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# Mortality from type 2 diabetes mellitus across municipalities in Mexico

Claudio Alberto Dávila Cervantes<sup>1</sup> and Emerson Augusto Baptista<sup>2\*</sup>

## Abstract

**Background** One in six Mexican adults' lives with type 2 diabetes mellitus (T2DM), which is the third leading cause of death in the country. Analyzing the geographic distribution of T2DM mortality helps identify regions with higher mortality rates. This study aimed to examine the spatial patterns of mortality from type 2 diabetes mellitus (T2DM) across municipalities in Mexico and to analyze the main contextual factors linked to this cause of death in 2020.

**Methods** We employed a spatial Bayesian hierarchical regression model to estimate the risk and probability of death from type 2 diabetes mellitus (T2DM) across Mexico's municipalities.

**Results** The SMR results revealed geographic and age-specific patterns. Central Mexico and the Yucatán Peninsula exhibited the highest excess mortality rates. For the population under 50 years of age, municipalities in Oaxaca had the highest T2DM mortality rates, whereas those aged 50 years old and older had the highest rates in Tlaxcala and Puebla. Socioeconomic factors such as low levels of educational attainment, lack of health services, dietary deficiency, and marginalization were positively associated with increased T2DM mortality risk. By contrast, GDP per capita showed a negative association. High-risk areas for T2DM mortality were prominent along the south of the Pacific Coast, the Bajío, Central Mexico, and southern Yucatán for those under 50, and along a central strip extending to the Yucatán Peninsula for the older population. Significant uncertainties in mortality risk were identified, with Central Mexico, Oaxaca, Chiapas, and Tabasco showing high probabilities of excess risk for those under 50 years of age and extended risk areas along the Gulf of Mexico for those 50 years old and older.

**Conclusions** The assessment and identification of spatial distribution patterns associated with T2DM mortality, and its main contextual factors, are crucial for informing effective public health policies aimed at reducing the impact of this chronic disease in Mexico.

**Keywords** Diabetes mellitus, Socioeconomic factors, Mexico, Municipalities, Bayesian hierarchical model

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**Text box 1. Contributions to the literature**

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- The study of diabetes at the municipal level helps gain deeper insights into the social determinants of health, highlighting disparities in healthcare access, socioeconomic factors, and environmental influences that contribute to differential disease burdens.
  - To estimate the risk and probability of death from type 2 diabetes in Mexico
  - We employed a spatial Bayesian hierarchical regression model as a methodological alternative to that used in previous studies
  - The results revealed geographic and age-specific mortality patterns
  - Socioeconomic factors were associated with increased T2DM mortality risk, while GDP per capita showed a negative association with T2DM mortality
- 

**Introduction**

Type 2 diabetes mellitus (T2DM) is a growing health concern worldwide. In 2021, an estimated 537 million individuals aged 20–79 were living with diabetes globally. Projections indicate that this number will rise to 783 million by 2045 [1]. The increase in T2DM will predominantly occur in low- and middle-income nations [2, 3], such as Mexico, where resources for treating the disease and its complications are limited. The main T2DM complications are cardiovascular disease, visual impairment due to diabetes retinopathy, kidney failure, and lower limb amputation [4]. The projected increase is linked to several factors, such as the aging population, which will mean a higher percentage of individuals over 60 living with T2DM, higher rates of obesity and increases in excess weight due to lifestyle changes (such as an increased calorie intake and a decrease in physical activity) [1, 2], and improved medical treatments, leading to higher survival rates among those with T2DM. Excluding the mortality risks associated with COVID-19, the International Diabetes Federation estimated that approximately 6.7 million individuals aged 20 to 79 years died worldwide from T2DM or its complications in 2021. This accounted for approximately 12.2% of the total deaths in these age groups [1]. Most of these T2DM-related deaths occurred in low- and middle-income countries [5], with the 35–64 age group being the most affected [1].

In 2021, Mexico ranked seventh globally for the highest rates of individuals living with T2DM, totaling around 14.1 million adults aged 20 to 79. This indicates that one out of every six Mexican adults are affected by this condition. The number is projected to rise to 21.2 million by 2045 [1], largely driven by the high prevalence of obesity and physical inactivity [6, 7]. In 2020, T2DM was ranked as the third leading cause of death in the country, following cardiovascular diseases and COVID-19, with 151,019 recorded deaths. Over the past three decades, mortality

associated with T2DM has surged by 77% in Mexico [8]. Mortality related to T2DM is associated with sociodemographic and economic inequalities [8], which have been exacerbated by the COVID-19 pandemic. For example, there was an estimated 41% increase in T2DM-related deaths in 2020 compared to the preceding period from 2017 to 2019, reflecting the significant impact the pandemic has had in Mexico [9].

Several social factors at the municipal level have been associated with the prevalence of T2DM. Socioeconomic factors like poverty [10] and income inequality [11], as well as social cohesion, can impact health behaviors and access to healthcare services, all of which are linked to T2DM [12]. Globalization and rapid urbanization can lead to sedentary lifestyles, increased consumption of processed foods, and higher levels of stress, all of which are also risk factors for T2DM. Furthermore, education level and access to education are associated with T2DM [13], likely influencing individuals' understanding and awareness of the health benefits of preventive behaviors [14]. Low educational attainment levels are also correlated to higher overweight and obesity rates [15].

Analyzing the geographic distribution of T2DM mortality facilitates the identification of geographic areas with higher mortality rates [16]. The risk factors for T2DM can vary significantly between regions. Thus, by studying diabetes at the municipal level, we can gain deeper insights into the social determinants of health, highlighting disparities in healthcare access, socioeconomic factors, and environmental influences that contribute to differential disease burdens. Consequently, examining type 2 diabetes at this scale provides valuable insights into the local disease burden, informing targeted strategies for prevention, public health planning, resource allocation, and policy development [12]. Therefore, the main objective of this study is to examine the spatial patterns of mortality from T2DM across municipalities in Mexico and to investigate the main contextual factors linked to this cause of death in 2020. For this purpose, we used a spatial Bayesian hierarchical regression model [17–19] based on the Integrated Nested Laplace Approximation (INLA) [20].

**Variables, data sources, and scale of analysis**

This study assembles data from multiple sources. Municipal-level deaths from type 2 diabetes mellitus (T2DM) (International Classification of Diseases, ICD-10 codes E110-E119) serve as the dependent variable in this study. Data on this cause-specific, which includes information on the cause of death by sex and municipality of residence, as well as age-specific (population under 50 years of age and those 50 years old and older), and comes from the National Institute of Statistics and Geography of Mexico [21]. We also used population estimates from

the Mexican Population Council (CONAPO). This population estimate is corrected for completeness, age misstatements, and international migration [22]. We selected 2020 to analyze T2DM mortality because the most recent municipal-level data for many socioeconomic indicators is from that year, as they are based on the 2020 Population Census.

We also analyzed five socioeconomic indicators that have been shown to correlate with the prevalence of T2DM: (i) low levels of educational attainment, which refers to individuals or populations that have not been able to access or achieve expected educational benchmarks for their age/learning level. Education is one of the main factors associated with the risk of T2DM [13]. This data was obtained from the 2020 municipal poverty measurement conducted by the National Council for the Evaluation of Social Development Policy [23]; (ii) lack of access to health services. This refers to the proportion of individuals who do not have access to essential healthcare services or face barriers to accessing healthcare facilities. This data also comes from the National Council for the Evaluation of Social Development Policy [23]. Access to healthcare is crucial for preventing the onset of T2DM and managing the disease to avoid serious complications [13, 24]; (iii) dietary deficiency, an indicator used by CONEVAL to measure municipal poverty, was utilized as a proxy for food insecurity [23]. Food insecurity significantly impacts the risk and management of T2DM

by forcing individuals to rely on low-cost, calorie-dense, nutrient-poor foods that are high in sugars, refined carbohydrates, and unhealthy fats, and by creating a stress environment that can lead to the development of insulin resistance and T2DM [25]; (iv) Since there is no gross domestic product (GDP) at the municipal level in Mexico, we used the gross value added from the 2019 Economic Census (INEGI) as a proxy. This variable is the best approximation of GDP that could be implemented to achieve the objectives of this study. GDP per capita is one of the most widely used socioeconomic predictors of mortality and health [26–32]; and (v) the marginalization index, which measures socioeconomic disparities across municipalities in Mexico [33].

Finally, the units of analysis used were the 2,469 Mexican municipalities, that are divided into thirty-two states and six regions (see Fig. 1).

## Methods

### Standardized mortality ratio (SMR)

Regional disparities in mortality rates often stem from differences in the age structures of populations. To facilitate comparisons across regions, researchers commonly employ the standardized mortality ratio (SMR), an indirect age-adjustment technique. SMR is calculated as the ratio of observed deaths in a given population to the expected number of deaths [34].



**Fig. 1** Mexico by regions and states

$$SMR_i = \frac{y_i}{E_i}$$

$$E_i = r_s * n_i$$

The formula for SMR involves dividing the observed deaths  $y_i$  in a municipality  $i$  ( $i=1, 2, \dots, 2468, 2469$ ) by the expected deaths  $E_i$ . The expected deaths  $E_i$  are determined by multiplying the mortality rate of a standard population  $r_s$  by the total population of municipality  $i$  ( $n_i$ ). A SMR exceeding one indicates excess mortality within the study population. Despite its unbiased nature in estimating mortality, the SMR method has some limitations. Notably, it does not elucidate the spatial structure inherent in these data and struggles to discern regions with limited or absent death records. This drawback has been highlighted previously [35].

### Bayesian spatial model

The Bayesian spatial model offers a remedy to the drawbacks inherent in the Standardized Mortality Ratio (SMR) approach. Because of its simplicity, SMR overlooks spatial dependencies between areas, which means that essentially no spatial structure in risk is modeled [36]. Moreover, the SMR can be easily affected when applied to areas with small populations, which may cause large fluctuations in the estimation [37]. By contrast, the Bayesian spatial model demonstrates superior efficacy in capturing spatial patterns by incorporating global and local information to mitigate instability [35].

Typically, health data encompass various outcomes, such as the number of deaths or occurrences of specific diseases, along with spatial and/or temporal factors. A key advantage of employing Bayesian modeling is its ability to accommodate unobservable variables, treating them as random effects within the model. This flexibility is particularly valuable when not all factors influencing outcomes can be measured directly. By considering all observed data and covariates, Bayesian inference facilitates the direct estimation of posterior probability distributions, with straightforward interpretation when posterior probabilities exceed or fall within confidence intervals. Consequently, the Bayesian approach has gained traction across disciplines for estimating potential risk factors.

In our study, we modeled the number of type 2 diabetes mellitus (T2DM) deaths, denoted as  $y_i$ , using a Poisson distribution, where a log-linear model is specified for T2DM mortality. The log-linear model is expressed as:

$$y_i \sim \text{Poisson}(E_i \theta_i)$$

$$\log(\theta_i) = \beta_0 + u_i + v_i$$

Here,  $E_i \theta_i$  represents the expected number of T2DM deaths in area  $i$  ( $E_i$ ), and  $\theta_i$  denotes the specific relative risk in that area.  $\beta_0$  quantifies the average T2DM mortality across all 2,469 municipalities;  $u_i$  is a spatially structured random effect modeled using an intrinsic conditional autoregressive distribution (iCAR),  $u \sim ICAR(W, \sigma_u^2)$  [17], whereas  $v_i$  is a spatially unstructured random effect modeled using an exchangeable prior,  $v_i \sim \text{Normal}(0, \sigma_v^2)$ .

Expanding upon this formulation, we incorporated covariates to assess their impact on T2DM mortality risk. The extended model is expressed as:

$$\log(\theta_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + u_i + v_i$$

Here,  $\beta_0$  represents the global intercept, while  $\beta_s$  are coefficients for the covariates. The model includes predictor variables, such as the percentage of the population with low levels of educational attainment ( $x_1$ ), percentage of the lack of health services ( $x_2$ ), percentage of the population with dietary deficiency ( $x_3$ ), gross domestic product (GDP) per capita ( $x_4$ ), and marginalization index ( $x_5$ ). The coefficients  $\beta_s$  are interpretable as relative risk (RR), indicating the percentage increase or decrease in T2DM mortality risk associated with a one-unit change in the respective covariate ( $x_j$ , where  $j=1, \dots, 5$ ). The Besag-York-Mollie (BMY) specification is adopted for this model, along with first-order neighborhood spatial weights [17].

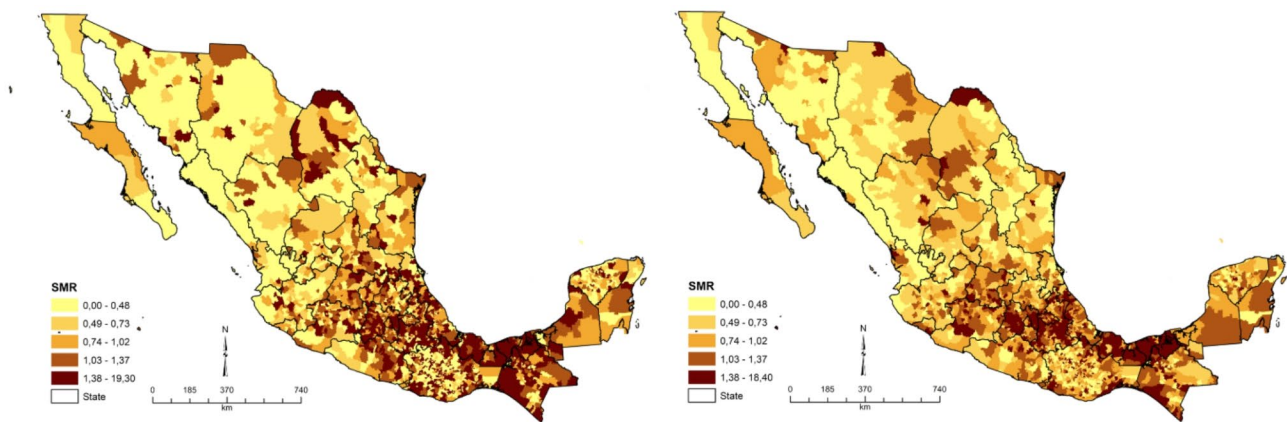
## Results

### Standardized mortality ratio (SMR)

Figure 2 shows the spatial distribution of SMR in 2020 across 2,469 municipalities in Mexico, for both the population under 50 years of age (left) and those 50 years old and older (right). Overall, excess mortality ( $>1$ ) was the most widespread in the regions of Central Mexico and Yucatán Peninsula. These regions are characterized by a lower socioeconomic development, limited access to healthcare facilities, a higher percentage of the population with dietary deficiencies, and higher marginalization. The municipalities of San Miguel Achiutla, San Pedro Nopala, and Abejones, all in the state of Oaxaca, have the highest T2DM mortality rates for the population under 50. Meanwhile, the municipalities of La Magdalena Tlaltelulco and San Pablo del Monte in Tlaxcala state, as well as Acatzingo in Puebla state, have the highest T2DM mortality rates for those aged 50 years and older.

### Spatial model

Tables 1 and 2 present the fixed effects ( $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ ) estimated by R-INLA. First, the two models ( $<50$  years of age and  $\geq 50$  years of age) agree on the algebraic sign (positive or negative) of all the



**Fig. 2** Standardized Mortality Ratio of T2DM by municipality in Mexico, 2020. Under 50 years old (left) and 50 years old and older (right)

**Table 1** Summary statistics for T2DM mortality: posterior mean, posterior standard deviation (sd) and posterior 95% confidence interval for the fixed effects of the model (< 50 years of age), Mexico, 2020

	Mean	sd	2.5%	50%	97.5%
Global intercept ( $\beta_0$ )	-0.666	0.544	-1.744	-0.662	0.391
Educational attainment ( $\beta_1$ )	0.013	0.003	0.006	0.013	0.020
Lack of health services ( $\beta_2$ )	0.001	0.002	-0.002	0.001	0.005
Dietary deficiency ( $\beta_3$ )	0.012	0.002	0.008	0.012	0.016
GDP per capita ( $\beta_4$ )	-0.134	0.088	-0.309	-0.133	0.036
Marginalization index ( $\beta_5$ )	0.003	0.009	-0.014	0.003	0.020

**Table 2** Summary statistics for T2DM mortality: posterior mean, posterior standard deviation (sd) and posterior 95% confidence interval for the fixed effects of the model ( $\geq 50$  years of age), Mexico, 2020

	Mean	sd	2.5%	50%	97.5%
Global intercept ( $\beta_0$ )	-2.376	0.308	-2.982	-2.376	-1.773
Educational attainment ( $\beta_1$ )	0.002	0.002	-0.001	0.002	0.006
Lack of health services ( $\beta_2$ )	0.006	0.001	0.004	0.006	0.008
Dietary deficiency ( $\beta_3$ )	0.009	0.001	0.007	0.009	0.011
GDP per capita ( $\beta_4$ )	-0.101	0.070	-0.238	-0.101	0.035
Marginalization index ( $\beta_5$ )	0.034	0.005	0.024	0.034	0.044

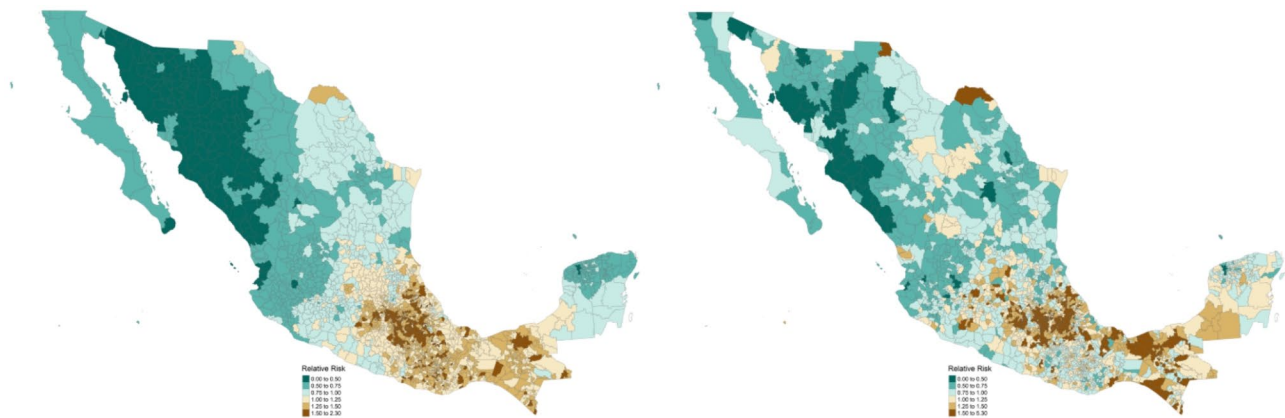
coefficient estimates. Furthermore, as they are reported on a natural scale, it is possible to interpret them as relative risks. In other words, an increase of one unit in the percentage of the population with low levels of educational attainment ( $\beta_1$ ) is associated with a 1.3% increase in the risk of death from Type 2 diabetes for populations under 50 years of age, and a 0.2% increase for those 50 years old and older. Regarding the percentage of the lack of health services ( $\beta_2$ ), although positive, the relationships are not very strong for either age groups. The percentage of the population with dietary deficiency ( $\beta_3$ ) also has a positive association with T2DM mortality, with increases of 1.2% and 0.9% in populations under 50

years of age and 50 years and older, respectively. On the other hand, an increase of one unit in GDP per capita ( $\beta_4$ ) is associated with a decrease of 13.4% and 10.1% in the risk of T2DM mortality, respectively. Finally, a one-unit increase in the marginalization index ( $\beta_5$ ) is associated with an increase of approximately 0.3% in the risk of death from T2DM for the population under 50 years of age, and 3.4% for those 50 years and older.

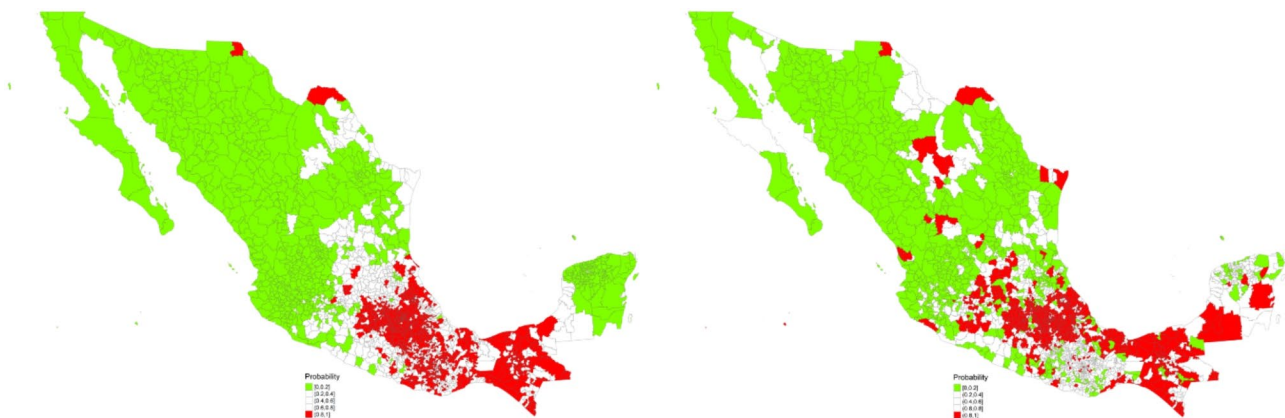
Figures 3 and 4 show the spatial distribution of the posterior mean of the specific relative risks,  $\varsigma_{it} = \exp(u_{it} + v_{it})$ , and their posterior probability of exceeding unity,  $p(\varsigma_{it} > 1 | \mathbf{y})$ , respectively. They should be interpreted as the residual RR for each municipality after the risk factors  $x_1, x_2, x_3, x_4$ , and  $x_5$  are considered.

The posterior mean of mortality from T2DM in 2020 (Fig. 3) exhibits well-defined spatial patterns, although it is more evident for the population under 50 years old (left). For this population age-group, the regions south of the Pacific Coast, The Bajío, Central Mexico, and south of the Yucatán Peninsula show  $RR > 1$ , indicating areas with higher risk than expected and, therefore, of greater interest. On the other hand, for the population 50 years old and older (right), there are more municipalities with exceptionally high risks (1.5 to 5.3), 341 out of 2,469 (13.8%), spreading from a central strip of Mexico to the Yucatán Peninsula.

The uncertainties in T2DM mortality risk in 2020 associated with the posterior means,  $p(\varsigma_{it} > 1 | \mathbf{y})$ , are shown in Fig. 4. The colors show municipalities with high (red) and low (green) probabilities. Notably, an increased risk, characterized by posterior probabilities surpassing 0.8 (excess risk), can be observed in Central Mexico and in the states of Oaxaca, Chiapas, and Tabasco for the population under 50 years of age (left). On the other hand, for the population 50 years old and older (right), an excess risk can be seen in Central Mexico, extending



**Fig. 3** Posterior mean for relative risks of T2DM mortality by municipality in Mexico, 2020. Population under 50 years of age (left) and those 50 years old and older (right)



**Fig. 4** Posterior probability of T2DM mortality by municipality in Mexico, 2020. Population under 50 years of age (left) and those 50 years old and older (right)

along the coast of the Gulf of Mexico, and encompassing the states of Chiapas, Campeche, Tabasco (southeast).

## Discussion

The assessment and identification of spatial distribution patterns associated with uncommonly high or low relative risks of mortality and morbidity are crucial for informing effective public health policies. However, conventional methodologies, although straightforward and efficient, often overlook the inherent spatial interdependence among geographical units [36]. Acknowledging the significance of addressing this relationship, we examined the spatial patterns of T2DM mortality across municipalities in Mexico and explored the main contextual factors linked to this cause of death in 2020.

Overall, the Standardized Mortality Ratio (SMR) results (Fig. 2) revealed notable geographic and age-specific patterns. Central Mexico and Yucatán Peninsula exhibited the highest excess mortality rates. For the population under 50 years of age, municipalities in Oaxaca had the highest T2DM mortality rates, while those

50 years old and older experienced the highest rates in Tlaxcala and Puebla. Socioeconomic factors, such as low levels of educational attainment, lack of health services, dietary deficiency, and marginalization, were positively associated with increased T2DM mortality risk. In contrast, GDP per capita showed a negative association (Tables 1 and 2). High-risk areas for T2DM mortality were prominent along the south of the Pacific Coast, The Bajío, Central Mexico, and southern Yucatán for the younger population, and along a central strip extending to the Yucatán Peninsula for the older population. Significant uncertainties in mortality risk were identified, with Central Mexico, Oaxaca, Chiapas, and Tabasco showing high probabilities of excess risk for those under 50 years of age and extended risk areas along the Gulf of Mexico for those 50 years old and older (Figs. 3 and 4).

One of the main findings was that the high-risk areas for T2DM mortality were in municipalities in the states of Chiapas, Tabasco, Oaxaca, Puebla, Guerrero, Tlaxcala, and Veracruz. According to CONAPO [33], these states are characterized by high levels of marginalization.

Furthermore, most of these states are characterized by low levels of overall educational attainment, high levels of food insecurity, and low levels of access to health services [38]. We also observed a relatively similar distribution of T2DM mortality risk among individuals under 50 years old and those 50 years old and older across municipalities in Mexico, although with a more homogeneous spatial pattern for the first age-group. This suggests that these states may harbor environments conducive to obesity and T2DM development, characterized by various factors that promote unhealthy lifestyles and elevated disease risk. These include high levels of marginalization, substandard diet quality, and limited access to healthcare services. Such conditions contribute to higher rates of obesity, a key risk factor for T2DM, leading to more severe disease progression and higher mortality rates owing to complications associated with poorly controlled diabetes.

We found that low levels of educational attainment are associated with higher risks of T2DM mortality. This finding aligns with existing research demonstrating that higher levels of education are associated with a reduced risk of developing T2DM and experiencing its complications [12, 14]. Lower levels of education may limit health literacy, which can lead to a poorer understanding of preventive measures, management strategies, and healthcare utilization related to T2DM [14]. This lower awareness may result in a delayed diagnosis, inadequate self-management, and higher mortality rates. Educational attainment also influences lifestyle behaviors that affect diabetes risk and mortality, such as diet quality, physical activity levels, and adherence to medical recommendations. Therefore, it is crucial to provide more educational resources to populations in high-risk regions to improve T2DM control [39].

We also found that a higher percentage of the population with dietary deficiencies had increased T2DM mortality. This finding aligns with other studies demonstrating that food availability [10] and food insecurity [25] are also associated with diabetes. Food insecurity often forces individuals to depend on low-cost, calorie-dense, nutrient-poor foods that are typically high in sugars, refined carbohydrates, and unhealthy fats [25]. These diets contribute to obesity and insulin resistance, which are primary risk factors for the development of T2DM. Poor access to healthy foods makes it difficult to maintain a healthy diet and has an adverse impact on diabetes care [12], which helps manage blood sugar levels. This can lead to poor glycemic control, increased complications, and higher mortality rates. Food availability, or lack thereof, is a significant source of chronic stress, which can contribute to the development of insulin resistance and T2DM. Chronic stress can lead to unhealthy eating behaviors, further increasing the risk of T2DM [40].

Moreover, heightened food insecurity impedes effective self-management diabetes. Stress associated with food insecurity may be related to a greater burden of diabetes [12].

An increase in municipal GDP per capita is associated with a decrease in the risk of T2DM mortality. As stated previously, GDP per capita is one of the most widely used socioeconomic predictors of mortality and health. This finding aligns with other studies that show that gross national per capita income is inversely linked to a rapidly growing trend of type 2 diabetes burden [5], that is, low- and middle-GDP areas have higher prevalence rates of T2DM [41, 42]. In areas with lower GDP, poor health awareness among diabetes patients often leads to significant delays in diagnosis and treatment, resulting in a severe burden of diabetes-related disability and complications [5]. People in these areas tend to have restricted access to high-quality nutritious foods, and instead consume high-calorie foods (often western-style), with low intake of fruits and vegetables, and high intake of sugar-sweetened beverages [43]. This can lead to obesity, accumulation of abdominal fat, and insulin resistance, which are strong risk factors for T2DM. In contrast, a higher GDP per capita usually correlates with better access to nutritious foods and positively impacts various health determinants crucial for the prevention and management of type 2 diabetes [42]. This leads to lower prevalence and better health outcomes in individuals with T2DM.

Finally, the results indicate that marginalization increases the risk of T2DM mortality. These outcomes align with those of other studies conducted in Mexico, which found that socioeconomic inequalities and higher rates of poverty are associated with a higher T2DM prevalence [44], and that the inequality gap in DM mortality between states has recently widened [45]. Marginalized populations often have reduced access to healthcare services, leading to delayed diagnosis and treatment of T2DM [46], and poorer compliance with diabetes treatment. This delay can result in more severe disease progression and higher mortality rates [47]. Economic constraints and limited access to healthy foods and recreational facilities can contribute to unhealthy diets and sedentary lifestyles, which are significant risk factors for T2DM [46]. Marginalized populations often face higher levels of stress owing to financial instability, unsafe living conditions, and social exclusion. Chronic stress can exacerbate the development of T2D [48], whereas financial barriers limit the ability to afford medications and regular medical check-ups, resulting in poor glycemic control and higher complication rates.

#### Limitations

The findings of this study should be interpreted with caution in light of these limitations. The first limitation

concerns data quality and availability. We used municipal-level data that may suffer from underreporting or misreporting in death certificates, leading to underestimation of T2DM mortality rates. Advanced and chronic type 2 diabetes mellitus leads to complications such as renal and coronary diseases, which are often the direct causes of death. Consequently, these conditions may ultimately be recorded as the primary cause of death [13]. To minimize underreporting, it is essential to emphasize the importance of physicians accurately completing death certificates [49]. Second, working with smaller populations can lead to a higher variability in mortality rates, making it difficult to detect significant trends or differences. Third, the associations analyzed in this study are based on aggregated data. We were unable to infer all identified associations at the individual or local level, as we used municipal-level variables. Thus, while our findings align with other spatial-epidemiological studies on T2DM, it is important that future research confirms whether the associations observed at the ecological level also hold true at the individual level [24]. Fourth, the analyses were conducted for 2020, an exceptional year for overall mortality due to the impact of the COVID-19 pandemic. As a result, it is important to interpret our findings within this context. We also recommend that future studies revisit this analysis in the coming years.

## Conclusion

In conclusion, this study on T2DM mortality in Mexico revealed statistically significant geographic patterns, with Central Mexico and the Yucatán Peninsula exhibiting the highest excess mortality rates. Socioeconomic factors, such as low levels of educational attainment, dietary deficiency, and marginalization, were positively associated with increased T2DM mortality risk, while GDP per capita showed a negative association. The Bayesian spatial model effectively captured spatial patterns of T2DM mortality. Despite limitations in data quality and availability, the findings highlight the crucial need to address T2DM risk factors at both individual and population levels to reduce the impact of this chronic disease in Mexico.

## Abbreviations

BMY	Besag-York-Mollie
CONAPO	Mexican Population Council
CONEVAL	National Council for the Evaluation of Social Development Policy
GDP	Gross domestic product
INEGI	National Institute of Statistics and Geography of Mexico
INLA	Integrated Nested Laplace Approximation
RR	Relative risk
SMR	Standardized Mortality Ratio
T2DM	Type 2 diabetes mellitus

## Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s13690-024-01432-z>.

## Supplementary Material 1

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### Author contributions

CADC contributed to the study design and the methodology, interpreted the results and prepared the original draft of the manuscript. EAB contributed to the study design and the methodology, performed the statistical analysis, interpreted the results and revised the manuscript. All authors approved the final version of the manuscript.

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The authors declare that no funds was received during the preparation of this manuscript.

### Data availability

No datasets were generated or analysed during the current study.

## Declarations

### Ethics approval and consent to participate

Not applicable.

### Consent for publication

Not applicable.

### Competing interests

The authors declare no competing interests.

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