that becomes problematic, particularly in the case of chronic-degenerative diseases when there are several conditions that coexist at the time of death (Bustamante-Montes et al., 2011; Fernández González et al., 2019).

The main goal of this research is to explore the spatio-temporal behavior of deaths from multiple causes associated with undernourishment, type 2 diabetes mellitus, hypertension, chronic kidney, ischemic heart, intestinal infectious, and cerebrovascular diseases between 2010–2020. For this, we analyze the relationship of these diseases with the physical availability of food by including the density of commercial food retail units and food establishments or restaurants reported in the National Statistical Directory of Economic Units of the National Institute of Geography and Statistics (INEGI, 2020a).

2. Materials and methods

2.1. Data sources

This study used time series from data reported on death certificates provided by the General Directorate of Health Information, from the Mexican Ministry of Health. These data integrate all the causes listed on a death certificate (DGIS, 2020) from 2010 to 2020. We use data for all the municipalities in the 32 states of the country. We construct time series of mortality due to multiple causes by including the number of cases according to the corresponding codes based on the tenth version of the International Classification of Diseases (ICD-10): intestinal infectious diseases (A00-A09), diabetes mellitus type 2 (E11), undernourishment (E40-E46), arterial hypertension (I10), ischemic heart diseases (I20-I25), cerebrovascular diseases (I60-I69), and chronic kidney disease (N18).

We also classify food retail business units in three groups: supermarkets, convenience stores, and grocery stores. Furthermore, depending on the level of ultra-processed food sales, restaurants are in one of three groups: a) fast food chains and franchises, b) Mexican snack restaurants, and c) inns, economy kitchens, and a la carte menu restaurants. We use the typologies from the International Industrial Classification of the North American Industry Classification System (INEGI, 2018).

We also adjust for the increase in municipalities during the 10-year period of the study as explained below.

2.2. Data standardization

According to the results of the most recent Population and Housing Censuses and Population Counts carried out during the last decade (2010–2020), the number of municipalities in Mexico increased from 2456 in 2010 to 2469 in 2020 (INEGI, 2020b). To calculate the population of the new municipalities in the census and intercensal years before their creation, we compare the geographical locations of localities in the country in the years 2010, 2015, and 2020 with respect to the existing municipal division in 2020. In turn, we subtract this population from the total population of the municipalities from which these localities come, so we only perform a redistribution of the population registered in the original year. With this, we obtain the weighting used to redistribute the population. The resulting databases of chronic non-communicable diseases were standardized allowing us to reconcile the time series of both the number of mortality cases and the population at mid-year based on the 2020 National Geostatistical Framework (INEGI, 2020c).

With the standardized population database, we perform a demographic reconciliation to harmonize the trends of the components of demographic change with the population by age listed in the Population and Housing Censuses, from which we determine the base population and population projections at mid-year. For the demographic reconciliation, we estimate the relative participation of each municipality in the total population of each state to which it belongs for each census and intercensal survey between 2010 and 2020. That is, for each municipality we calculate the proportion it represents of its respective state population in 2010, 2015, and 2020, and linearly interpolate these proportions to estimate the corresponding shares for each year.

We then multiply the estimated annual proportions by the population of each state to obtain the estimates at the municipal level. In

Mexico, intercensal surveys take place five years after the census, and the next census takes place 5 years after the survey. Let P_t and P_{t+5} be the listed populations for a given state in two consecutive census and intercensal events (e.g., 2010 and 2015), and p_t and p_{t+5} the corresponding figures at the municipal level (Eq. (1)).

$$P_t = \sum_{i=1}^{n} p_{i,t} \quad \text{and} \quad P_{t+5} = \sum_{i=1}^{n} p_{i,t+5} \tag{1}$$

We calculate census and intercensal municipal proportions (of each event) using Eq. (2).

$$w_{i,t} = \frac{p_{i,t}}{P_t} \quad \text{and} \quad w_{i,t+5} = \frac{p_{i,t+5}}{P_{t+5}} \tag{2}$$

2.3. Statistical analyses

Using a yearly time series of 11 years at the municipal level, we estimate temporal scan statistics to identify years with higher relative risk using SaTScan. Then, we estimate flexibly shaped spatial clusters for each year using FleXScan. The resulting clusters with the density of retail food establishments and food establishments per hundred thousand inhabitants are then integrated. Finally, using the Kruskal-Wallis we test whether there are statistically significant differences between groups of municipalities with high risk rates and the densities of different types of establishments. Once we identified the years with the highest relative risk, we estimated flexibly shaped spatial scan statistics for the set of municipalities with the highest relative risk rates for each of the seven diseases in each period.

2.3.1. Temporal scan statistics

We apply the temporal scan statistical method, which uses a window that moves in one dimension –time–, defined in the same way as the height of the cylinder used by space-time scan statistics (Kulldorff et al., 1998). We also use a discrete Poisson model to analyze temporal groups of cases of undernourishment, type 2 diabetes mellitus, hypertension, chronic kidney, ischemic heart, intestinal infectious, and cerebrovascular diseases using SaTScan v10.0 (Kulldorff and Information Management Services Inc., 2018). For the analyses, we use the year as the unit of time, a significance level of 0.05, and a maximum temporal group size of 25 % of the study period for years with high relative risk rates.

2.3.2. Flexibly shaped spatial scan statistics

Once the years with the highest relative risk were identified, we estimate flexibly shaped spatial scan statistics proposed by Tango and Takahashi (2005). This algorithm can detect irregularly shaped clusters, unlike algorithms based on circular windows, which tend to overestimate the extent of a cluster (Tango and Takahashi, 2005).

We use a likelihood ratio test to identify spatial clusters. We calculate the number of expected and observed cases for each cylinder. The null hypothesis, H_0, was: "There is no previously indicated difference in the risk of each disease between the interior and the exterior of the cluster", and the alternative hypothesis, H_A, was: "There is a greater risk of diseases within the cluster". We state both hypotheses under the assumption that it is not possible to know the size of a cluster *a priori* and that the population at risk is not uniformly distributed. We calculate the number of expected cases, μ, using Eq. (3).

$$\mu = p * \frac{C}{P} \tag{3}$$

Where p is the population x within the cluster, C is the total number of deaths from multiple causes in the range x, and P is the total population x observed in the spatial entities (municipalities) during a particular period (Linton et al., 2014). The ratio of observed-to-expected cases represents the risk within the cluster, and the relative risk represents the risk within the cluster compared to the national one (Linton et al., 2014). We estimate the relative risk within each cluster using Eq. (4).

$$RR = \frac{c/\mu}{(C-c)/(C-\mu)} \tag{4}$$

where RR is the relative risk for a given cluster Z, c is the total number of cases within the cluster, μ is the total number of expected cases within the cluster, and C is the total number of cases in the country. To test whether the clusters are statistically significant, we estimate the log-likelihood ratio (LLR) using a Monte Carlo randomization with 999 repetitions (Kulldorff and Nagarwalla, 1995). The cluster with the highest likelihood ratio will be the most likely one (Hohl et al., 2020). We estimate the p-value by comparing the probability range of the real data sets with the probability values of the random data sets. We used ArcGIS for the spatial representation of results.

2.3.3. Analysis of clusters with higher relative risk and food availability

To explore the differences between clusters with higher relative risk and the relationship between the physical availability of food, we estimate the annual density per hundred thousand inhabitants at the municipal level of each of the retail commercial units of supermarkets, convenience stores, grocery stores, fast food chains and franchises, Mexican snacks restaurants and inns, economy kitchens, and a la carte menu restaurants.

These estimates were then integrated with clusters identified through flexibly shaped spatial scan statistics. We used the Kruskal-Wallis test for the analysis of differences. This test identifies whether there is a statistical difference in k independent groups for each indicator (density of retail business units and restaurants). For the Kruskal-Wallis test, the null hypothesis is that there is no difference in the median values of the groups. Conversely, the alternative hypothesis is that there is a difference in the median values of the groups. So, if the value of the statistic is greater than the chi-squared distribution, then there is a significant difference in the median values of the groups. If the value of the statistic is not greater than the chi-squared distribution, then there is no significant difference in the median values of the groups. When the test is statistically significant, the result shows a difference in at least two groups and, thus, it is not a random result (Núñez-Colín, 2019).

3. Results

3.1. Temporal scan statistics and flexibly shaped spatial scan statistics

Our findings indicate that type 2 diabetes mellitus and hypertension exhibit the highest relative risk (RR $>$ 2). Specifically, for type 2 diabetes mellitus and hypertension, the year 2020 had 2.27 and 2.23 times higher risk of developing the disease compared to the previous years, respectively. An RR value of 1 suggests no difference in risk, while RR values greater than 1 suggest an increased risk (see Table 1). We also find that the year 2020 had the highest combined mortality rates.

Fig. 1a-g shows maps with the locations of 30 statistically significant clusters or groups of municipalities by disease (p-value < 0.001). These maps also show the cluster with the highest probability based on the likelihood ratio. That is, the group that is least likely to occur due to chance. Our findings for the clustering models indicate that the cluster with the highest probability for cerebrovascular, ischemic heart, chronic kidney, arterial hypertension, and type 2 diabetes mellitus diseases is in the central-northern corridor of the country. This cluster is composed by municipalities of Mexico City and some contiguous ones of the State of Mexico: Azcapotzalco, Coyoacán, Gustavo A. Madero, Iztapalapa, Álvaro Obregón, Cuauhtémoc, Venustiano Carranza, Atizapán de Zaragoza, Ecatepec de Morelos, Naucalpan de Juárez, Nezahualcóyotl, and Tlalnepantla de Baz (see Table 2). The undernourishment cluster is located on the border between the states of Aguascalientes, Guanajuato, and Jalisco, in the municipalities of Aguascalientes, El Llano, San Francisco de los Romo, León, Encarnación de Díaz, Lagos de Moreno,

Table 1
Cause of death and rates of increased relative risk in the study period.

Disease	Period with higher relative risk	Relative risk for the period	Annual rate per 100,000 inhabitants for the period	Annual rate per 100,000 inhabitants between 2010–2020
Intestinal infectious diseases	2015–2016	1.24	4.9	4.2
Type 2 diabetes mellitus	2020	2.27	176.0	87.0
Undernourishment	2013–2014	1.34	22.1	17.5
Arterial hypertension	2020	2.23	258.5	129.4
Ischemic heart diseases	2019–2020	1.97	172.6	103.7
Cerebrovascular diseases	2013–2014	1.36	56	43.9
Chronic kidney disease	2019–2020	1.48	71.6	52.8

and San Juan de los Lagos. Lastly, our results show clusters of intestinal infectious diseases in the state of Chiapas, in the municipalities of Chalchihuitán, Chamula, Chenalhó, Larráinzar, Mitontic, Tenejapa, and Zinacantán.

3.2. Malnutrition, relative risk, and food availability

We explore the relationship between the 30 statistically significant clusters by disease (high relative risk) and the physical availability of food per hundred thousand inhabitants. We check the mean values of each type of establishment according to the temporal correspondence with the period in which each disease had the highest likelihood ratio in two groups: municipalities with high relative risk and low relative risk (the remaining municipalities). Our results indicate there are statistically significant relationships ($p < 0.05$) for all economic units for the seven diseases (see Table 3). More specifically, high-risk municipalities have a higher average density of convenience stores, supermarkets, fast food chains and franchises, and Mexican snack restaurants, while municipalities with low risk have a higher density of grocery stores and inns, economy kitchens, and a la carte menu restaurants.

4. Discussion

4.1. Temporal dynamics of diseases associated with poor nutrition

Our first important result is that 2019–2020 had the highest recorded frequencies during the evaluated period (2010–2020). The diseases with the highest frequencies are type 2 diabetes mellitus, arterial hypertension, ischemic heart disease, and chronic kidney disease, the first three with a relative risk of around 2. We relate this to the COVID-19 pandemic, a massive infection caused by the recent severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that rapidly spread throughout the world in 2020 (Sacks et al., 2020) and increased the use of health services and, thus, the availability of more and better records by people with ailments associated with poor nutrition. Among the risk factors for suffering complications from SARS-CoV-2, there are comorbidities predominantly linked to hypertension, diabetes, and obesity, as well as cardiovascular and kidney diseases, including high triglycerides and cholesterol (Romero-Nájera et al., 2021). There is evidence that people with diabetes are more susceptible to adverse outcomes and death from respiratory infections (Yende et al., 2010). Still, the mechanism that increases the risk of infection and hinders the recovery of these patients is not well understood. This could be linked to a chronic inflammatory state that alters the glucose metabolism and deregulates the immune system, or kidney, vascular, and cardiovascular complications associated with diabetes and increasing age (Knapp, 2013).

In the case of cerebrovascular diseases and undernourishment, the years with the highest relative risk were 2013–2014. Nonetheless, both diseases show a decreasing trend. In the case of cerebrovascular diseases, this may be due to a decrease in the prevalence of dyslipidemia and smoking in the country (Dávila Cervantes, 2020). While in the case of undernourishment, the pattern of decline may be related to the implementation of national food aid programs, such as the Education, Health and Food Program (PROGRESA), the Human Development Opportunities Program (OPORTUNIDADES), the Social Milk Supply Program (LICONSA), the School Breakfast Program of the System for the Integral Development of the Family (DIF) (Carmen Morales-Ruán et al., 2013), and the National Program Mexico Without Hunger (Huesca Reynoso et al., 2016). In the case of intestinal infectious diseases, the years with the highest risk were 2015–2016, also with a general decreasing trend, a situation that has been occurring since the 1980s due to the improvement of hygienic conditions, urbanization, promotion of the use of oral rehydration therapy and the National Breastfeeding Strategy (Olaiz-Fernández et al., 2019).

4.2. Spatial dynamics of diseases associated with poor nutrition

The central-northern corridor of Mexico City and some adjoining municipalities of the State of Mexico comprise the cluster with the highest probability for cerebrovascular diseases, chronic kidney disease, arterial hypertension, ischemic heart disease, and type 2 diabetes mellitus. A large concentration of population characterizes this region. For instance, by 2020, the 12 municipalities it contains represented 8.3 % of the national population (10,698,700 inhabitants), with a very low level of marginalization (CONAPO, 2020). One study that looked into the relationship between marginalization and nutrition found that the lower the marginalization, the higher the figures for anthropometric measurements, total and low-density cholesterol, as well as higher glucose associated with unhealthy diets that are often easily offered in large cities (Vidal-Batres et al., 2021).

The central-southern part of the state of Aguascalientes and northeast of Jalisco concentrate the core of the Undernourishment cluster (2013–2014). The dynamics of two distinct age groups have an association with this result. In the case of the state of Aguascalientes, one study recently pointed out that there exists a greater nutritional risk associated with the presence of depression in older adults in this state (Ramírez Orozco et al., 2022).

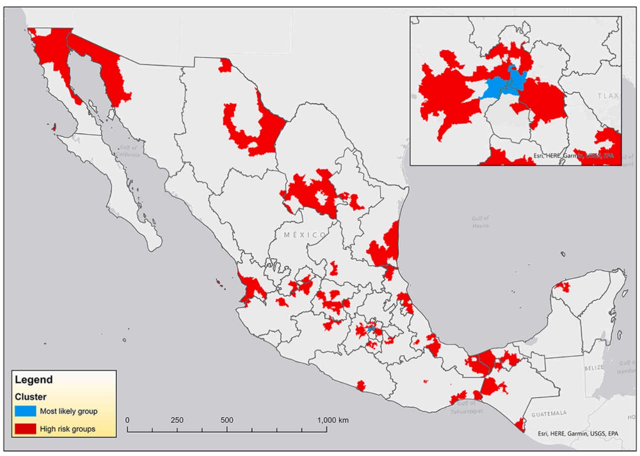
For the region of the highlands of the state of Jalisco, local media from the state capital's main university has already associated undernourishment with lower age ranges (The University of Guadalajara - https://archivo.udgtv.com/noticias/multimedia/aqueja-desnutricion-a-ninos-de-primaria-en-lagos-de-moreno/).

Regarding intestinal infectious diseases, the most likely cluster (2015–2016) is in the highlands region of the state of Chiapas. This result is not surprising, as this is one of the states with the highest rates of infectious diseases, many of them related to the supply and quality of water for human consumption, with special emphasis on highly marginalized populations that live in hard-to-reach areas, like the Altos de Chiapas region (Trujillo-Vizuet et al., 2022).

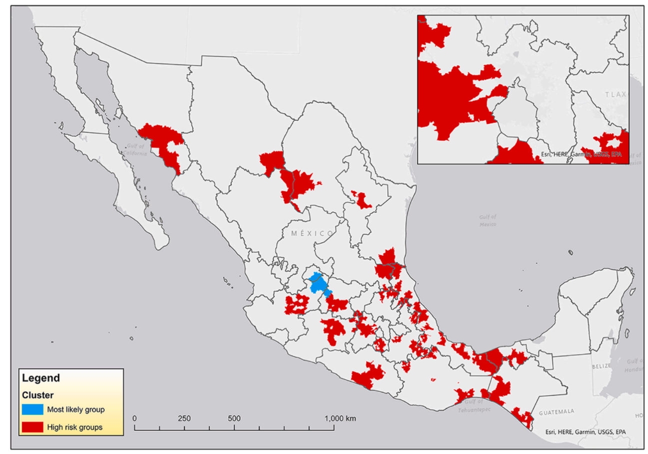
4.3. The role of food environments

Our results show there is a relationship between the municipalities with the highest relative risk and the physical availability of food (food environments). In other words, from Table 3 we see that municipalities with a higher relative risk of suffering from diseases associated with poor nutrition have more convenience stores, supermarkets, fast food chains and franchises, and Mexican snack restaurants. Conversely, the municipalities with lower relative risk have a higher density of grocery stores and inns, economic kitchens and a la carte menu restaurants, which are assumed to offer a greater supply of foods with higher nutritional value (Atanasova et al., 2022; Pineda et al., 2021). There is also a relationship between the highest concentration of convenience stores, fast food chains and franchises, and Mexican snacks with obesogenic food environments characterized by sales of sugary drinks, unhealthy snacks, and ultra-processed foods (Atanasova et al., 2022) located in medium and large cities.

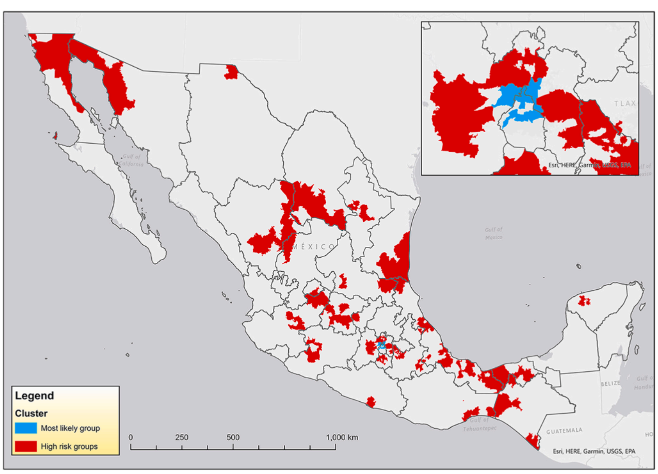
There is proof that, in Mexico, there is an association between the increase in the density of convenience stores and increases in body mass index (Pineda et al., 2021). This is worrying because the expansion strategies of convenience stores are not framed as part of any government regulation that addresses the repercussions on purchasing habits shaped in the population due to the ease of finding fatty, sugary, and salty products at low prices, with extensive opening hours, and with shorter transfer times. Together, these issues place convenience stores in a privileged position compared to supermarkets and grocery stores that offer more varied and healthier foods at higher prices and, sometimes, farther from homes (Reyes-Puente et al., 2022).



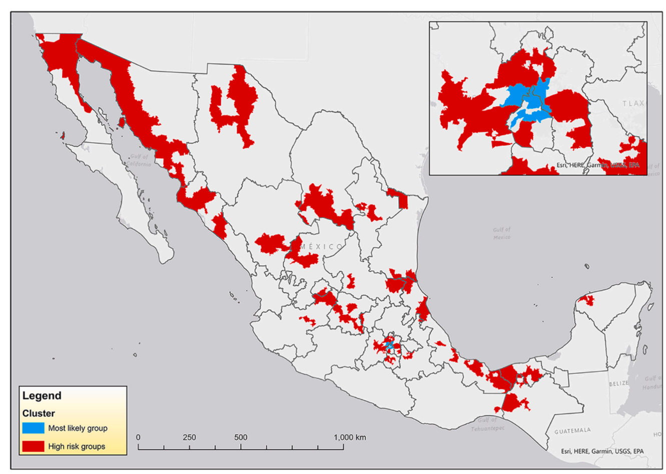
a) Cerebrovascular diseases



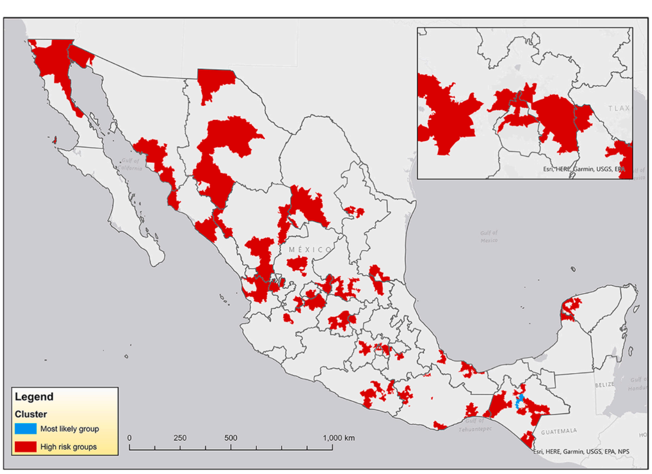
b) Undernourishment



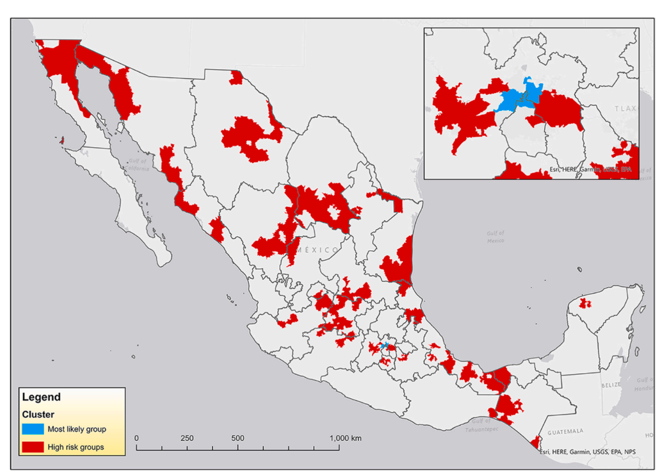
c) Chronic kidney disease



d) Arterial hypertension

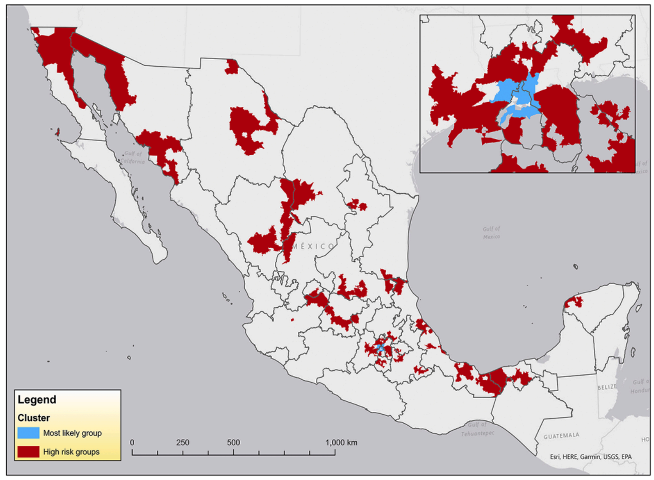


e) Intestinal infectious diseases



f) Ischemic heart diseases

Fig. 1. Maps of locations of groups of statistically significant clusters for each type of disease (in color).



g) Type 2 diabetes mellitus

Fig. 1. (*continued*).

Table 2
Clusters by type of disease with the highest likelihood ratio (*p*-value < *0.001*).

Multiple causes of death	Number of municipalities	Period	Log-likelihood ratio	Observed	Expected	Relative risk
Cerebrovascular diseases	8	2013–2014	3325.71	4215	887.852	4.36510
Undernourishment	7	2013–2014	728.314	1843	393.182	4.68740
Type 2 diabetes mellitus	12	2020	23,667.2	33,111	7928.24	4.17634
Arterial hypertension	12	2020	29,577.9	45,197	11,643.1	3.88187
Intestinal infectious diseases	6	2015–2016	393.575	382	16.25863	23.49521
Ischemic heart diseases	8	2019–2020	12,048.3	29,876	8020.83	3.72480
Chronic kidney Disease	11	2019–2020	5824.1	19,447	5863.89	3.31640

Table 3
Average density of food-selling economic units per hundred thousand inhabitants according to the type of relative risk.

Diseases	Relative risk (number of municipalities)	Grocery stores	Convenience stores	Supermarkets	Chains and franchises	Mexican fast food	Inns
		(per 100,000 inhabitants)					
Cerebrovascular (2013–2014)	Low ($n = 2221$)	3987.20	154.04	6.38	257.16	511.06	522.07
	High ($n = 248$)	3213.09	224.52	25.67	376.56	749.29	290.12
Undernourishment (2013–2014)	Low ($n = 2164$)	3991.61	163.08	7.31	264.15	519.59	528.57
	High ($n = 305$)	3236.48	147.20	15.44	304.65	644.26	287.33
Type 2 diabetes mellitus (2020)	Low ($n = 2277$)	6823.52	302.09	12.61	975.18	2224.71	513.15
	High ($n = 192$)	5136.13	465.28	46.65	1134.14	2989.66	328.25
Arterial hypertension (2020)	Low ($n = 2283$)	6849.73	301.60	12.62	978.56	2238.01	514.71
	High ($n = 186$)	4759.97	476.64	47.67	1097.76	2851.16	303.12
Intestinal Infectious (2015–2016)	Low ($n = 2226$)	4719.61	197.16	8.73	349.11	1290.56	518.29
	High ($n = 243$)	3376.22	205.11	23.41	415.52	1470.12	319.93
Ischemic heart (2019–2020)	Low ($n = 2208$)	6881.53	298.86	12.34	974.68	2211.43	513.76
	High ($n = 261$)	5059.26	443.59	39.79	1077.61	2892.46	371.97
Chronic kidney (2019–2020)	Low ($n = 2228$)	6821.71	304.24	12.83	960.25	2186.83	519.71
	High ($n = 241$)	5461.07	405.85	37.56	1219.53	3176.39	305.21

One of the limitations of this study is that flexible spatial scan statistics limit the number of maximum nearest neighbors for candidate clusters to 30, due to the heavy computational load (Tango, 2021). Future work could consider the use of Bayesian scan statistics because they can incorporate prior information about the size, shape, and impact of clusters, leading to both increased detection and more easily interpretable results. Another possibility is segmenting mortality cases according to population, in five-year periods, to delve deeper into age groups with the highest number of deaths, as well as their food environments. Related to food environments, in this study we explore the density of various commercial food retail units and food establishments, so in future work we can also study the probability of obtaining food in these types of place, according to socioeconomic and cultural aspects, within the clusters obtained through gravity models.

5. Conclusions

The retrospective temporal analysis between 2010–2020 allowed the identification of years with the highest rates of diseases associated with poor nutrition. We observe trends of increased mortality from type 2 diabetes mellitus, arterial hypertension, ischemic heart disease, and chronic kidney disease in 2020. This is related to the increased use of health services derived from the outburst of COVID-19 infections. The recent pandemic made visible the details of the conditions of those comorbidities in Mexico that led infected patients to worsen and even die. Conversely, for the same period, intestinal infectious diseases, undernourishment, and cerebrovascular diseases show decreasing trends in the country.

With the spatial methods we used, we identified the main municipal groups in Mexico that present a higher relative risk of suffering from diseases associated with poor nutrition. We find that Mexico City and its adjoining northern municipalities from the State of Mexico have significant clusters on 5 of the 7 evaluated diseases, and thus represent a hot spot and a spatial continuum of poor nutrition in Mexico. Our results have the potential to help direct the spatial prioritization of resources and campaigns to prevent and treat these types of diseases, since they currently represent a threat to public health and their attention requires novel generalized health promotion campaigns, together with policies and programs besides the existing ones.

The density of convenience stores, fast food chains and franchises, and Mexican snack restaurants plays a very important role in the behavior of mortality from diseases associated with poor nutrition. Hence, it is necessary to take measures to regulate their presence and the quality of the food sold in these establishments. Furthermore, it is essential to encourage and protect grocery stores and businesses such as inns and a la carte restaurants that offer the population food with higher nutritional content at affordable prices.

Despite the important contributions of this study and their use as a basis for future analyses, a niche of opportunity is the comprehensive inclusion of the food environment in the analysis, and not just the component of the physical availability of food. Subsequent studies should consider the economic, political, and sociocultural contexts and their changes over time. Moreover, they would need to address other spatial scales of the local dynamics of groups with a high relative risk of suffering from diseases related to poor nutrition and their possible relationships with feeding practices.

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CRediT authorship contribution statement

José Mauricio Galeana-Pizaña: Conceptualization, Methodology, Data curation, Writing – original draft, Formal analysis, Writing – review & editing, Project administration, Funding acquisition. **Leslie Verdeja-Vendrell:** Conceptualization, Methodology, Data curation, Writing – original draft, Formal analysis. **Raiza González-Gómez:** Conceptualization, Methodology, Data curation, Writing – original draft, Formal analysis. **Rodrigo Tapia-McClung:** Conceptualization, Methodology, Data curation, Writing – original draft, Formal analysis, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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