Socio-spatial vulnerability index of type 2 diabetes mellitus in Mexico in 2020

Enrique Ibarra- Zapata,[1] Darío Gaytán-Hernández,[2] Yolanda Terán-Figueroa,[2] Verónica Gallegos-García,[2] Carmen del Pilar Suárez-Rodríguez,[3] Sergio Zarazúa-Guzmán,[4] Omar Parra Rodríguez[5]

[1]Faculty of Agronomy and VeterinaryScience, Universidad Autónoma de San Luis Potosí, San Luis Potosí; [2]School of Nursing and Nutrition, Universidad Autonoma de San Luis Potosi, San Luis Potosi; [3]Academic Coordination Southern Huasteca Region, Autonomous University of San Luis Potosí; [4]School of ChemicalSciences, Universidad Autónoma de San Luis Potosí, San Luis Potosí; [5]Environmental Agenda, Universidad Autónoma de San Luis Potosí, San Luis Potosí, Mexico

Abstract

This study aimed to estimate a socio-spatial vulnerability index for Type 2 Diabetes Mellitus (T2DM) at the municipal level in Mexico for 2020. It incorporated factors such as poverty, social backwardness, marginalization and human development. This retrospective, ecological study analyzed 317,011 incident cases of T2DM in 2020 utilizing multi-criteria decision analysis, with weighted values were assigned to each vulnerability criterion. A multiple linear regression model was developed, complemented by cluster and outlier analyses using Mora'n *I* and a local clustering method. Spatial autocorrelation with high clustered values was found across 17.7% of Mexico (p<0.001). Conversely, 37.8% of the territory showed a pattern of low values without significant evidence of grouping. The analysis revealed 117 nodes of very high vulnerability forming six focal areas, 172 nodes with high vulnerability across five areas, 168 nodes with medium vulnerability in two areas, 112 nodes with low vulnerability across 16 areas and 152 nodes with very low vulnerability in 24 focal areas. This approach used proved to be robust offering a technical-scientific basis for guiding T2DM prevention strategies and actions using a spatial/epidemiological approach. It is recommended that future strategies take into account the factors mentioned to be effective.

Correspondence: Darío Gaytán-Hernández, Avenida Niño Artillero no. 130, Zona Universitaria San Luis Potosí, San Luis Potosí, Mexico.
Tel: +52.1.4448572766
E-mail: dgaytan@uaslp.mx

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Introduction

Type 2 Diabetes Mellitus (T2DM) has been escalating globally at an alarming pace. In 2019, it was one of the leading causes of death in the world according to the World Health Organization (WHO), resulting in 2.0 million fatalities (WHO, 2023). Similarly, in Mexico, T2DM caused the death of 151,019 individuals in 2020 amounting to a mortality rate very close to 12 per 10,000 inhabitants (Instituto Nacional de Estadistica y Geografia, 2021). Since 2000, it has been the primary cause of death among women and the second leading cause among men (Instituto Nacional de Salud Pública, 2020). Globally, the number of people living with T2DM was estimated at 463 million in 2019, as number projected to rise to 578 million by 2030 and 700 million by 2045 (International Diabetes Federation, 2019). In Mexico, there were 8.6 million people aged 20 and older diagnosed with T2DM as of 2018 (Secretaria de Salud, 2019).

Vulnerability, a concept comprising multiple dimensions, is critical to this issue (American Diabetes Association, 2024). In public health, the social component acts as a strategic axis reflecting and affecting the issue at hand (PAHO/WHO, 2020). Vulnerability is linked to the level of development in affected areas, where social factors such as poverty, lack of social progress, marginalization and human development play a pivotal role, thus widely manifesting the disease (Pizarro, 2001; Blaikie *et al*., 1996). Moreover, incorporating a spatial component into public health issues facilitates the development of intervention strategies by consideringthe dynamics and heterogeneity of the territory, which significantly aids decision-making (Buzai, 2014).

A data-driven approach, incorporating various social criteria, is indispensable in assessing a disease (Kivimaki, 2020). Applying geographic methods and techniques to a public health issue such as T2DM enables the integration of numerous variables, thereby facilitating the creation of a robust health risk mapping model. It is pertinent to point out that the prevalence of diabetes increases when income is low, and it also makes diagnosis and treatment difficult (Tang *et al.,* 2003). T2DM is intrinsically related to lifestyles and these are directly associated with vulnerability to health problems. This, in turn, affects the ability to access various essential services for living, many of which are provided by the state (*e.g.*, health services, care and the right to health). Therefore, adopting a socio-spatial approach enables the identification of geographical areas with conditions that may be critical to the prevalence of a disease that has reached epidemic proportions globally, including T2DM (Editverse, 2024).

Currently, the mechanisms through which social and economic inequality impact health remain unclear (Kivimaki, 2020). Hence, this study aimed to estimate a socio-spatial vulnerability index at the municipal level for T2DM within Mexico based on the situation in 2020 incorporating factors, such as poverty (PP), social backwardness (SB), the marginalization index (MI) and the human development index (HDI).

Materials and Methods

Characteristics of the study

This retrospective, ecological study encompassed 317,011 new cases of T2DM diagnosed in 2020 among individuals aged 24 years and older across 2,469 municipalities in Mexico.

Research procedures

We created a spatial database by employing geographic methods and techniques, through GeoDa 1.22, QGis and ArcMap softwares, combining data onT2DM cases as the dependent variable with various independent variables (Secretaría de Salud, 2020). Data on all variables were available at the municipal level. These included population in poverty (Consejo Nacional de Evaluación de la Política Nacional de Desarrollo Social, 2021), social backwardness (Consejo Nacional de Evaluación de la Política Nacional de Desarrollo Social, 2021) — an indicator of social deficits such as education, health, basic services, quality of living, and spaces, MI as a measure to identify various deficiencies including access to education, inadequate housing, and insufficient income (Consejo Nacional de Población, 2021) and the HDI reflecting life expectancy, educational attainment and income per capita (United Nations Development Program, 2023). We processed these variables using the method of homogeneous fields, linking alphanumeric attributes (e.g., municipal code) with the Shapefile outlines of municipal administrative boundaries in Mexico.

Data classification, which includes both dependent and independent variables, was achieved using the Jenks natural breaks classification method, which assigns class boundaries based on significant differences between values, thereby allowing for a more meaningful grouping of data points (ESRI, 2024). The number of classes or categories into which to divide the classification is open and we coses the following, multiple categories: very low (VL); low (L); medium (M); high (H); very high (VH). Natural breaks are specific classifications of the data, so the classes are based on the natural, inherent groupings of similar values and maximize the differences between classes. The boundaries of these categories are established where there are noticeable differences between the values of the data being classified.

The original values were standardizedinto an index ranging from 0 to 0.9. This was done using a reclassification tool called *Recalssify*, which aided in the cartographic depiction of variouscontinuous suitability maps for each criterion (Petry *et al*., 2005). This technique is considered the best for spatial representation and is divided into five distinct classes: very low, low, medium, high, and very high (Table 1).

Statistical analysis

The GeoDa 1.22 (https://geodacenter.github.io/), QGis (https://www.qgis.org/), ArcMap (https://www.esri.com/en-us/arcgis/products/), PASW Statistics 18 (http://www.spss.com.hk/statistics/) and Excel software (https://www.excelsoftware.com/) were used for statistical analyses. Multi Criteria Analysis (MCA) allowed us to estimate the socio-spatial vulnerability index to T2DM with two geostatistical tests aimed at enhancing local decision-making in health-based planning, prioritization and resource allocation (Baxendale & Buzai, 2011). With PASW Statistics 18 software, the model was formulated as follows: four independent numerical variables (PP, SB, MI, HDI) and the dependent variable (T2DM) were integrated. A multiple linear regression model was run, which provided among its results, the standardized beta coefficients of each independent variable, which represent the weight that each independent variable has on T2DM as estimated with a rule of three. These percentages were considered as given by experts and were assigned as decision criteria for the MCA in GeoDa. The statistically significant weights derived from standardized beta coefficients (c_{j2}, c_{j3}, c_{j4}, and c_{j5}) were allocated as scores specifying the vulnerability criteria of the independent variables. The initial spatial representation within the MCA decison framework MCDA (Figure 1a,b,c,d,e, illustrate the spatial dynamics and original value behaviour of the variables, something com-

Table 1. Vulnerability index ranges for type 2 diabetes mellitus in Mexico.

Variable	Vulnerability				
	Very low	Low	Medium	High	Very high
c_{j1}-T2DM	<119	120/447	448/1,268	1,269/3,366	3,367/8,688
c_{j2}-PP	< 18,139	18,140/50,355	50,356/119,561	119,562/323,435	323,436/816,934
c_{j3}-SB	-1.5550/-0.8171	-0.8172/-0.2094	-0.2095/ 0.6242	0.6243/1.9851	1.9852/6.8270
c_{j4}-MI	-2.3180/-0.9576	-0.9577/-0.1584	-0.1585/0.5982	0.5983/1.6156	1.6157/4.3682
c_{j5}-HDI	<0.4891	0.4892/0.6176	0.6177/0.6954	0.6955/0.7612	0.7613/0.9367

T2DM, type 2 diabetes mellitus; PP, poverty; SB, social backwardness; MI, marginalization index; HDI, human development index; c_{j1}, dependent variable; c_{j2}, c_{j3}, c_{j4}, and c_{j5}, decision criteria (independent variables); MCDA, multi-criteria decision analysis.

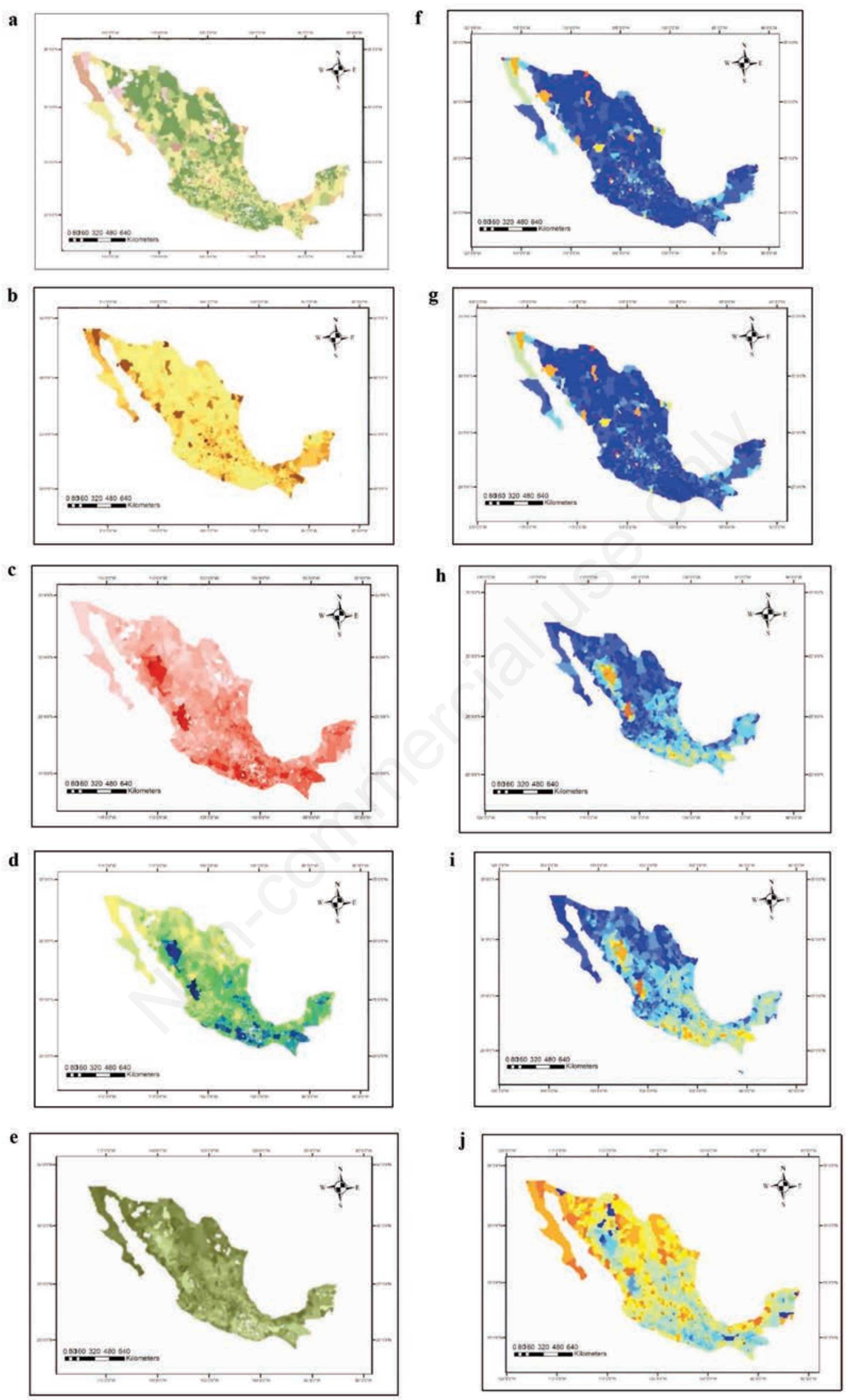

Figure 1. Standardized values and weight assignments in the multi-criteria decision analysis for calculating the socio-spatial vulnerability index of type 2 diabetes mellitus in Mexico.

plemented by estimating the spatial distribution patterns of the standardized criteria, depicted in cold (blue) for lower values and warm (red) shades for higher values (Figure 1f,g,h,i,j).

The MCDA applied the weighted overlay technique (ArcMap, 2021), a value measurement model enabling the calculation and comparison of numerical scores (reclassified), thus synthesizing an overall value for the c_j and the w_j (the weights assignedto the variables), based on expert judgment (Table 2). This integration of multiple decision-making criteria (Thokala *et al*., 2016) underscores the utility of MCDA asa geo-technological tool instrategic decision-making (Puig, 2018).

Cluster and outlier analysis was conducted using Anselin's Local Moran's *I* and the high-low clustering method (Anselin, 1988) to discern spatial valueconcentrations of clusters separated into five classes: high/high (HH), high/low (HL), low/high (LH), low/low (LL) and no significance (NS). This analysis evaluated the spatial autocorrelation of T2DM MCDA at the municipal level, reflecting positive, negative, or non-autocorrelation based on *Z* scores and *p*-values (Celemín 2009). A concentration of HH values signifies a statistically significant association and, hence, a higher intensity of clustering, contrasting with low values (LL) and delineating regions of positive, negative or atypical concentrations (Songchitruksa & Zeng, 2010). The spatial association between the dependent variable c_{j1}- T2DM and the T2DM MCDAscore was further assessed using the weighted sum model, achieving coverage values ranging from 0 to 1, indicating territories with no association to those with strong correlation. Geographic techniques thus potentiate health-related decision-making processes, including authorization, prioritization, defining coverage or funding, benefits access, disease classification, resource allocation for research and development, and more (Puig, 2018).

Results

The socio-spatial vulnerability index for T2DM in the Mexican Republic at the municipal scale shows the distribution patterns or spatial trend of T2DM using cartographic geometric overlays (Figure 2).

A significant clustered spatial autocorrelation was identified (z = 42.853, p<0.001). Furthermore, the investigation revealed a clustered spatial distribution of HH values (z = 10.442, p<0.001). The global and local statistical techniques enabled us to confirm the statistically significant outcome of the MCDA model for

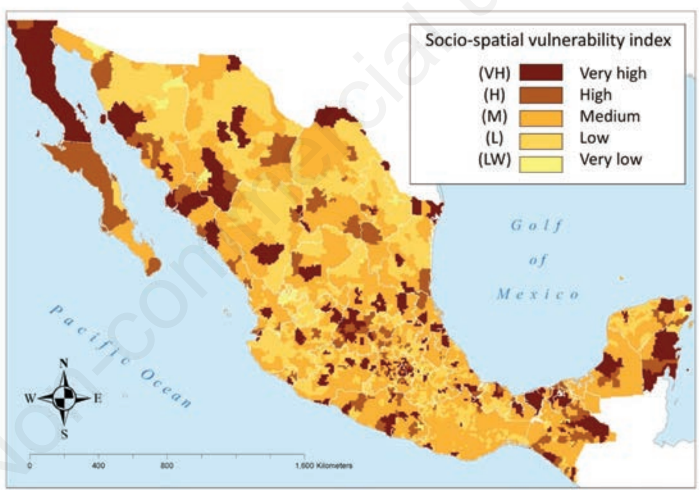

Figure 2. Model of the socio-spatial vulnerability index for type 2 diabetes mellitus in Mexico.

Table 2. Measures of central tendency of cj, standardized cj and weights in calculating the socio-spatial vulnerability index of type 2diabetes mellitus in Mexico.

c_j	Minimum	Maximum	Mean	Classification for cut-off	Standardized criteria	W_j
c_{j1}-T2DM MCDA	1	8,688	129.3	Jenks natural breaks classification	VL: <0.1	-
c_{j2}-PP	55	816,934	22,943		L: 0.2–0.3	9.2
c_{j3}-SB	-155.006	682.709	-0.00065		M:0.4–0.5	61.4
c_{j4}-MI	-2.318	43.682	-0.00054		H:0.6–0.7	6.6
c_{j5}-HDI	0.309657	0.936731	0.67445		VH:0.8–0.9	22.8

T2DM, type 2 diabetes mellitus; PP, poverty; SB, social backwardness; MI, marginalization index; HDI, human development index; cj1, dependent variable; c_{j2}, c_{j3}, c_{j4}, and c_{j5}, decision criteria (independent variables); MCDA, multi-criteria decision analysis; VL, very low; L, low; M, medium; H, high; VH, very high; Wj, assignment of weights to each variable.

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T2DM, specifically that 17.7% of Mexico's area exhibited HH clusters while 37.8% featured LL clusters. Additionally, 44.6% of the territory was classified as non-significant with respect to clustering (Figure 3).

Regionally, the HH clusters were predominantly found in central and south-eastern Mexico, extending from the Huasteca region (Potosina-Veracruzana) through to Chiapas, including a coastal strip along the Pacific that encompasses Michoacán, Oaxaca, Guerrero, and Chiapas. This area represents 11.6% of the national territory. Meanwhile, HL clusters, covering 6.0% of the country, are primarily located in north-western Mexico, touching the borders of Sonora, Sinaloa, Chihuahua and Durango, with smaller areas in the Northeast, between San Luis Potosí, Nuevo León, and Tamaulipas, and some focal points along the Pacific Coast in Jalisco, Colima and Nayarit (Figure 3a).

The spatial behavior of the primary LL cluster led to its largest territorial expansion, accounting for 36.1% of the area. This expansion covered parts of the northern states, extending diagonally from the southwest from Colima and Michoacán to the northeast in Tamaulipas, reaching the border between Mecico and the United States. In contrast, the primary LH cluster had the smallest territorial extension (1.7%), spreading across multiple clusters from the central part of the country towards the Southeast, affecting most states in this region (Figure 3b).

As seen in Table 2, the socio-spatial vulnerability index for T2DM in Mexico varied from very high to very low (Table 2). In areas with a very high socio-spatial vulnerability index, 117 nodes form 6 focal areas, encompassing 617 municipalities: among them, Chontla, Gutiérrez Zamora, Pajápan and 64 more in the state of Veracruz; in the state of Guerrero: General Eleodoro Castillo, San Miguel Totolapan, Coahuayutla de José María Izazaga and 61 more was accounted for; in the state of Chiapas: Altamirano, Ocosingo and 42 more; in the state of Chihuahua: Guachochi, Bocoina and 18 more; in the state of Durango: Tamazula and 10 more; in the state of San Luis Potosí: Santa Catarina, Aquismón and 18 more; and in the state of Tamaulipas: San Nicolás and 3 more. Areas with a high index include 172 nodes across five focal areas involving 1,254 municipalities, including Villa Sola de Vega, Santa cruz Zenzontepec, Zimatlán de Alvarez and 424 more in the state of Oaxaca; Ozuluama de Mascareñas, Chinanpa de Gorostiza, San Andrés Tuxtlaand 128 more in the state of Veracruz; and Tlachichuca, Alpatláhuac and 109 more in the state of Puebla.

Areas with a medium index comprised 168 nodes defining two extensive focal areas (Baja California Peninsula and the rest of Mexico), which are integrated by 1,898 municipalities including Amatepec, Tlataya, Ixtapan de la Sal and 88 more in the state of México; Arteaga, La Huacana and 99 more in the state of Michoacán; and Valparaiso, Jiménez de Teúl and 35 more in the state of Zacatecas.

The low vulnerability index is composed of 112 nodes involving 16 focal areas, with only one extending from the North to the central region of the country, covering 966 municipalities. Among them, Talpa de Allende, Atenguillo, Ameca and 120 more in the state of Jalisco; Montemorelos, Cadereita de Jiménez, Lampasos de Narajoand 43 more in the state of Nuevo León; Bacalar, Tulúm and 7 more in the state of Quintana Roo; and Silao, Romita, Salamanca and 36 more in the state of Guanajuato.

The very low vulnerability index consists of 152 nodes marking 24 focal areas, involving 506 municipalities including Tijuana, Mexicali in the state of Baja California Norte; La Paz and 5 more in the state of Baja California Sur; and Hermosillo, General Plutarco Elias Calles and 14 more in the state of Sonora (Figure 4).

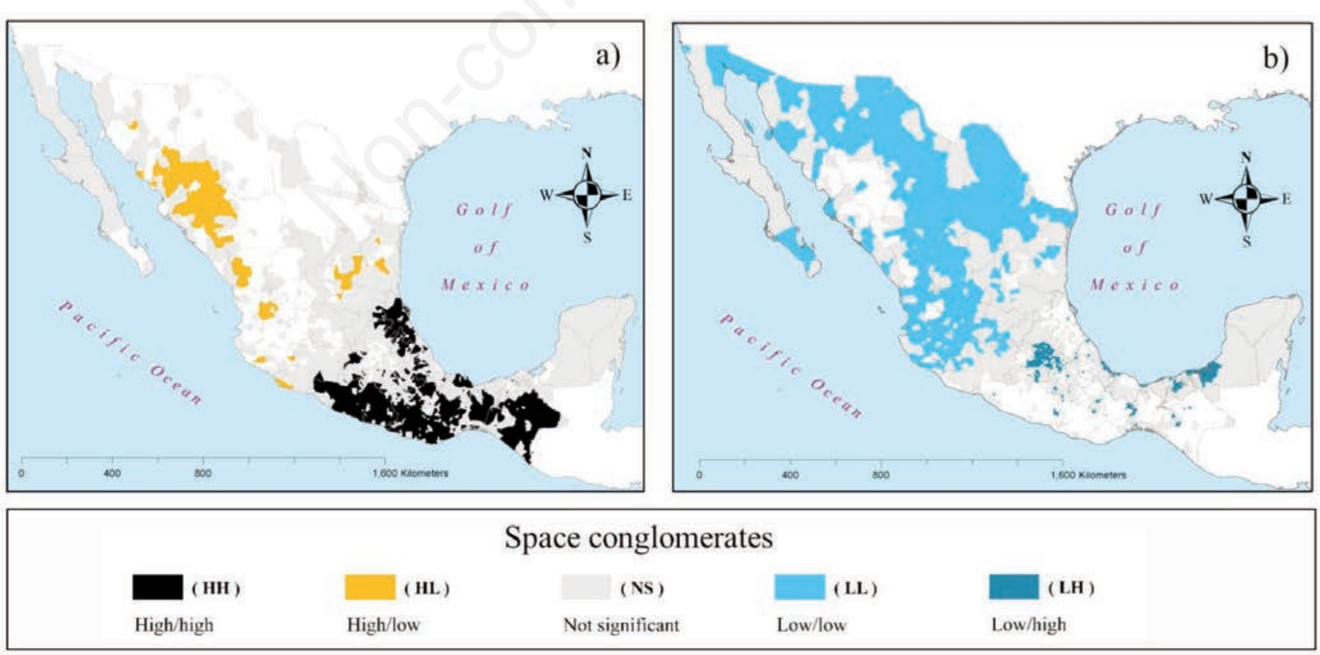

Figure 3. Spatial autocorrelation of the multi-criteria decision analysis of variables affecting the socio-spatial vulnerability of type 2 diabetes mellitus in Mexico.

The most significant vulnerability identified (i.e. the very high vulnerability) was in the states of Oaxaca, Veracruz, and Guerrero, primarily due to their high MI and SB levels (Consejo Nacional de Evaluación de la Política Nacional de Desarrollo Social, 2021). Additionally, it is estimated that, on average, 78.3% of the municipalities in these states have a low or medium HDI level (United Nations Development Program, 2023), while about 63.4% of their population live in poverty (Consejo Nacional de Evaluación de la Política Nacional de Desarrollo Social, 2021). Thus, this geographic area is considered vulnerable due to deprivation, poverty and limitations, such as poor health, malnutrition, lack of drinking water, drainage services, among others).

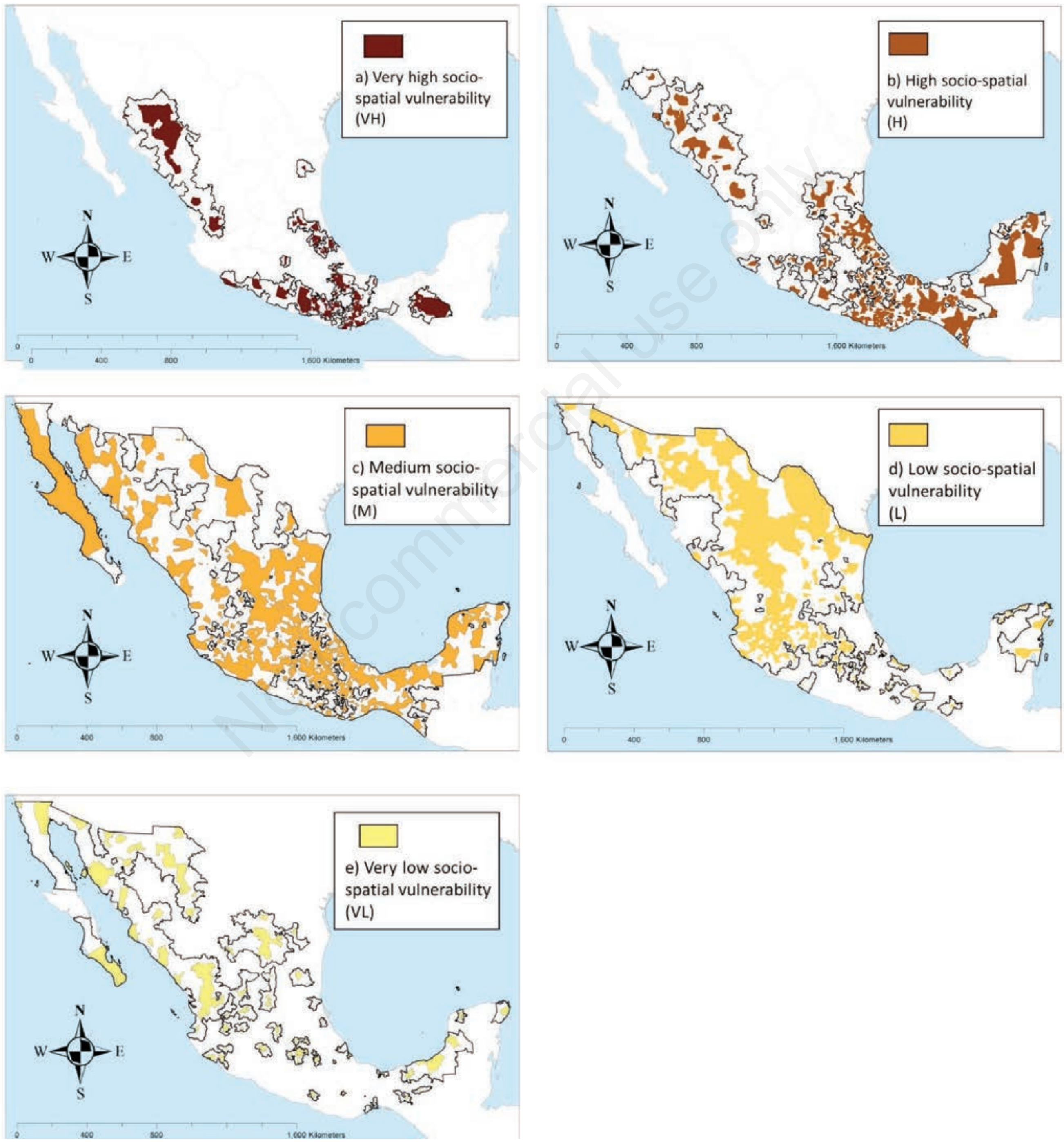

Figure 4. Spatial distribution patterns of the socio-spatial vulnerability for type 2 diabetes mellitus in Mexico.

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Discussion

Although no studies similar to this one in Mexico were found, the results indirectly align with those from other geographic studies. For example, a study conducted in the U.S. identified a relationship between poverty and diabetes across several counties (Hipp, 2015). In Ecuador, a study found that low income is related to diabetes, as this condition significantly correlates with nutritional problems, a direct factor for T2DM (León *et al*.,2019). Our findings are also consistent with non-geographic publications that indicate marginalization as a T2DM determinant (Moreno *et al*., 2014). It is even believed that the disease's risk has a global reach (IntraMed, 2018). Furthermore, the SB index encompasses various social deprivations, including illiteracy and education, which impact the development and management of diabetes (Hernández, 2024). Poverty is another determinant, with 81% of diabetes cases occurring in middle and low-income countries (Federación Mexicana de Diabetes, 2022).

While poverty alone does not cause T2DM, it influences the disease's development, as affected populations often cannot afford healthy food, medical care, or necessary medications (WHO, 2017). Our findings corroborate another study that found a negative beta coefficient between the HDI and the prevalence of T2DM in Europe and Central and South America (Mendoza *et al*., 2017). After all, the relationship between HDI and T2DM prevalence may vary by country, year, and world region, partly due to its multifactorial nature (Schinca, 2009). This complexity makes it challenging to pinpoint the various combinations of risk and protective factors identified (PAHO, 2022). Obesity, for instance, is a well-established risk factor for T2DM (Candib, 2008), yet its causes are manifold and can affect populations across the HDI spectrum. Additionally, Geographic Information Systems (GIS) have played a pivotal role in supporting health institutions' decision-making processes (PAHO, 2001), underscoring the importance of robust methods in addressing this issue.

Given the continuous rise in T2DM cases, it is crucial to explore potential solutions that could stem the negative trend revealed here. The epidemiological maps developed through this study constitute one such tool, aiding in formulating targeted public health strategies. While these maps offer valuable insights into the interplay of key indicators affecting T2DM, conclusions drawn from them should be approached with caution due to several study limitations, including lack of consideration for well-documented risk factors such as obesity and lifestyle. Generalized results for the populations of identified geographical areas may overlook important disparities within these groups, and there is a lack of sex-stratified data, which could reveal significant differences in T2DM prevalence.

Finally, it should be admitted tha this was an ecological study, in which there may be inaccuracy in the data, where the ecological fallacy is present attributing characteristics of groups to individuals. Despite our promising findings, further research is highly recommended. It is crucial to develop and implement strategies that address the needs of populations that are vulnerable due to poverty, marginalization, social exclusion, and limited human development, as these factors significantly influence the management and progression of T2DM.

It is recommended that future ecological studies include other variables: temperature and data on sociodemographic variables identified as factors obtained at a higher spatial resolution. This problem not only affects the quality of life of patients, but also has a great financial impact on families, state and federal health institutions, and the costs of campaigns and specific programs for this condition, among other direct consequences. As well as the exploration of other techniques for data analysis, such as binary logistic regression.

Conclusions

The method employed in this study proved highly effective; geospatial modelling allows for identifying vulnerability limits to T2DM, pinpointing areas with anomalous patterns, and delineating zones of high and low vulnerability clusters. This approach serves as a valuable scientific and technical resource for guiding preventative measures or care strategies for T2DM, utilizing a spatial and epidemiological perspective. Since the independent variables represent a certain differential weight on T2DM and the areas of greatest vulnerability have been identified, this information can be useful for planning more specific and targeted preventive measures as well as care strategies.

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