Spatial Analysis of COVID-19 in Zacatecas, Mexico: Local spatial patterns and influential factors

Análisis espacial de COVID-19 en Zacatecas, México: Patrones espaciales locales y factores que influyen

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Abstract
Spatial analysis-based planning (SABP) is vital for addressing priority issues. The study aimed to analyze local spatial patterns and factors influencing the distribution of COVID-19 in Zacatecas through GIS and geostatistical methods. The Bayesian rate was calculated and GWLR models adjusted. Local patterns were evident, showing a relationship between COVID-19 and comorbidities, marginalization index, and 911 calls for gender violence. Three significant hot spots were identified in areas with greater inequalities. Isn't just about identifying a hot spot, is analyzing that the causal relationship between comorbidities and COVID-19 is particularly pronounced, these are the places where we can think in terms of SABP to support public health policy to modify pre-existing conditions not just about this current pandemic.
Keywords: COVID-19, spatial analysis, GWLR, hot spot.

Resumen
La Planeación Espacial Estratégica es vital para abordar problemas prioritarios. El objetivo fue analizar patrones espaciales locales y factores que influyen en la distribución de COVID-19 en Zacatecas a través de SIG y métodos geoestadísticos. Se calculó la tasa bayesiana y se ajustaron modelos GWLR. Los patrones locales fueron evidentes, pues muestran una relación entre COVID-19 y comorbilidades, marginación y llamadas 911 por violencia de género. Se identificaron 3 *hot spots* en áreas con mayores desigualdades. No se trata solo de identificar *hot spots*, sino de analizar que la relación causal entre comorbilidades y COVID-19 es pronunciada; estos son los lugares donde en términos de SABP se apoyan las políticas de salud pública para modificar condiciones preexistentes, no solo durante pandemia.
Palabras clave: COVID-19, análisis espacial, GWLR, *hot spot*.

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Introduction

In 2019, the emergence of the SARS-CoV-2 coronavirus variant led to COVID-19, a disease responsible for over 6.5 million deaths worldwide. Preventative measures such as social distancing and mask-wearing were implemented to curb its spread. In response to this devastating situation, the global scientific community focused on developing vaccines to protect against SARS and ultimately reduce the mortality rate. However, individuals with comorbidities like diabetes, hypertension, obesity, and autoimmune diseases were at heightened risk from COVID-19.

A critical aspect of an epidemic is its spatial transmission, which is primarily influenced by epidemic mechanisms, human mobility, and control strategies. Prompt comprehension of the spatial dynamics of COVID-19 or other diseases is essential for devising prevention and control measures, as well as allocating medical resources (Gatrell & Eliott, 2014; Kim & Castro, 2020).

The methods most commonly employed for public policy planning and implementation in Mexico, such as the current Sectoral Health Program 2020-2024 derived from the National Development Plan 2019-2024 and the National Governing Policy on Vaccination against SARS-CoV-2 for COVID-19 prevention, focus on factors like marginalization, poverty, social backwardness, and human development (relative living conditions of the population). However, these methods overlook the active role of space.

Campos-Alanís *et al*. (2020) advocates for incorporating space as a distributor and redistributor of welfare opportunities stemming from strategic public services within the Mexican territory. In essence, supply and demand must interact within the territory to effectively achieve welfare objectives.

A prime example of the necessity to include space as a distributor and redistributor of healthcare opportunities is COVID-19. The first case in Mexico was detected on February 27, 2020 in Mexico City. The issue was recognized as a priority on March 23, 2020, and declared a decree in the Official Gazette of the Federation (DOF) on March 27, 2020. The national policy was established on December 8 of the same year, laying the groundwork for the guiding policy on COVID-19 vaccination (DOF, 2021).

Considering the uneven distribution of the pandemic across Mexican territory, spatial representation and analysis are essential for identifying areas that demand in-depth examination and for explaining the observed disparities. Numerous studies reveal spatial patterns that demonstrate a spatial overlap of high rates of chronic diseases with high rates of COVID-19 (Bauer *et al*., 2021; Deguen & Kihal-Talantikite, 2021). In these areas, comorbidities intersect with the inequality of social determinants of health (Yyanda *et al*., 2020; Ramírez & Lee, 2020; Raymundo *et al*., 2021).

Within this context, the current research aims to discern local variations in the spatial distribution of COVID-19, through GIS and geo-statistical methods at the municipal territorial disaggregation scale. The Bayesian spatial rate of SARS-CoV-2 was calculated. Geographically Weighted Local Regression (GWLR) Models were adjusted for the following purposes: Developing effective local public policy strategies, monitoring and managing individuals with chronic health conditions, supervising and controlling vaccinated and recovered people.

This research's contributions are conducted within the framework of the National Strategy for COVID-19 prevention, with the goal of generating and transferring results at the highest level of spatial detail, thus assisting decision-makers in epidemiological surveillance within the state of Zacatecas or any other state in the country. Consequently, the primary objective of this study is to analyze local spatial patterns and factors influencing the distribution of COVID-19 in the state of Zacatecas. Specific objectives include detecting cluster presence, modeling the sociodemographic and health characteristics associated with local distribution, and pinpointing the areas of highest vulnerability in order to prioritize intervention strategies throughout the territory of Zacatecas as a case of study.

1. Methodology

1. 1. Study case

The research was conducted in the state of Zacatecas, which served as a study area for the application of the proposed methodology. Located in north-central Mexico, Zacatecas lies between longitudes 104º 21' 14.40" W and 100º 44' 31.20" W, and latitudes 21º 02' 30.84" N and 25º 07' 30.72" N. The state consists of 58 municipalities, with a population of 1 622 138, of which 48.8% are men and 51.2% are women.

As part of Mexico's metropolitan areas, Zacatecas offers a suitable location for analyzing contagion patterns. The Zacatecas-Guadalupe metropolitan area (MZ) encompasses a diverse range of urban and non-urban patterns and has the highest population density (figure 1). Demographically, this area includes regions with critical and very high vulnerability to COVID- 19 (Salazar, 2020).

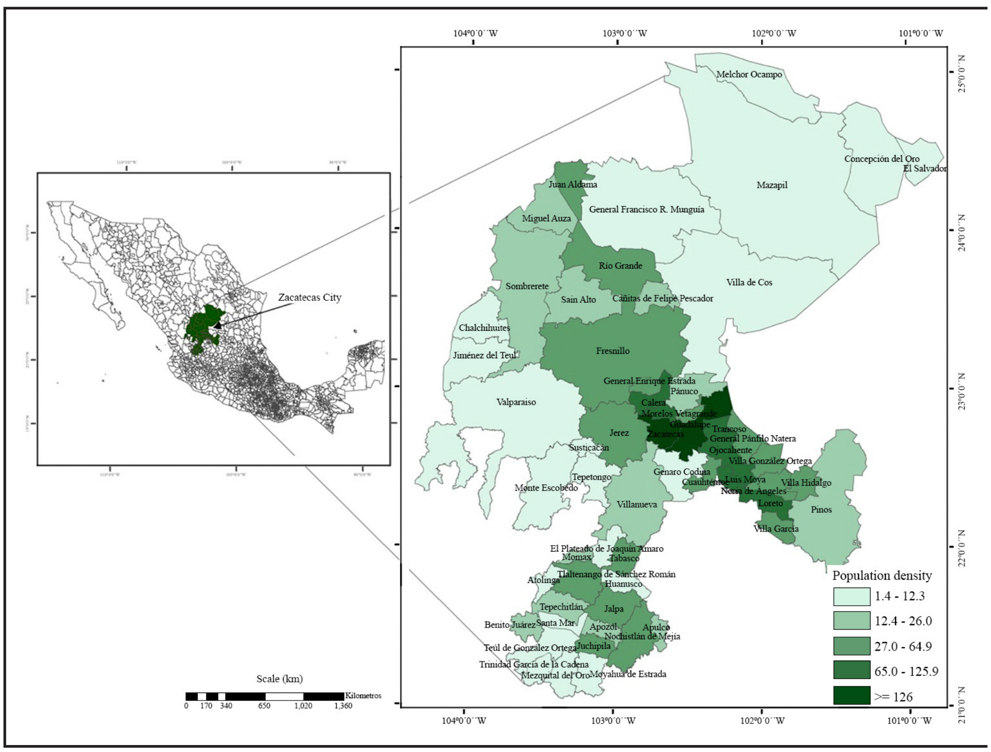

FIGURE 1

Study area: Depicts the population density distribution and highlights the state of Zacatecas as the focal region for implementing the proposed methodology

Source: own elaboration based on data from the 2020 Population and Housing Census of the INEGI.

1. 2. Sources and Instruments

From a territorial standpoint, the spatial distribution of COVID-19 cases result from random factors that characterize specific locations. This research utilized municipal geostatistical area (AGEM) data for the period from February 2020 to December 2022, encompassing all 58 municipalities within the State of Zacatecas. We combined three data sets at this scale for the spatial analysis. For the first of these, cumulative SARS-CoV-2 COVID-19 positive cases (72238) and deaths (3978), comorbidities (62749) such as obesity (17075), diabetes mellitus (13692), hypertension (20839), and asthma (11143) case-counts were drawn from the records of the Epidemiology and Statistics Department, State Health Services of Zacatecas (SSZ).

These comorbidities were included like possible factors influencing the distribution of COVID-19 in the state of Zacatecas because they can increase the severity of sequelae and overall mortality of COVID-19. In their study in Zacatecas state, Méndez-Fausto *et al*. (2022) described that these comorbidities alter the production of co-stimulatory inhibitory molecules sCTLA-4 and sCD40 in subjects recovering from COVID-19.

For the second data set, population data was extracted from the 2020 Mexican census, carried out by the National Institute of statistics and Geography (INEGI), which also provided socio-demographic information. The chosen socioeconomic covariates fall into two categories. Those related to individual are expressed as percentage amongst female and male, namely: Illiteracy and lacking social healthcare protection. Other covariates are descriptors of the municipalities themselves, namely: marginalization index which is an overall measurement of deprivation and lack of basic socioeconomic resources in the Mexican population, as well as urban inequality.

For the third data, Executive Secretariat of the National Public Security System (SESNSP) supplied 27594 records of 911 calls for family violence and gender violence from 2020 to 2022 and 38 551 case file register in The National Database and Information Bank on Cases of Violence against Women (BANAVIM).

In Mexico, emergency calls to the unique 9-1-1 number for gender-based violence are not formal reports to an authority; they solely represent potential incidents of violence specifically against women, as outlined in the National Catalog of Emergency Incidents under the number 309 - 30903. The SESNSP defines Gender violence as:

> Any violent act based on the female sex that has or may result in physical, sexual, or psychological harm or suffering for the woman, as well as threats of such acts, coercion, or arbitrary deprivation of liberty, whether they occur in public or private life (SESNSP, 2024: 95).[1]

In our study, only valid calls were considered −those received in service centers that were directed to a law enforcement agency for attention− as they relate to potential incidents posing a risk to or violating women. However, there is no record to determine how many of these valid calls resulted in formal complaints or how many did not. The BANAVIM information is sourced from all public or private institutions that make up the National System for Preventing, Addressing, Sanctioning, and Eradicating Violence against Women at the State and Municipal levels.

1. 3. Methods. Spatial area analysis

1. 3. 1. Bayesian spatial rate

The Bayesian rate (SEBS) was calculated as a risk estimator for each AGEM, with weights proportional to the underlying population at risk (Gatrell & Elliott, 2014). The SEBS estimate for risk at location is:

$$\pi_i^{EB} = w_i r_i + (1 - w_i)\theta \quad (1)$$

$$w_i = \frac{\sigma^2}{(\sigma^2 + \mu/P_i)} \quad (2)$$

Where:
P_i: the population at risk in the municipality i, AGEM
μ: mean of the a priori distribution estimated from the observed COVID-19 cases
σ^2: variance of the a priori distribution estimated from the observed cases per year/month

$$\sigma^2 = \frac{\sum_{i=1}^{i=n} P_i\,(r_i - \mu)^2}{\sum_{i=1}^{i=n} P_i} - \frac{\mu}{\sum_{i=1}^{i=n} P_i/n} \quad (3)$$

In the SEBS the prior distribution that strength is borrowed from to correct for variance instability is localized. The extent of the localized prior is defined through the weight's matrix. Is based on a locally varying reference mean and variance. SEBS comes from Bayesian statistics, where the estimate obtained from the data is combined with *prior* information to derive a posterior distribution.

The estimated spatial effects to identify areas with higher or lower rates than expected based on the risk estimator for each AGEM.

1. 3. 2. Spatial autocorrelation

Spatial autocorrelation is a fundamental pillar for analyzing COVID-19 distribution and variability. The spatial statistics of the Moran Global Index were applied to identify and characterize its behavior in one of three basic spatial patterns: clustered, dispersed, or random.

$$Moran's\ I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{4}$$

Where z_i represents the deviation of an attribute for feature i from its mean $(x_i - X)$, w_{ij} denotes the spatial weight between feature i and j, n corresponds to the total number of features, and S_0 signifies the aggregate of all spatial weights.

A matrix of spatial weights was generated to represent the spatial structure of the data for each AGEM. The conceptualization of spatial relationships, based on the contiguity of polygons, has been utilized as a general neighborhood criterion (Queen). In our experience, this conceptualization proves to be one of the most effective options and is also widely employed in the literature (Gatrell & Elliot, 2014).

In order to identify spatial clusters among the 58 AGEM of the state of Zacatecas with high or low values, the spatial statistics of Moran's Local Index method were applied as local indicators for the variables that exhibited a statistically significant p-value in the global spatial autocorrelation. Additionally, providing insights into "outliers". The spatial outliers or atypical value refers to a location where the variable of interest has a significantly different value than its neighbors.

$$\text{Local } Moran's,\ I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1,\, j \neq i}^{n} w_{i,j} (x_j - \bar{X}) \tag{5}$$

1. 3. 3. Geographically Weighted Local Regression (GWLR) Models

This method employs a specific type of regression modeling for spatial analysis that aims to replicate the geographically varying attributes of the association between COVID-19 and a set of independent variables locally, specifically socio-demographic and health variables in our study. GWLR incorporating multivariate spatial characterization.

The innovation in this version of traditional regression techniques is that it allows for investigating the presence of spatial non-stationarity in the relationship between COVID-19 and independent variables locally. It fits a sub-model for each observation in space, considering weighted neighboring observations. GWLR is a localized form of regression employed to model spatially varying relationships (Fotheringham & Brunsdon, 2010; O'Sullivan, 2003).

Specifically, we assumed that the number of COVID-19 cases Y_i in municipality $i = 1,...,58$ is Poisson distributed with mean μ_i, conditional on measured covariates:

$$\log(\lambda_i) = \beta_0(u_i, v_i) + \beta_1(u_i, v_i).x_{1i} + \beta_2(u_i, v_i).x_{2i} + \ldots\beta_k(u_i, v_i).x_{ki} + \epsilon_i \quad (6)$$

Where:

$\log(\lambda_i)$ is the natural logarithm of the expected COVID-19 count for observation i_{AGEM},

$\beta_0(u_i, v_i), \beta_1(u_i, v_i), \ldots, \beta_k(u_i, v_i)$ are the locally varying regression coefficients at location (u_i, v_i),

$x_{1i}, x_{2i}, \ldots, x_{ki}$ are the independent variables for observation i_{AGEM},

ϵ_i represents the error term.

In the context of Poisson regression, COVID-19 is a count, and the natural logarithm of the expected count is modeled as a linear combination of the independent variables with spatially varying coefficients. The weights used to estimate these coefficients are determined based on the spatial proximity of observations.

This study utilizes the Neighborhood type distance band parameter, an adaptive Kernel bandwidth method to provide the spatial local weighting in the model. The data were projected using a WGS 1984-UTM Zone 13 projected coordinate system.

$$w_{ij} = exp\left(-\frac{1}{2}\, x \left(\frac{d_{ij}}{b_j}\right)^2\right) \quad (7)$$

Where:

w_{ij} are i values and j values in the AGEM, d_{ij} Euclidean distance between j values and i values in each AGEM and b_j bandwidth.

GWLR allows for the exploration of spatial variations in the relationships between the count variable and its predictors, providing a more nuanced understanding of the spatial patterns within the data. To models comparison, we use the Akaike Information Criterion (AIC). The AIC is a measure that balances the goodness of fit of a model, we choose the model with the lowest AIC as the most suitable for describing the spatially varying relationships in our data (Fotheringham & Brunsdon, 2010; O'Sullivan, 2003).

2. Results

2. 1. COVID-19 Spatial dynamics

Between 2020 and 2022, a total of 72 238 confirmed cases of COVID-19 were reported in the state of Zacatecas, with a crude incidence rate of 4122.54 per 100 000 population and a case- fatality ratio of 5.62%.

The SEBS analysis generated darker red areas that indicate a higher intensity of COVID-19 rates. The mean posterior rate for Zacatecas state is 0.0114 with a 95% credible interval of (0.03132, 0.00413). The mean posterior rate for female is 0.01183 with a 95% credible interval of (0.00399, 0.03188) and the mean posterior rate for male is 0.01174 with a 95% credible interval of (0.00479, 0.03057). Figure 2 illustrate the posterior relative risk estimates for both sexes, thends to emphasize broad sub regional trends. Note how the patterns are much stronger in the center and the lower map. The revealing excess risk in the northeast of Concepción del Oro, the center of Fresnillo, Morelos, Guadalupe, and Zacatecas, the southwest of Tlaltenango de Sánchez Román, and the south of Nochistlán de Mejía, suggesting the presence of spatial autocorrelation, where nearby locations have similar rates. Clusters and hotspot identification with elevate or reduce rates may suggest AGEM with similar risk factors or characteristics.

The highest distribution of lethality is concentrated in six municipalities, as illustrated in figure 3. These include Valparaíso, Calera, Jerez y Villanueva to the center and southwest with the presence of clusters (High-high, HH). With outlier pattern Tlatenango de Sánchez Román and Nochistlán de Mejía, classified as an upper outlier (High-low, HL) relative to the others values within the selected region, locations with a much higher lethality than its surrounding neighbors.

Based on figure 2 and figure 3, Tlaltenango de Sánchez Román and Nochistlán de Mejía are municipalities with COVID-19 highest risk and show high-low outlier of deaths rate.

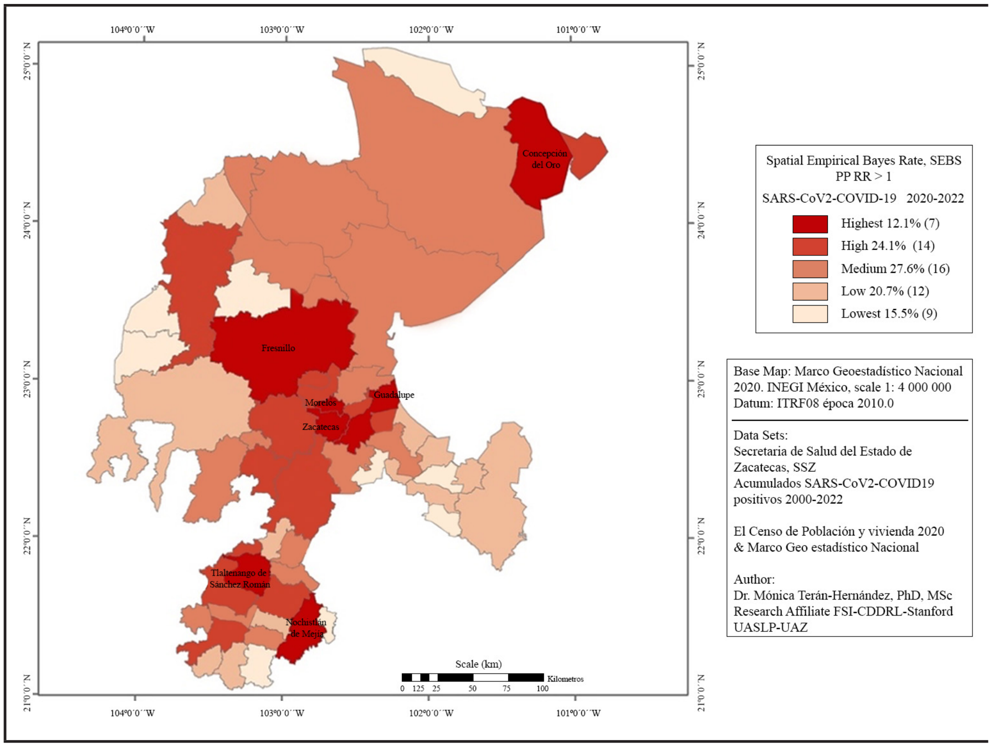

FIGURE 2
Posterior Relative Risk Estimates using SEBS
Source: Own elaboration.

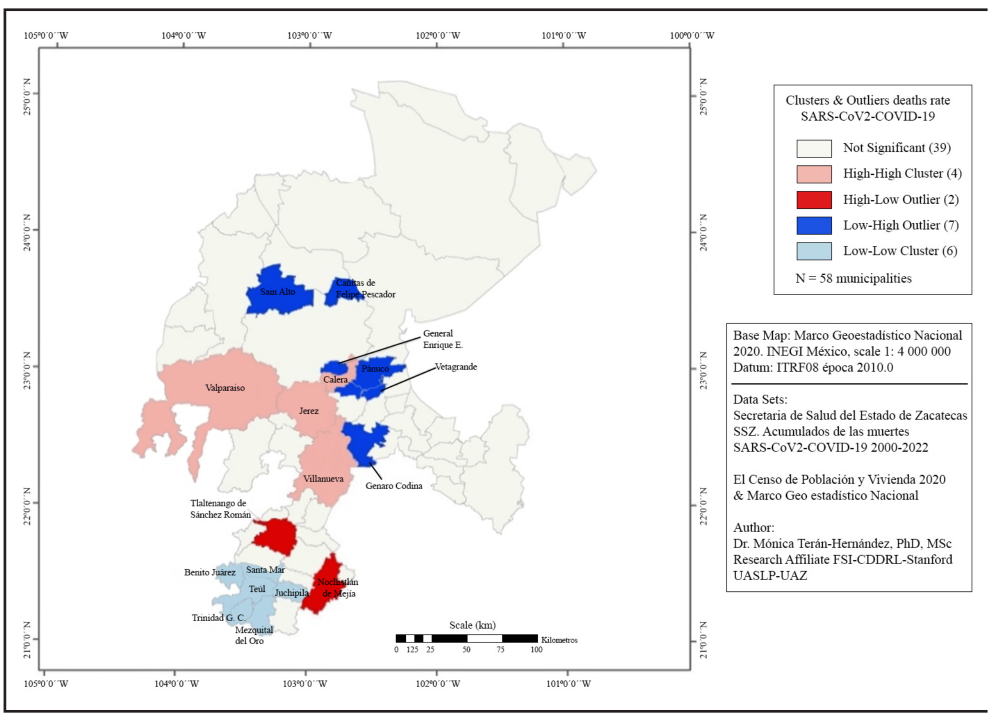

FIGURE 3
Clusters and Outliers of Death Rates
Source: Own elaboration.

The global spatial autocorrelation analysis demonstrates a positive correlation and spatial dependence of SARS-CoV2-COVID-19 risks across the municipalities of Zacatecas. The local spatial autocorrelation analysis further reveals differences in their areal distribution (refer to figure 4). The Global Moran's I value of 0.994207 indicates that there is indeed spatial correlation between the spread and distribution of COVID-19 in Zacatecas (Moran's I $p < 0.05$).

In figure 4, note the distribution characteristics of COVID-19 risk municipalities across. The presence of spatial clusters (High-high, HH or low-Low, LL) or outlier (Low-high, LH) is most conspicuous in the center and south-west areas. The pattern of spatial heterogeneity of HH and LH is generally stable in the center, whereas LL demonstrates variations in the south. For both sexes, have a high COVID-19 rate surrounded by municipalities that also have high pattern. HH pattern is formed by the municipalities of Jerez and Zacatecas, while the LL pattern is formed by Mezquital del Oro and Teul de González Ortega (refer to figure 4a and b), municipalities with a low COVID-19 rate surrounded by municipalities in this same situation. In the case of men, Figure 4c shows that the HH pattern in the center-south is comprised of Jerez, Calera, and Zacatecas.

HH Clusters can be seen in greater detail in the Jerez and Zacatecas, characterized by a high population concentration and an intense flow of people from different locations. These are the zones that compromise the majority of businesses (figure 4c).

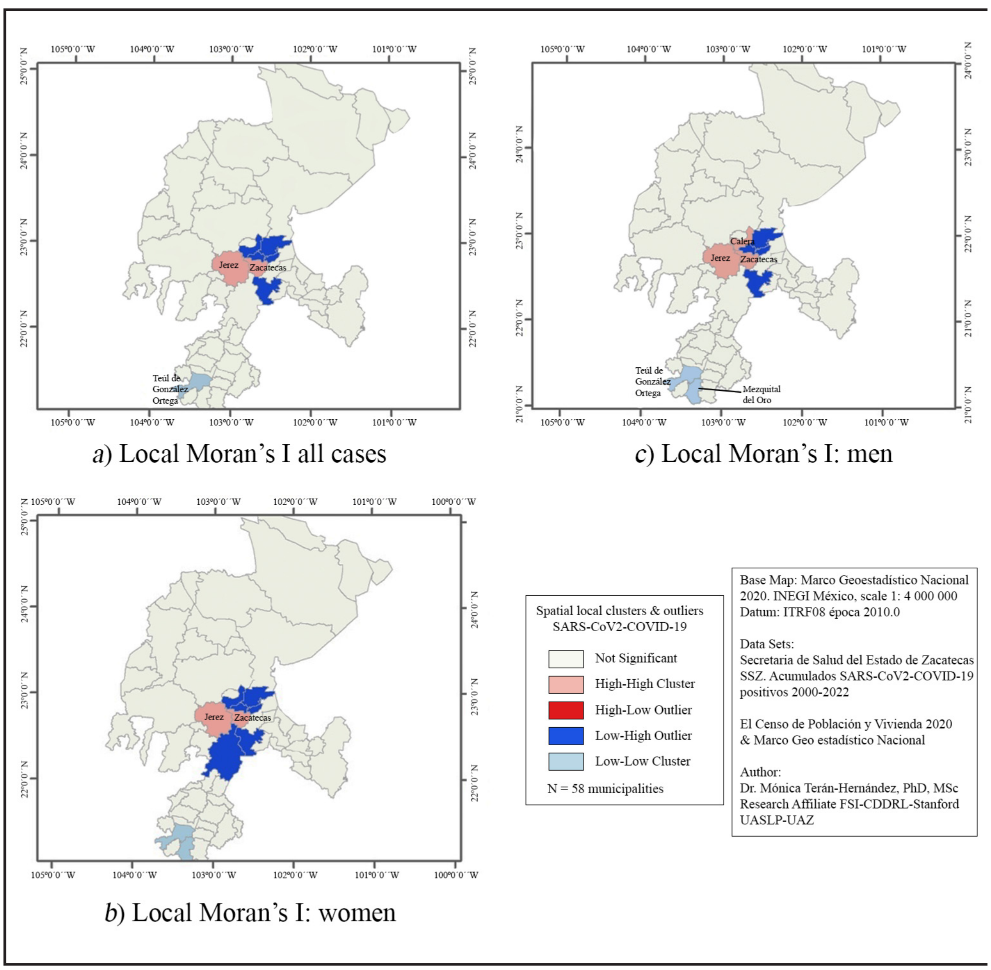

FIGURE 4
Spatial Local Clusters and Outliers of SARS-CoV-2 COVID-19 using Local Moran's I
Source: Own elaboration.

For both sexes, Morelos, Pánuco, Vetagrande and Genaro Codina are municipalities (Low-High outlier) with a low COVID-19 rate near municipalities with high. Women gender shows spatial local outlier, particularly in Villanueva. Municipalities in white are non-significant regions with a $p > 0.05$,, municipalities for which it is not possible to confirm whether spatial autocorrelation is present. They correspond to municipalities that show no correlation to the COVID-19 rate in neighboring municipalities.

The concentration of local clusters and outliers in Zacatecas State shows: a spatial correlation, which indicates whether nearby locations have similar rates, where are the unexpectedly high rates across the study area and locations with anomalous patterns. These results enabled us to address the following questions:

Is the relationship between COVID-19 and $\beta_1 X_1, \beta_2 X_2,...,$ uniform throughout Zacatecas State?

Which variables play a crucial role in explaining the spatial dynamics of COVID-19?

In which regions are each of these variables most important locally?

What are the AGEM that are experiencing the highest COVID-19 rate?

2. 2. Influencing factor analysis

The Moran's I test showed a statistically significant overall spatial autocorrelation between COVID-19 rate and five of the variables measured at the same aggregation level, as shown in table 1. It is observed that calls to 911 for gender-based violence have the most significance *p-value* of 0.000013. It is worth noting that within the category of family violence crimes, incidents of gender-based violence have shown a significant increase over the years, reaching a peak in 2020, 2021, and 2022 ($p < 0.05$). During the study period the difference between the calls to 911 for gender-based violence and the case file generated for victims of violence by BANAVIM is 28.4%.

By utilizing GWLR models, spatially varying relationships were identified, providing insight into the variability of COVID-19 across the Zacatecas territory at an AGEM scale. The best-fit model (model number 2) explained more than 80% of the variability (R-squared 0.8709). The overall fit of the GWLR model is satisfactory with five covariates. We choose the model number 2 with the lowest AIC = 143.021979 suggesting it provides the best overall fit among the estimating three models. As the most suitable for describing the spatially varying relationships in our data. Covariates:

$$\begin{aligned}\log(\lambda_i) = {} & \beta_0(u_i, v_i) + \beta_1(u_i, v_i).\ \textit{Marginalization Index}_i + \beta_2(u_i, v_i).\ \textit{Obesity}_i \\ & + \beta_3(u_i, v_i).\ DM_i + \beta_4(u_i, v_i).\ \textit{asthma}_i \\ & + \beta_5(u_i, v_i).\ \textit{family violence 911 calls \& gender}_i + \epsilon_i\end{aligned}$$

Model 1 GWLR with small bandwidth: AIC 151.319225, Model 2 GWLR with medium bandwidth: AIC 143.021979 and Model 3 GWLR with large bandwidth: AIC 148.734509.

Figure 5 highlights some variables that explain the spatial dynamics of SARS-CoV2- COVID-19, with local p-values ranging from 0.8 to 1.0 (statistical significance). Notably, diabetes mellitus, asthma, and 911 calls for family and gender violence. On the other hand, obesity demonstrated a moderate effect with a prediction ranging between 0.50-0.75. The marginalization index exhibits the lowest impact.

To ensure the correct specification of the models, we applied the spatial autocorrelation statistic (Moran's $I = -0.104202$) to the residuals. The analysis revealed that the patterns in the residuals are spatially random, and the predictions demonstrate a good fit, as depicted in figure 6.

Regarding the local importance of each characteristic, figures 7a-7e illustrate the predictive, regional, and local variation in the explanatory variables of the model, mapping the coefficient of each of the statistically significant covariates.

TABLE 1
Statistical Significance of Moran's Global Index of the variables evaluated $p <= 0.05$*

Feature	Index	*p-value*
Sociodemographics		
Female	0.104199	0.091699
Male	0.106863	0.087226
No health services	0.140001	0.032520*
Marginalization Index	0.160086	0.013918*
Illiteracy	0.170033	0.014019*
Health: Comorbidities		
Obesity	0.099490	0.013064*
Diabetes mellitus (DM)	0.139314	0.038596*
Hypertension	0.096449	0.108479
Asthma	0.094102	0.041068*
Family violence 911 calls & Gender	0.351550	0.000013*

Source: Own elaboration.

For instance, diabetes mellitus is a significant factor that influences the spatial dynamics of COVID-19 in the state, demonstrating a positive correlation, as illustrate in figure 7a. The region with the highest range of coefficients (> 1.5) is predominantly distributed in the southern areas, mainly in the 18 municipalities: El Plateado de Joaquín Amaro, Momax, Tabasco, Atolinga, Tlaltenango de Sánchez Román, Huanusco, Tepechitlán, Jalpa, Benito Juárez, Santa Mar, Apozol, Apulco, Nochistlán de Mejía, Teúl de González Ortega, Juchipila, Trinidad García de la Cadena, Mezquital del Oro and Moyahua de Estrada bordering Jalisco and Aguascalientes. Valparaiso, located in the southwest, stands out among the municipalities with coefficients between 1-1.5. The lowest values, indicating less influence of this variable on COVID-19 cases, are concentrated in the north, center, and east of the state.

The COVID-19 and asthma ratios exhibit the highest range of coefficients (>1.5) in the north and center of the state, bordering the limits of Coahuila and the north of the state of San Luis Potosí (Real de Catorce and Vanegas, historically significant mining areas). Conversely, the lowest values are concentrated towards the south of the state, indicating that this variable has less influence on COVID-19 cases in these areas (refer to figure 7b).

Figure 7c displays the positive association between obesity and COVID-19. The region with the highest range of coefficients is distributed in the central east, mainly in 17 municipalities bordering the state of San Luis Potosí. This result is linked to the spatial pattern that this disease exhibited in the HH pattern cluster analysis. The lowest values are concentrated towards the south of the state, encompassing 12 municipalities, including Tepechitlán, Jalpa, Apozol, Benito Juárez, Teul de González, and Mezquital del Oro. Furthermore, figure 7d illustrate the positive association between marginalization index and COVID-19.

The area with the highest range of coefficients is distributed in the north of the state, with the lowest values concentrated towards the south and east of the state. Notably, the municipality of Melchor Ocampo to the north and Apulco to the northeast exhibit different spatial patterns.

Lastly, figure 7e displays the region where the coefficients of the relationships between COVID- 19 and family violence 911 calls & gender are greater than 1.5. This area is distributed in the center-east of the state, bordering the limits of Saltillo and the north with the state of San Luis Potosí. The lowest values are concentrated towards the south of the state.

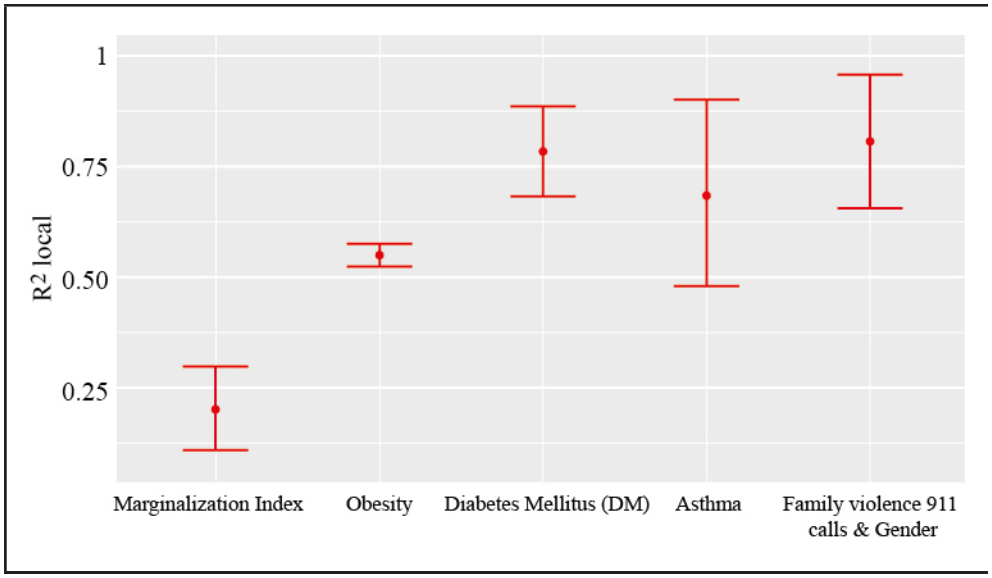

FIGURE 5
GWLR local *pvalue* ≥ 0.50
Source: Own elaboration.

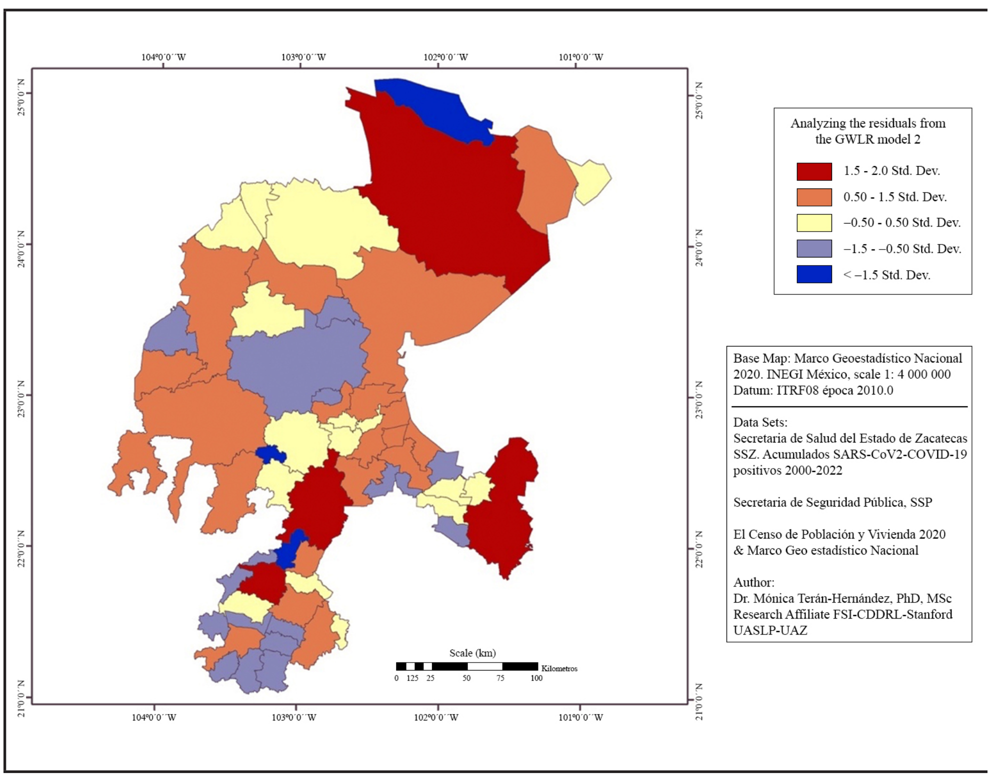

FIGURE 6
Regression Residuals from GWLR Model 2
Source: Own elaboration.

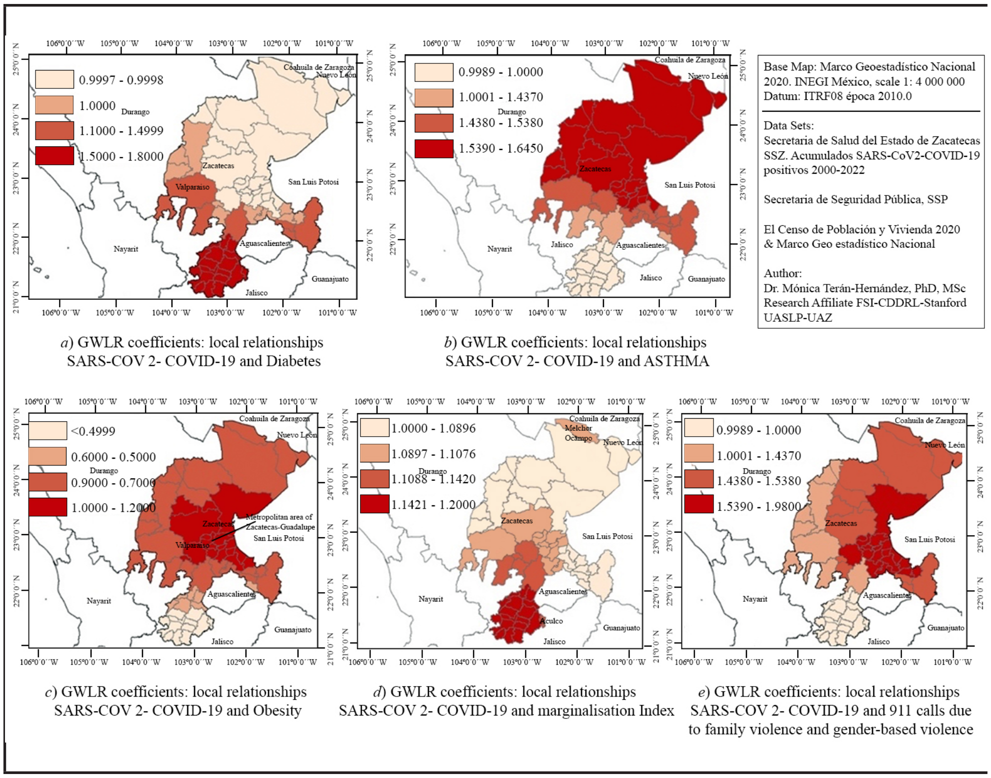

FIGURE 7
GWLR Model 2 Coefficients
Source: Own elaboration.

2. 3. Hot spot detection

Finally, figure 8 shows the predicted spatial pattern of SARS-CoV2-COVID-19 based on the GWLR model 2, areas with similar local coefficient used to identify areas with distinct risk factors contributing to COVID-19. Three important hot spot areas are identified that will be reaching the highest rates if the multivariate spatial characterization is preserved (see table 2).

TABLE 2
Hot spot analysis

Hot spot	Level of confidence	z-score	*p-value*	Agem’s
1	99%	> 2.58	< 0.01	Center: Jerez, Center-west: Calera, Pánuco, Vetagrande and Zacatecas
2	95%	1.96−2.58	< 0.05	In addition to the municipalities of the hot spot 1 are added the following: Northwest-Saín Alto; Center-north: Cañitas and Fresnillo; Center: General Enrique Estrada, Morelos and Southwest: Genaro Codina
3	90%	1.65−1.96	< 0.10	In addition to the municipalities of the hot spot 2 are added the following: Center-east: Guadalupe and North: R. Grande
z-score = 3.629848 *p*-value = 0.000284				

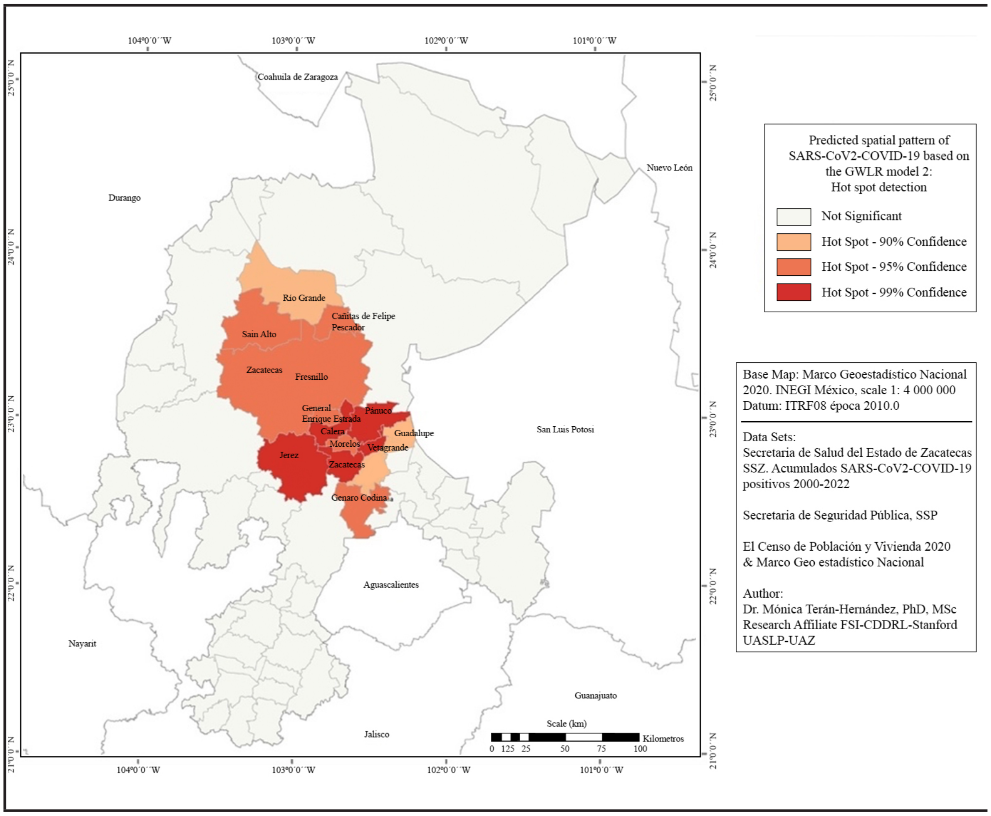

FIGURE 8
Hot spot detection
Source: Own elaboration.

Prospective

Events such as the COVID-19 pandemic have highlighted the vulnerability in our societies and tested government institutions to respond effectively to such contingencies. A very recent case, but of a different nature, is the disaster caused by Hurricane Otis in the Port of Acapulco, which forces us to improve disaster prevention systems of all types, to improve the government organization and the private and social sectors to provide more accurate responses to social needs in a contingency.

This work presents the advantages of using spatial analysis tools to respond to emergencies and to be able to identify key elements to generate a more effective current in government and social action, however, it is necessary to highlight the need to have more and better sources of information, with a higher level of disaggregation than that presented in this research and that would undoubtedly offer more effective and localized results. Contribution was made to the National Vaccination Strategy and local intervention. Considering the findings, spatial analysis can provide feedback to policymakers, supporting public health policy and local actions.

Is not just about identifying a hot spot, but about analyzing that the causal relationship between certain comorbidities and SARS-CoV-2 is particularly pronounced, and these are the places where we can think in terms of Public Health Emergency, as there is something that can be done on the public health front to modify some of the pre-existing conditions, and it is not necessarily just about this current pandemic but also future pandemics.

Spatial modeling allows us to anticipate catastrophic events by creating scenarios that answer the question what *would happen if...?* Surely there will be new pandemics in the future and more natural disasters, but knowledge exists in educational institutions and must be linked to the needs of the social and government sectors to respond to their needs, an example of this is this work.

Discussion and conclusions

Improvements in our understanding of the spatial variation in the spread of diseases could lead to development of innovative local strategies, which improve their impact on morbidity and mortality worldwide, and modify some of the pre-existing conditions to ameliorate the public health (Terán-Hernández & González-Curiel, 2023; Alves *et al*., 2021; Gatrell & Elliott, 2014). Notably, there are significant variations in the geographic distribution of COVID-19 incidence and mortality within the state.

A contribution of this study, the article evaluates important factors to determine the spatial location of COVID-19 cases between 2020 and 2022, as well as identifying some factors that influence the morbidity/mortality. These factors include comorbidities, sociodemographic data, and elements like family and gender violence. Furthermore, it identifies some factors that had not been previously associated with COVID-19. In this context, significant associations were found. This allows for suggesting possible mechanisms involved, which could be considered by decision-makers.

Indeed, as mentioned in the article, the spatial distribution of the posterior relative risk estimates for both sexes revealing excess risk Concepción del Oro, Fresnillo, Morelos, Guadalupe, Zacatecas, Tlaltenango de Sánchez Román, and Nochistlán de Mejía, suggesting the presence of spatial autocorrelation, where nearby locations have similar rates. Clusters and hot spot identification with elevate or reduce rates may suggest AGEM with similar risk factors or characteristics. We are 95% confident that the true disease rate in Zacatecas state falls within the interval (0.03132, 0.00413). This provides a range of plausible values for the rate. The mean posterior rate for female and the mean posterior rate for male showed no statistically significant differences.

Both the risks of infection and death at the state level exhibit positive spatial autocorrelation. Kang *et al*. (2020) similarly found significant spatial correlations in their analysis of the spatial transmission of COVID-19 in China. The study reveals that the spatial pattern of COVID-19 in Zacatecas is concentrated in clusters of territorial units in the same condition, primarily in the metropolitan area of Zacatecas-Guadalupe. The overall spatial autocorrelation index was 0.51, indicating that the spatial pattern of COVID-19 is clustered at the state level.

The analysis of the geographic distribution of the local spatial autocorrelation of COVID-19 cases highlights disparities between neighboring municipalities. These spatial disparities are linked to the context that characterizes the place, where geographic location generates spatial patterns that are clustered based on "Tobler's first law of geography" (Miller, 2004).

The analysis by local clusters at AGEM level, provides a more specific approximation of the behavior of COVID-19. The highest risk areas are clustered in the center-south, and the pattern of the municipality of Guadalupe (very high) to the north and Sain Alto (very low) neighboring Fresnillo (very high) is notable. The highest lethality rates are clustered in the center-south, with Jerez and Calera being the highest. These findings are consistent with studies conducted by De la Luz *et al.* (2020), which suggest that the geographic distribution of COVID-19 is heterogeneous, and associations with contextual factors where the population lives indicate inequities (Gatrell & Elliott, 2014).

The GWLR model 2 had a good fit and allowed us to improve the accuracy of local associations influencing COVID-19 dispersion among the AGEM that make up the state of Zacatecas and to identify the variation of locally weighted regression coefficients across the territory. The model 2 improves the fit by capturing local variations and the residuals are spatially random indicates that the model accounts for spatial patterns in the data and the local R-squared value is relatively high, suggesting than the model explains a significant proportion of the variability in COVID-19.

The GWLR model 2 reveals that DM, asthma, and obesity are the main comorbidities that explain the observed local variation. Furthermore, family violence 911 calls & Gender and Marginalization index.

Méndez-Fausto *et al*. (2022) observed that the population with obesity generated higher levels of natural antibodies (anti-N-SARS-CoV2-IgG) in response to the infection. This is because obesity per se, is characterized by a low-grade inflammatory process, a condition that promotes the humoral response, leading to antibody production.

Diabetes mellitus and respiratory system diseases such as asthma and obesity are risk factors for the severity and sequelae of COVID-19 with increased weight, with results similar to those reported by Estefania *et al*. (2021). Likewise, Bello-Chavolla *et al*. (2020) found that a high burden of cardiometabolic comorbidities predisposes individuals to more severe disease, thus increasing the severity of sequelae and overall mortality.

Several studies show that diabetes is the strongest predictor of morbidity and mortality due to COVID-19 followed by obesity, hypertension, and chronic renal failure (Raymundo *et al*., 2021; Alves *et al*., 2021; Deonarine *et al*., 2021; Moonsammy *et al*., 2021; Wang *et al*., 2021). In Mexico, there is a high presence of these chronic diseases (CD).

Of the confirmed cases of COVID-19 in our country, 52.43% are women and 47.57% are men, 12.35% suffer from hypertension, 10.21% from obesity, 9.23% from diabetes, and 5.78% from smoking (Gobierno de México, 2022). It should be noted that 80% of those who died had two associated comorbidities, mainly hypertension, diabetes, and obesity, a pattern similar to that found in our study. In the absence of comorbidity, the prevalence of lethality in COVID-19 is 3.8%; in the presence of hypertension and diabetes, the lethality increases to 54.1%, diabetes and obesity 36.8%, and in obesity and hypertension 28.1% (Correa *et al*., 2022).

The National Health and Nutrition Survey 2020 on COVID-19 reports CD as the second national health need (25%) in adults aged 20 years and older. At the national level, a prevalence of CD of 10.32 in the population aged 20 years and older are reported. Zacatecas reported a prevalence between 9.89 and 10.90. By 2020, the mortality rate was 11.95 per 10 000 inhabitants, affecting people aged 65 and over the most. The pandemic affected the increase in overall mortality from January to September 2021 (INEGI, 2022).

Regarding antibody production in recovered patients, there is a statistically significant difference between those with obesity and those with normal weight, with the group with obesity having the highest production of antibodies. This may be due to the presence of a pre-existing acute inflammatory condition that could prevent immune auto-regulation of antibodies (Gobierno de México, 2022).

Recovered patients with hypothyroidism and asthma showed the lowest antibody production (15.84 COI and 15.61 COI, respectively), followed by DM (29.73 COI) and HT (63.57 COI) (Estafania *et al*., 2021). The comorbidities that explain the local variation observed in this study share two characteristics: the pro-inflammatory state and the attenuation of the innate immune response, increasing the risk of death and sequelae to COVID-19 (Méndez-Fausto *et al*., 2022).

Notice that particulate matter (PM) with diameters ≤10μm is listed as the main indicator of air quality in urban and industrial areas (mining sector is one of the main industries), is a major pollutant, responsible for respiratory infections, asthma, lung disease, COPD, and importantly compromised immune system. The Zacatecas state concentrates more than 46.4% of the national production of silver (1st place of 13), 18.7% of gold (3rd place of 10), 62.8% of lead (1st place of 8), 47.9% of zinc (1st place of 8), and 9.2%-14.5% of copper (2nd place of 9) (Gupta *et al*., 2020; Arregocés *et al*., 2021).

The State of Zacatecas is a federative entity with multiple activities, including mining, with 16 municipalities standing out. In this context, the source for the formation of particulate matter (PM) could occur during the operations of blasting, extraction, movement, and treatment of various minerals and metals. Up to now, there is no available information on the concentration of PM in the study locations due to the lack of a monitoring system; the authors infer its possible presence due to the aforementioned activities (García-Gutiérrez, 2019). On the other hand, it has been documented that PM is associated with different lung diseases. For example, prolonged exposure to PM increases the prevalence of COPD, asthma, cancer, etc. (Kyung *et al*., 2020).

In the present study, illiteracy and lack of healthcare services were included as covariates in the Moran's Global Index were statistical significance but in the spatial patterns identified by GWLR the best sociodemographic predictor was Marginalization index. Illiteracy and lack of healthcare services effects could potentially impact the ultimate goal of managing and controlling the pandemic in the State of Zacatecas. In this regard, municipalities facing issues of illiteracy and insufficient healthcare services were identified due to: *a*) Geographical location, *b*) Local economic activity, and *c*) Influence of external factors on the family nucleus (violence, insecurity, organized crime, etc.). Interestingly, it was observed that those municipalities experiencing both covariates coincided with the lethality of COVID19.

It is worth noting that within the category of family violence, incidents of gender-based violence have shown a significant increase over the years in Zacatecas state, reaching a peak in 2020, 2021, and 2022 (p <0.05). The COVID-19 pandemic exacerbated family and gender-based violence due to various factors such as confinement, restricted mobility, uncertainty, and economic pressure, among others. Recent studies report that these factors trigger violence. Cultural tendencies, education, socioeconomic levels, and substance abuse are among the predisposing factors to this type of violence (Da Silveira Arruda *et al*., 2022; Arregocé *et al*., 2021; Rocha *et al*., 2021).

The coefficient for gender-based violence exhibits the highest impact (statistical significance). These restrictions, while they contained the COVID-19 pandemic, also had effects on Mexican families in a developing economy very similar to other Latin American countries. This included an increase in uncertainty, stress, pressure due to the economic situation, a shift in power dynamics, improvised distance learning, and consequently, the need for mothers to leave their jobs to return to home and childcare responsibilities. This resulted in job loss and other factors that are considered triggers for violence.

Family and gender violence are a serious public health problem not only in Zacatecas but also at the national level. Ramirez-Aldana *et al*. (2022) and López-Hernández & Rubio (2020) found that the concentration (agglomeration) of people and services in such a built environment (rapid and generally unplanned urbanization in the peripheries, where most of the population and the urban poor live today) creates risks that shape the epidemiological vulnerability of the population.

Bello-Chavolla (2020) reports result similar to those found in this study that comorbidities and structural determinants of health play a more important role in increasing the severity of the disease and the conditioning risk of lethality by COVID-19.

These findings suggest that consider how the spatially varying of the GWLR coefficients can inform more effective resource allocation or policy strategies where the relationship between variables differs significantly across the territory of Zacatecas state. Indeed, as mentioned in the article, comorbidities and the marginalization index improve the model's ability to capture local variations. Additionally, it identifies some factors that had not been previously associated with COVID-19 like gender-based violence.

Preventive measures should be taken in terms of public health policy considering the location of the main clusters by type of comorbidities, in addition to the relative living conditions of the population within Mexico, as they represent additional burdens to morbidity, and mortality due to COVID-19.

Isn't just about identifying a hot spot, is about analyzing that the causal relationship between certain comorbidities and COVID-19 is particularly pronounced, these are the places where we can think in terms of Spatial analysis- based planning to support public health policy to modify pre-existing conditions not just about this current pandemic.

Contribution was made to the National Vaccination Strategy and local intervention. Considering the findings, spatial analysis can provide feedback to policymakers, supporting public health policy and local actions.

Moreover, it is important to conduct further studies on family and gender violence in situations of confinement. A spatial overlap study is suggested to indicate the territorial dimension of potential 24/7 access to resources and support, such as care centers, shelters, and 911 call services and the case file of the formal complaints that Banavim collect.

This prioritizes critical populations and monitoring and helps to link with key actors to strengthen immediate intervention and avoid deterioration in the family system and impact on integral health.

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Mónica Terán-Hernández: conceptualización, curación de datos, análisis formal, metodología, investigación, *software*, validación, visualización, recursos, adquisición de fondos y redacción–borrador original.
Juan Campos-Alanís: validación, revisión.
Bruno Rivas-Santiago: validación, revisión.
Irma Elizabeth González-Curiel: conceptualización, investigación, administración de proyectos, recursos, adquisición de fondos y redacción–borrador original.

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