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Unveiling historical data and socioeconomic drivers of disaster risk at national and municipal levels in Guatemala

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Abstract

Guatemala faces acute disaster vulnerability due to the combined effects of geological hazards, climatic variability, and socio-economic inequality. This study applies a mixed-method design, combining descriptive interpretation of disaster trends with quantitative statistical modeling to analyze disaster patterns and socio-economic drivers at national and municipal levels. National-scale disaster events (n = 171, 1902–2024) were obtained from EM-DAT, while municipal records (n = 11,256, 1988–2015) came from DesInventar. The analysis employed multiple linear regression, Poisson regression, and Random Forest models to identify predictors of disaster occurrence. Results indicate that total population (β = 0.00084, $p < 0.001$), road distance (β = −0.037, $p < 0.001$ in linear; β = 0.0016, $p < 0.001$ in Poisson), and Human Development Index (β = 118.2, $p < 0.001$) were consistently significant. Municipalities with higher population density and infrastructure, mostly urban areas, report more disasters, reflecting both greater exposure and improved reporting. Earthquakes and floods are the most lethal hazards, while hydrometeorological events show strong links to El Niño–Southern Oscillation variability, aggravating food insecurity and economic losses, particularly in rural and indigenous communities dependent on rainfed subsistence agriculture. The findings highlight the need for differentiated data-driven disaster risk reduction strategies that address both urban exposure and rural vulnerability. Key recommendations include strengthening early warning systems, improving infrastructure resilience, incorporating traditional knowledge into risk assessments, and integrating socio-economic indicators into national DRR planning to enhance Guatemala's preparedness and resilience.

Keywords: Disaster risk reduction, Hydrometeorological and seismic hazards, Socioeconomic vulnerability, Climate variability, El Niño South-Oscillation, Statistical disaster modeling

1 Introduction

Disasters have devastating impacts worldwide, but their effects are particularly severe in developing countries due to a combination of high vulnerability, socio-economic disparities, and inadequate institutional capacities as reported by Akram et al. [4]. Countries in these regions experience a disproportionate share of disaster-related losses, affecting lives, livelihoods, and infrastructure [26, 53]. Emphasis is placed on tropical countries because weather extremes such as excessive heat, droughts, floods, among others are more frequent in these countries, which also exhibit low-income economies [70]. The recurrence of extreme weather events, geological hazards, and environmental degradation exacerbates existing socio-economic inequalities, making recovery and building resilience challenging and increasing long-term vulnerability [7, 41, 51]. Additionally, climate change intensifies the frequency and magnitude of climate-related disasters, leading to significant humanitarian crises and economic setbacks. Understanding the historical patterns of vulnerability and underlying drivers of disasters in these regions is essential for developing targeted risk reduction strategies and improving adaptation measures at local and national levels [8].

Analyzing disaster trends at the national, sub-national, and municipal levels provides valuable insights into their temporal and spatial distribution, helping to identify patterns, high-risk areas, and socio-economic factors influencing disaster risk [22]. By examining how disasters impact different regions and populations over time, policymakers and researchers can develop more effective mitigation and adaptation strategies. Municipal-scale analyses allow for a more localized understanding of disaster impacts, recognizing that vulnerability and exposure vary significantly between urban, peri-urban, and rural areas. Additionally, spatial and temporal assessments can highlight regions where early warning systems (EWS), amongst other disaster risk reduction strategies, such as infrastructure improvements, and social programs are most needed, ultimately guiding evidence-based decision-making [18]. This research uses the framework of the risk triangle: hazard, exposure and vulnerability (Intergovernmental Panel on Climate Change [36]. This study aims to identify and quantify the socioeconomic and territorial drivers of disasters in Guatemala and to evaluate how these drivers interact with hazard occurrence to shape patterns of vulnerability. The proposed methodology explicitly assesses the extent to which specific variables intensify exposure and vulnerability under existing hazard conditions, thereby clarifying their role in explaining observed disaster impacts.

The use of disaster databases such as EM-DAT (https://www.emdat.be/) and DesInventar (https://www.desinventar.org/) is critical for understanding and analyzing historical disaster occurrences [57]. EM-DAT provides national-scale data on disaster events, allowing researchers to assess large-scale trends, economic losses, and overall mortality rates. In contrast, DesInventar offers a more localized perspective, enabling detailed municipal-level assessments of disaster frequency, magnitude, and impacts. Together, these databases facilitate a comprehensive examination of how disasters have evolved over time and how different hazards interact with socio-economic vulnerabilities. By leveraging both sources, this study seeks to bridge the gap between national-scale analyses and localized disaster risk assessments, ultimately improving disaster risk governance and policy planning in Guatemala [17].

Guatemala is highly susceptible to both geological and hydrometeorological hazards due to its geographical location. In addition, a significative difference of socio-economic conditions among its population in which increasing immiseration and concentration of wealth is related to different levels of exposure and vulnerability to disasters [19]. The country experiences frequent earthquakes, volcanic eruptions, storms, hurricanes, floods, landslides, and droughts exacerbated by its complex topography and climatic variability. Guatemala ranks among the countries with the highest risk to disasters ranking 44th worldwide according to the World Risk Report 2024 [11]. Additionally, the country is highly vulnerable to prolonged dry periods, often linked to the El Niño–Southern Oscillation (ENSO), which, amongst other things, disrupts agricultural production and food security [45]. The combination of environmental, social, economic, and institutional challenges intensifies disaster risk, affecting millions of people each year [65]. In addition, the country's 22 indigenous groups have unique risk perceptions and traditional knowledge, which should be incorporated into municipal and national Disaster Risk Reduction (DRR) strategies [10].

Statistical models integrating hazard, exposure, and vulnerability factors provide valuable insights into the drivers of disaster risk [55]. While hazards define the potential threat (using historical disasters occurrence), exposure—measured through population density and infrastructure—determines what is at risk, and vulnerability—linked to socioeconomic conditions—influences the severity of impacts and the capacity to recover from them. In the future, it is necessary to consider the key risks and reasons for concern, instead of only considering the realized risks and observed impacts due to prioritize informed decisions of adaptation related responses [47]. By analyzing these factors together, such models help identify key predictors of disaster occurrences, guiding risk reduction strategies, resource allocation, and resilience planning [23, 52].

Despite existing studies on disaster impacts, empirical evidence at the municipal scale in Guatemala remains limited regarding how socio-economic factors such as population, infrastructure, and inequality interact with natural hazards to shape disaster occurrence and impacts, rather than acting as sole or universal drivers of disasters. This study addresses that gap by combining national and municipal disaster databases with statistical models to identify key predictors of disaster frequency. In doing so, it provides a more localized understanding of disaster drivers, offering actionable insights for policymakers to strengthen disaster risk reduction (DRR) and adaptation strategies tailored to Guatemala's diverse socio-economic and geographic contexts. This research is guided by the following question: What are the historical trends of disasters in Guatemala from 1902 to 2024? Furthermore, it goes beyond previous studies that mainly focused on descriptive examples of disaster impacts.

This study aims to unveil historical disaster patterns and analyze the socio-economic drivers influencing disaster risk at national and municipal levels in Guatemala. Specifically, the objectives are: (i) to conduct a national-level analysis using the EM-DAT database to identify long-term disaster trends, (ii) to perform a local-scale analysis using the DesInventar database to examine disaster frequency and impacts at the municipal level, and (iii) to apply three statistical models—multiple linear regression, Poisson regression, and Random Forest—to the local dataset in order to determine the most relevant predictors of disaster totals. The results will allow stakeholders to anticipate which drivers are most strongly associated with future negative impacts, providing critical inputs for developing disaster risk reduction (DRR) strategies tailored to the municipal level.

2 Materials and methods

This study focuses on the totality of Guatemala, with emphasis in each of the 340 municipalities of the country. Using a mixed-methods approach that integrates qualitative and quantitative analyses, this study examines the spatial and temporal distribution of disasters, identifies key risk factors, and provides evidence-based recommendations for disaster risk reduction. The findings will contribute to a better understanding of how historical disasters have shaped Guatemala's vulnerability and resilience, supporting future disaster preparedness and policy interventions.

2.1 Study area

Guatemala's geological and tectonic features make it highly prone to seismic and volcanic activity. The country lies along the convergent margin of the Caribbean and Cocos plates and the conservative margin of the Caribbean and North American plates, leading to frequent earthquakes and active volcanism. The Motagua-Polochic fault system, a major transform fault, extends across the country, generating significant seismic hazards [31]. Guatemala's lithology is diverse, comprising volcanic deposits, sedimentary formations, and metamorphic rocks, which increases landslide susceptibility and soil fertility. The presence of more than 30 volcanoes, including active ones such as Fuego, Pacaya, and Santiaguito, further amplifies the geological hazards faced by the country [60]. Additionally, steep slopes and deeply incised valleys contribute to frequent mass movements, particularly during heavy rainfall events.

Guatemala's climate is characterized by significant spatial and temporal variability, influenced by elevation, latitude, rain-shadow effects from high mountains, and proximity to water bodies. The country experiences a bimodal climate with a dry season from November to April and a rainy season from May to October, with regional variations [33, 43] and a relative minimum between July and August known as the Midsummer Drought or commonly known as *veranillo* or *canícula*, in Spanish [42]. The Pacific lowlands have a tropical savanna climate, while the highlands exhibit temperate conditions with cooler temperatures. The El Niño–Southern Oscillation (ENSO) significantly affects rainfall patterns, leading to changes in the seasonality of the rainy season which results in seasonal droughts or intense storms that impact agricultural production, water availability, and hydroelectric generation, amongst others. Guatemala's hydrographic network consists of numerous rivers, including the Motagua, Polochic, and Usumacinta, which are vital for irrigation, hydropower, and ecosystem functions. However, deforestation, soil degradation, overuse, and urban expansion have increased vulnerability to floods, erosion, and water scarcity [69].

The country's diverse landscapes support a variety of ecosystems and land uses, ranging from tropical rainforests in the northern lowlands to pine-oak forests and agricultural lands in the highlands. Guatemala's life zones, classified by Holdridge's system, include tropical moist forests, subtropical forests, and cloud forests, each supporting distinct biodiversity [49]. Soils vary significantly, with fertile volcanic soils favoring agricultural activities, while degraded and shallow soils in mountainous areas limit productivity. The economy is primarily driven by agriculture, manufacturing, and services, with coffee, bananas, and sugar among the main exports. Guatemala City, the capital and largest urban center, concentrates economic and political activity, while other major cities, such as Quetzaltenango and Escuintla, play key roles in regional development. With a population exceeding 17 million, Guatemala faces significant socio-economic challenges, including high poverty rates and levels, inequality, and rural–urban disparities, which exacerbate disaster vulnerability and complicate risk management efforts, in specific in Mayan indigenous communities which accounts for 43,75% of the population of the country [34, 64]. Guatemala has 22 departments (regional units) and 340 municipalities (local units).

2.2 Research design and ethical considerations

This study adopted a mixed-method design combining descriptive/qualitative and quantitative approaches. The qualitative aspect consisted of the classification, interpretation, and contextualization of disaster events at national and municipal scales, while the quantitative aspect relied on statistical and machine-learning models to identify predictors of disaster occurrence. Disaster databases (EM-DAT and DesInventar) are internationally recognized and widely used in disaster risk studies. To ensure reliability, only records meeting established EM-DAT criteria (≥10 deaths, ≥100 affected, international assistance, or state of emergency) were included. While EM-DAT records were filtered using its standard inclusion criteria, DesInventar records were not subjected to these thresholds due to their distinct purpose of documenting local-scale disaster events. For DesInventar, data cleaning involved removing incomplete or inconsistent entries, cross-checking events with official national reports where possible, and standardizing classification codes. Multiple analysts reviewed the processed data to minimize bias and error.

The study relied exclusively on publicly available secondary data (EM-DAT and DesInventar). No personal, sensitive, or identifiable information was used. Therefore, ethical risks were minimal. The analysis was conducted under institutional guidelines of the University of Costa Rica for the responsible use of open-source and secondary datasets. No specific institutional review board (IRB) approval was required as the study did not involve human participants.

2.3 National disaster profile

This study conducts a mixed-method analysis, combining descriptive interpretation of disaster categories with quantitative statistical modeling of the distribution and occurrence of disasters in Guatemala, utilizing data from various sources to examine the frequency, magnitude, and spatial distribution of catastrophic events in detail. National-scale disaster event records were obtained from EM-DAT, managed by the Centre for Research on the Epidemiology of Disasters (CRED), which compiles comprehensive global data on disaster events. With extensive coverage and detailed records, it serves as a robust indicator for analyzing the frequency and impact of disasters across different regions.

The database used for this study includes 171 disaster events that met at least one of the following criteria: at least 10 fatalities, 100 affected people, an international assistance request, or a state of emergency declaration (CRED, 2024). The analyzed timeframe spans from 1902 to 2024, covering major disasters that significantly disrupted key departments or municipalities.

Disaster cause group were classified following the EM-DAT scheme into hydrological, geophysical, meteorological, climatological, biological, transport, industrial, and miscellaneous categories. Meteorological disasters are associated with short-term atmospheric processes such as storms and extreme rainfall, whereas climatological disasters reflect longer-term climate anomalies, including droughts and heatwaves. Hydrological and geophysical disasters originate from water-related and solid Earth processes, respectively, while biological and technological categories encompass disease outbreaks and human-induced accidents. Events reported by disaster type are classified as flood, road (accidents), storm, earthquake, volcanic activity, mass movement, epidemic, drought, air (pollution), extreme temperature, fire (structural), wildfire, and others.

EM-DAT data was processed using R Studio to identify key trends in national disasters. Events were categorized by type, chronological occurrence, total affected population, adjusted total damage, and total fatalities. Descriptive statistics, such as percentages and frequencies, were employed to classify and summarize disaster occurrences by type. Temporal patterns were further examined through data visualization techniques, including the creation of graphs.

2.4 Local disaster analysis

This methodology follows a systematic series of procedures for obtaining, cleaning, processing, and analyzing disaster data documented in the DesInventar database, which obeys to a Disaster Inventory System (as it can be consulted in their website: https://www.desinventar.org/). This database allows researchers to visualize disasters in a local spatial distribution at a municipal level, identifying trends, categorizing disasters by type, and interpreting patterns of human impact. It also facilitates the visualization of disasters to enhance DRR dialogs within stakeholders at different government levels. The database includes information about losses and damages related to emergencies and disasters and it has a flexible database structure, and its information is provided by data, maps, graphics, among others.

The local disaster analysis covers the period from 1988 to 2015 which is the DesInventar database timeframe. Data processing was performed using RStudio (version 2023.12.0 + 369), utilizing tools such as *tidyr*, *DescTools*, *ggplot2*, and *dplyr*, to optimize the organization, analysis, and visualization of information. The historical dataset was extracted from the DesInventar platform, containing records of disaster events classified by department and municipality in Guatemala (see Supplementary material). This database spans 27 years (1988–2015) and includes various types of disasters: hydrometeorological, geological, biological, and anthropogenic.

Data were cleaned by removing incomplete records, such as those lacking dates or precise spatial information at the municipal or departmental level. Standardization and data wrangling were performed in R using the tidyr and dplyr packages to correct typographical errors, harmonize disaster classifications, and normalize textual attributes, ensuring consistent event categorization. The cleaned data were aggregated by department, municipality, and year, and descriptive statistics were computed using functions from the DescTools package to characterize spatial and temporal patterns of disaster occurrence and identify areas with relatively higher or lower event frequency. Graphical analyses supporting these interpretations were produced using ggplot2.

The human impact of disasters was assessed using the death and injury columns, which were aggregated by department to sum the figures for fatalities and injuries in each region. The data were transformed into a long format to create comparative graphs showing disaster severity in terms of human impact. Disasters were classified into five main categories: Hydrometeorological (tropical storms, floods, droughts, and hurricanes), Geological (earthquakes, landslides, and volcanic eruptions), Biological (plagues), Anthropogenic (explosions, forest fires, infrastructure failures, negligence, and deforestation). Other events are explosions, short circuits, leaks, negligence, failure, design error, deforestation, human errors, behavior, localization and deterioration of the environment. Unknown are the events with insufficient information for classification.

Maps were produced to depict the spatial distribution and frequency of disaster events. Classifications included the evaluation of additional indicators such as HDI and GDP, among others. The results obtained through statistical and graphical analyses were interpreted to identify patterns in disaster occurrences, evaluating the frequency of specific types in determined geographic areas. Additionally, the impact in terms of mortality and injuries was discussed, highlighting the most vulnerable regions and exploring potential underlying causes of these trends.

2.5 Statistical models

This study employed a comprehensive statistical approach to identify the most relevant variables that explain disaster totals (DIS) at the municipal level. Following the IPCC (2014), disaster risk is defined as risk = hazard × exposure × vulnerability. In this study, hazards are represented by historical disaster records, exposure by population and infrastructure variables, and vulnerability by socio-economic indicators such as GDP and HDI. The analysis involved four main components: a correlation matrix, a multiple regression model, a Poisson regression model, and a Random Forest model. All analyses were conducted using R software (version 2023.12.0 + 369), and key packages such as stats, MASS, and randomForest were used to implement the models.

The analysis began with a correlation matrix to assess the linear relationships among the variables and to identify potential multicollinearity issues. Correlation matrices were computed using the cor() function in R. This step allowed for a preliminary understanding of how variables like total road distance (RT), road density (RD), population total (POB), population density (PD), Gross Domestic Product per capita (GDP), land use category (LUC), and Human Development Index (HDI) relate to disaster totals (DIS). These are the most consistently available and standardized data for Guatemala. A visual representation of the correlations was created using the corrplot package, which provided insights into the strength and direction of these relationships.

A multiple linear regression model was developed to quantify the impact of the explanatory variables on disaster totals (DIS). This model was implemented using the lm() function from the stats package, with DIS as the dependent variable and RT, RD, POB, PD, GDP, LUC, and HDI as independent variables. The regression model provided coefficients, standard errors, t-values, and *p*-values to assess the statistical significance of each predictor. Diagnostic plots were also generated to evaluate model assumptions such as linearity, homoscedasticity, and normality of residuals. All the variables used are available in the Supplementary material.

Given that DIS represents count data, a Poisson regression model was constructed using the glm() function from the MASS package, specifying the Poisson family. This model was appropriate for examining the relationship between disaster counts and the explanatory variables while accounting for the non-normal distribution of count data. The coefficients and associated z-values were analyzed to identify significant predictors, and the model's goodness-of-fit was evaluated using the residual deviance and Akaike Information Criterion (AIC).

To capture non-linear relationships and assess the importance of each variable in predicting disaster totals, a Random Forest model was applied using the randomForest package. The model was trained with 500 trees (ntree = 500), using DIS as the response variable and RT, RD, POB, PD, GDP, LUC, and HDI as predictors. A total of 500 trees were used in the Random Forest model to ensure result stability and minimize overfitting, following common practice for balancing predictive accuracy and computational efficiency. The importance of each variable was evaluated based on *IncNodePurity*. The Random Forest model provided a robust assessment of variable importance, especially in the context of complex and potentially non-linear relationships among predictors.

3 Results

3.1 Guatemala national disaster profile

The analysis of EM-DAT recorded data of Guatemala for 1902–2024. In total and over this time, the database reports that these disasters have resulted in 81,583 fatalities, affected over 27 million people, and caused economic losses exceeding 12 million USD. However, EM-DAT primarily captures large-scale events, and smaller, localized disasters are likely underrepresented, which may lead to an underestimation of cumulative economic losses. At first glance, 1976 appears as the year in which damage due to disasters has the biggest economic impact (around USD 5.400.000.000) mainly derived from the very intense earthquake that impacted most of the country early that year. Recent years such as 1998, 2005 and 2010 also report economic impacts above USD 1.200.000.000 (Fig. 1). Many hurricanes and heavy rainfall affected the region that decade, most notably Mitch (1998), Stan (2005) and Agatha (2010).

Figure 2 shows that the principal disasters in Guatemala are hydrological (30%) and geophysical (19%) in first and second place. Meteorological and climatological disasters also stand out with 15 and 6% respectively. In addition, Fig. 3 confirms that floods are the events that had been reported more frequently during 1902–2024. Road impacts, storms and earthquakes appear to be trending in the reports gathered. Hydrological and seismological events may have impacts in infrastructure such as road density.

Communications infrastructure, such as roads, are highly vulnerable to damage caused by different types of disasters in Guatemala. The topography of the country and the volcanic nature of soil in large parts of its territory increases their vulnerability during hydrometeorological, seismic and volcanological events, among others.

Total damage in '000 U.S. dollars by cause group in Guatemala for 1902–2024 is shown in Fig. 4. Most of the total damage was caused by geophysical, hydrological, meteorological and climatological disasters. Geophysical disasters are the ones that caused more than 50% of the economic impact in 1902–2024. Disasters of this type include landslides, lahars, volcanic eruptions, floods, among others. Deaths at a

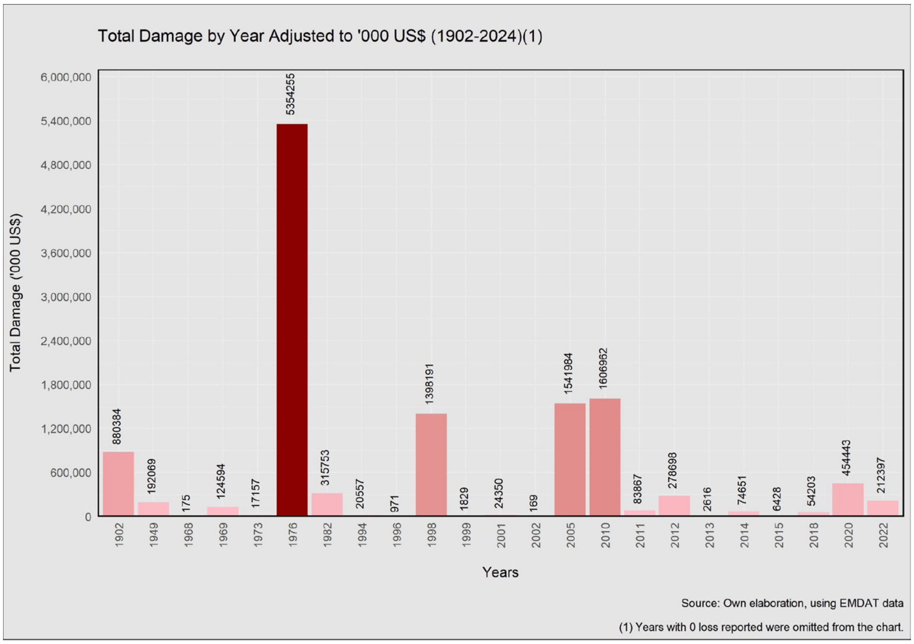

Fig. 1 Total damage by year in Guatemala adjusted to '000 U.S dollars for 1902–2024. Source: EMDAT

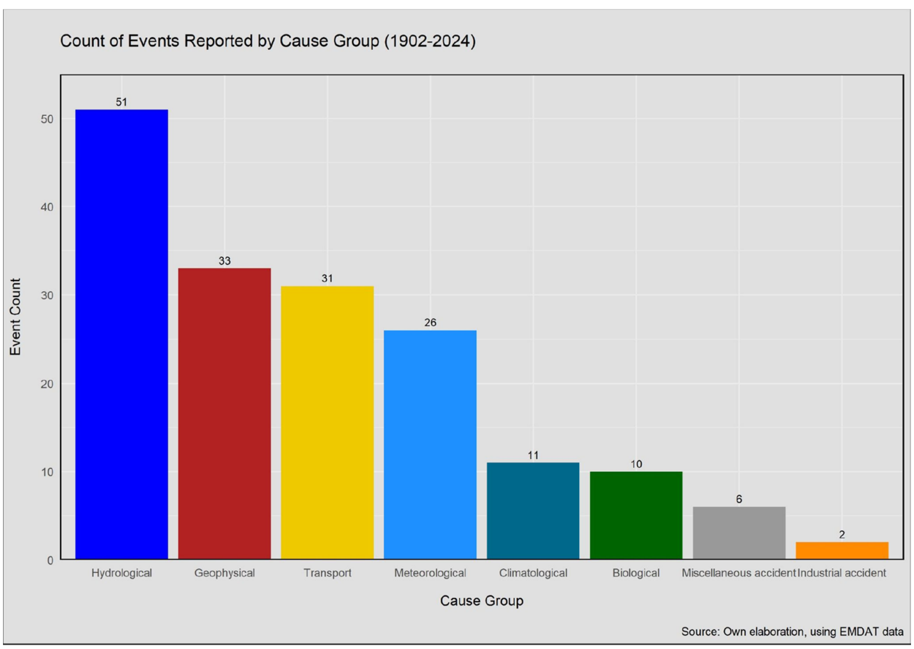

Fig. 2 Count of events reported by cause group in Guatemala for 1902–2024. Source: EMDAT

national level due to disasters are mainly caused by floods ($n = 41.074$), earthquakes ($n = 27.729$) and volcanic activity ($n = 7.461$).

Meteorological disasters were responsible for 35% of the total damage by cause group, and Hydrological and Climatological disasters accounted respectively for 12

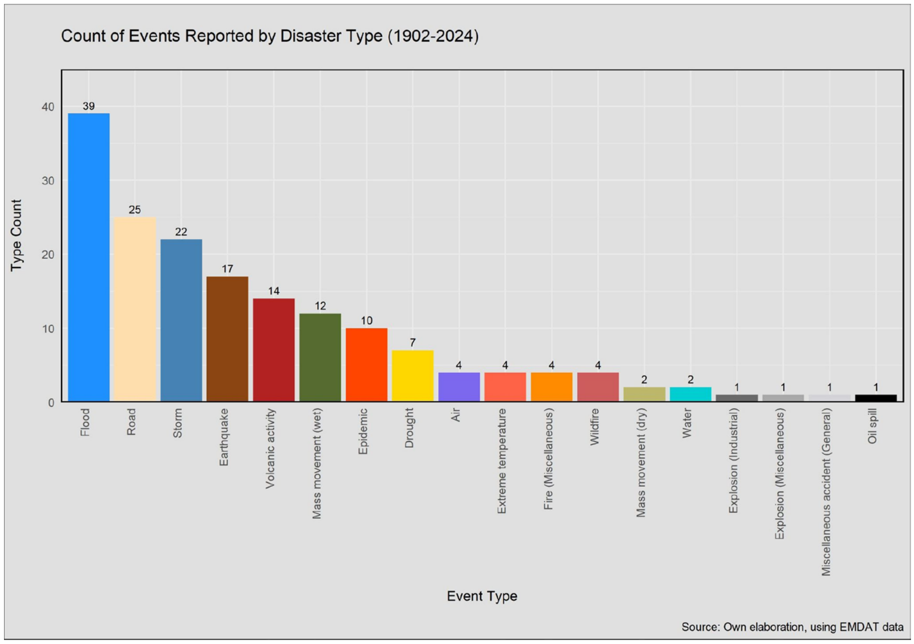

Fig. 3 Count of events reported by disaster type in Guatemala for 1902–2024. Source: EMDAT

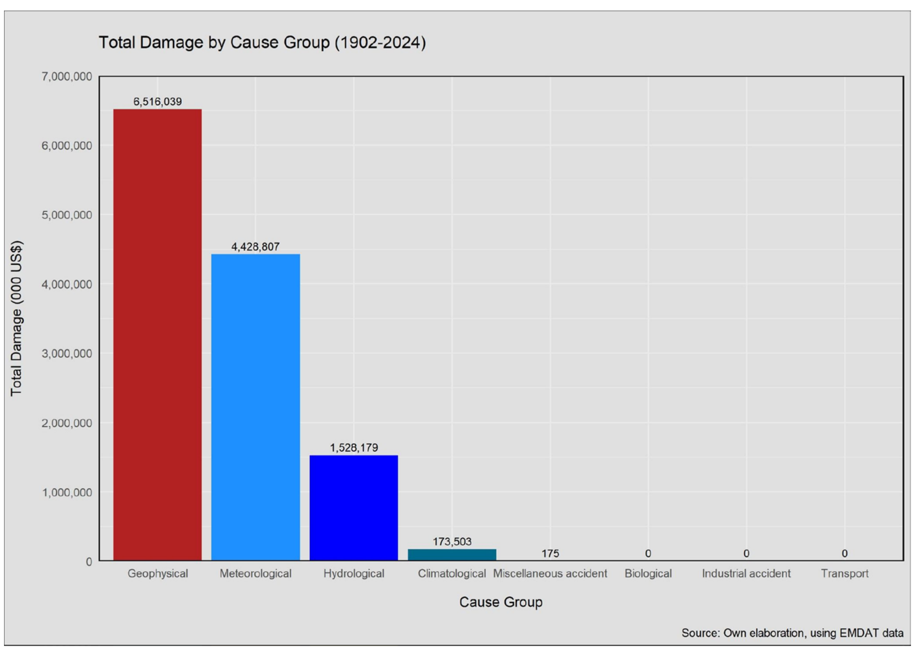

Fig. 4 Total damage in '000 U.S. dollars by cause group in Guatemala for 1902–2024. Source: EMDAT

and 1% of the total damage in this category. Other types of disasters such as biological, industrial and transportation were neglectable when measuring the total damage by cause group in 1902–2024.

Floods, earthquakes, volcanic activity and storms are responsible for the total deaths caused by disasters at a national level. Other event types, such as mass movements (i.e. landslides), droughts and extreme temperatures, account for a smaller number of deaths than the total ones by event type.

3.2 Municipal-scale analysis

DesInventar disaster records at the departmental and municipal scales cover the period 1988–2015. At the departmental level, Guatemala Department reported the highest number of disaster events, followed by Escuintla and Quetzaltenango, each exceeding 400 events. This pattern is closely associated with population density and economic concentration, as Guatemala hosts the country's largest metropolitan area, Quetzaltenango is the core of the second largest urban region, and Escuintla plays a strategic role in national trade due to its proximity to Puerto Quetzal. Departments such as Alta Verapaz and San Marcos, characterized by high vulnerability, population density, and similar geophysical settings, also recorded elevated disaster frequencies (Fig. 5).

At the municipal scale, Guatemala City and its surrounding municipalities—notably Mixco and Villa Nueva—accounted for the highest number of disaster events between 1988 and 2015, representing 52% of all municipal-level disasters (Figs. 6 and 7). These municipalities form the country's main metropolitan area and share comparable geophysical conditions, while differing in socioeconomic characteristics, particularly poverty levels in Villa Nueva. Additional municipalities such as Puerto Barrios and Panzós reported more than 90 events, reflecting exposure to hydrometeorological hazards from the Caribbean and, in the case of Panzós, the influence of extreme rainfall despite its predominantly rural character.

Temporally, disaster occurrence peaks in 1998 and 2014, with subsequent years also showing above-average event counts. The 1998–1999 La Niña episode coincided with increased floods and landslides, amplified by the impacts of Hurricane Mitch,

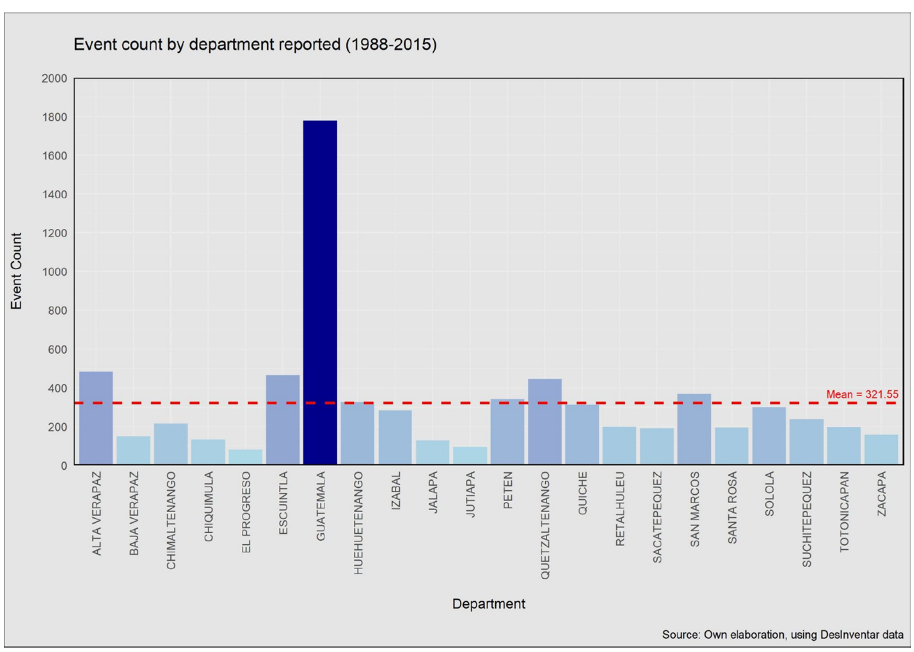

Fig. 5 Event count by department reported in Guatemala for 1988–2015. Source: DesInventar

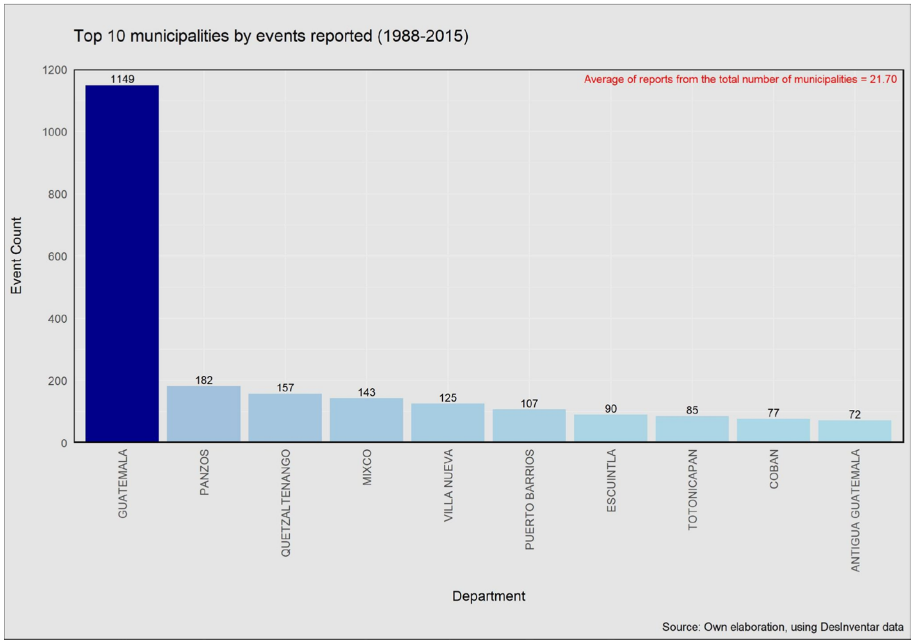

Fig. 6 Top ten municipalities by event reported in Guatemala for 1988–2015. Source: DesInventar

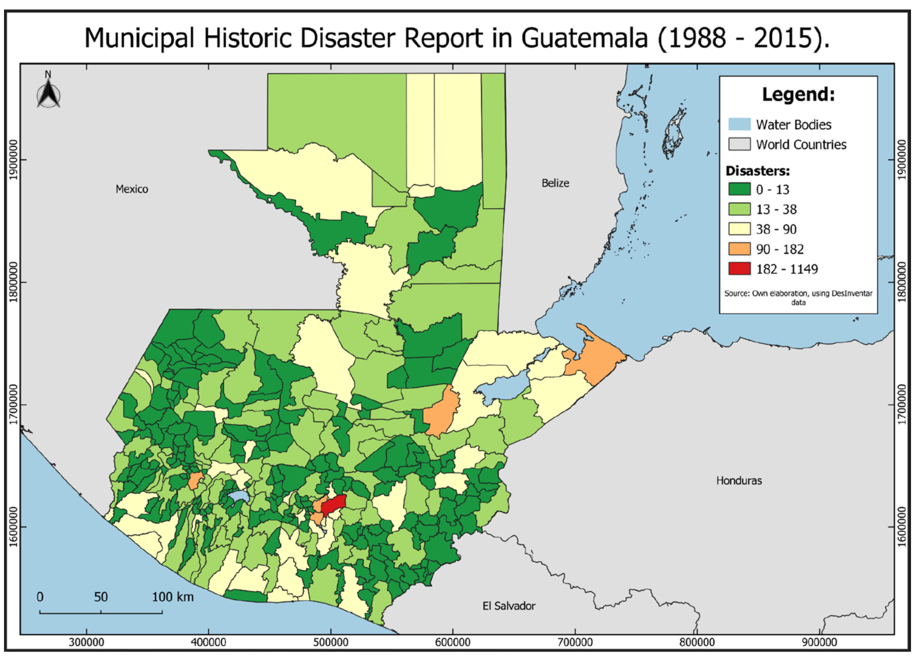

Fig. 7 Spatial distribution of the municipal historic disasters reported in Guatemala for 1988–2015. Source: DesInventar

the most devastating event in recent Central American history. Conversely, the 2014–2015 El Niño period is associated with droughts and extreme temperature events. These findings highlight how major climatic extremes and landmark disasters can increase vulnerability over prolonged recovery periods.

Hydrometeorological events accounted for 64% of all disasters during 1988–2015, while other hazard types represented 19%. Guatemala, Quiché, and San Marcos recorded the highest numbers of injured individuals, with Guatemala and San Marcos also reporting the highest mortality. In San Marcos, this pattern reflects a combination of seismic exposure, socioeconomic stressors, and geographic location. Similarly, Quiché and San Marcos, located in the Guatemalan highlands with annual precipitation ranging from 900 to 2000 mm and mean temperatures between 10 and 18 °C, are highly prone to floods, landslides, and frost events, with poverty levels near 66% further increasing vulnerability.

Economic exposure is concentrated in urban and industrial municipalities within the metropolitan area, including Villa Canales, Petapa, San José Pinula, Fraijanes, Guatemala, and Mixco, which rank among the top municipalities by GDP. High GDP values are also observed in the Pacific and Caribbean regions, linked to port infrastructure, and in Occidente and the Central Highlands, where topography supports productive agricultural systems. Cobán stands out as the principal economic center in northern Guatemala, driven by coffee, cardamom, and cocoa production.

Municipalities with the highest Road Density (RD)—including Mixco (11.01), Guatemala (10.86), and Villa Nueva (10.73)—are concentrated in the metropolitan region, indicating greater response capacity. High RD values are also observed in Quetzaltenango, Salcajá, and La Esperanza, reinforcing the link between infrastructure density and economic importance. Notably, road-related landslide impacts affected only 490 people between 1902 and 2024, suggesting that RD and total road length may reduce, rather than exacerbate, vulnerability—an assumption explored statistically in subsequent analyses.

Population exposure remains strongly concentrated in Guatemala City, with over 1.2 million inhabitants, followed by municipalities such as Mixco, Quetzaltenango, Cobán, and Escuintla. High population densities are also observed in coastal municipalities near Puerto Quetzal and Puerto Barrios, increasing exposure to tropical cyclones. The highest population density values occur in Petapa, Mixco, Guatemala, and Villa Nueva, while secondary clusters appear in the highlands, including Quetzaltenango, Salcajá, and La Esperanza, where disaster risk reduction strategies should be prioritized.

Finally, Human Development Index (HDI) values range from 0.75 to 0.79 among the top municipalities, with Guatemala, Mixco, and Petapa ranking highest. In contrast, municipalities in Huehuetenango, Alta Verapaz, and Sayaxché (Petén) exhibit lower HDI values (0.50–0.56), reflecting persistent poverty and heightened vulnerability. These spatial contrasts underline how disaster impacts in Guatemala emerge from the interaction between hazard exposure, population concentration, infrastructure, and uneven socioeconomic development.

3.3 Statistical analysis

The correlation matrix (Fig. 8) shows various relationships between the independent variables and the Disasters observed (DIS) at the municipal level. The variable POB exhibits a significant positive trend with DIS, supporting the idea that more populated districts experience more disasters due to greater exposure. In contrast, the relationship with PD is less direct; while some densely populated areas face higher risk, others may

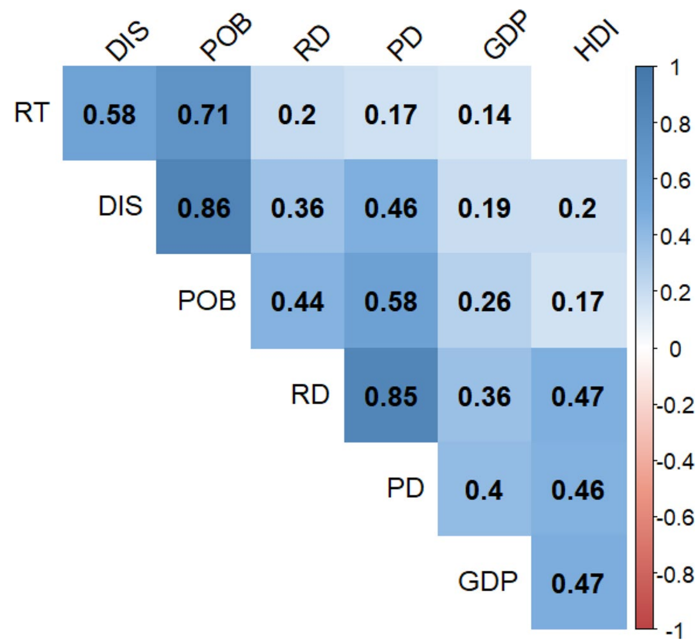

Fig. 8 Correlation matrix of the total number of disasters occurring by municipality and other socioeconomic factors. Variables: *RT* road distance, *RD* road density, *POB* population total, *PD* population density, *GDP* gross domestic product per capita, *HDI* Human Development Index related to *DIS* disaster totals

benefit from better infrastructure and preparedness, highlighting the need for context-specific analysis.

The variable RT presents a negative relationship with DIS, suggesting that in regions with a larger road network, the impacts of disasters may be lower, possibly due to improved access and faster response capacity. In contrast, RD does not show a clear correlation with DIS, indicating that the mere presence of roads does not necessarily reduce vulnerability. GDP and HDI variables show mixed relationships with DIS. While a higher HDI is associated with an increase in disasters, this could reflect a higher occurrence of events in more developed areas, highlighting the complexity of these socioeconomic factors in explaining disasters. GDP shows a positive correlation with disaster frequency, possibly due to greater exposure and event reporting in economically active areas.

In this study, a multiple linear model was employed to assess the socioeconomic and geospatial factors that best explain the occurrence of total disasters (DIS) in a country (Table 1). Using municipal data, the explanatory variables included total road distance (RT), road density (RD), total population (POB), population density (PD), gross domestic product per capita (GDP), human development index (HDI), and categorized land use (LUC). The model explained 76.81% of the observed variability in TDI, with an adjusted R-squared of 76.32%, indicating a robust fit and significant predictive capacity. The overall significance of the model (F-statistic = 156.6, $p < 2.2\text{e}{-16}$) highlights the relevance of the selected variables in explaining the occurrence of disasters at the municipal level.

The results show that total population (POP) and human development index (HDI) are key predictors, with highly significant positive coefficients ($p < 0.001$). This suggests that areas with higher population and human development experience a higher number of reported disasters, possibly due to higher exposure and density of

Table 1 Multiple regression model

Model terms	Estimate	Std. error	t value	Pr(>|t|)
(Intercept)	−7.854e+01	2.042e+01	−3.846	0.000144***
RT	−3.736e−02	1.073e−02	−3.482	0.000564***
RD	2.939e+00	2.023e+00	1.453	0.147234
POB	8.401e−04	4.187e−05	20.063	<2e−16***
PD	−2.006e-02	5.746e−03	−3.490	0.000547***
GDP	−7.843e−04	4.440e−04	−1.766	0.078273#
HDI	1.182e+02	3.454e+01	3.423	0.000697***
LUC	1.900e−01	4.744e−01	0.400	0.689061

Variables: *RT* road distance, *RD* road density, *POB* population total, *PD* population density, *GDP* gross domestic product per capita, *HDI* Human Development Index related to *DIS* disaster totals

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '#' 0.1 '' 1. Residual standard error: 31.88 on 331 degrees of freedom. 1 observation deleted due to missingness. Multiple R-squared: 0.7681, Adjusted R-squared: 0.7632, F-statistic: 156.6 on 7 and 331 DF, *p*-value: <2.2e−16

Table 2 Poisson regression model

Model terms	Estimate	Std. error	z value	Pr(>|z|)
(Intercept)	5.945e−01	1.578e−01	3.767	0.000165***
RT	1.626e−03	4.828e−05	33.680	<2e−16***
RD	−3.156e−02	1.157e−02	−2.728	0.006375**
POB	9.058e−08	1.341e−07	0.676	0.499252
PD	1.454e−04	2.909e−05	4.998	5.78e−07***
GDP	4.290e−07	2.887e−06	0.149	0.881871
HDI	2.996e+00	2.616e−01	11.455	<2e−16***
LUC	−3.521e−02	3.847e−03	−9.151	<2e−16***

Variables: *RT* road distance, *RD* road density, *POB* population total, *PD* population density, *GDP* gross domestic product per capita, *HDI* Human Development Index related to *DIS* disaster totals

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '#' 0.1 '' 1. Dispersion parameter for Poisson family taken to be 1. Null deviance: 13,626.4 on 338 degrees of freedom. Residual deviance: 3740.6 on 331 degrees of freedom. 1 observation deleted due to missingness. AIC: 5151.4; Number of Fisher Scoring iterations: 5.

infrastructure susceptible to damage. On the other hand, population density (PD) had a significant negative effect, indicating that densely populated areas might have better adaptation measures or infrastructure better prepared to face disasters. In contrast, total road distance (RT) was negatively associated with DIS. However, variables such as road density (RD) and land use (LUC) were not statistically significant, suggesting that their impact on disasters might depend on the lack of reliable roads or access to vehicles for some people, in specific those not in or near urban centers, and these facts are not captured by the simple linear model.

The generalized linear model (GLM) with Poisson distribution was used to analyze the relationship between total disasters (DIS) and various socioeconomic and geospatial variables at the municipal level (Table 2). The analysis revealed that several variables are significant in predicting the occurrence of disasters. The variable RT (total road distance) showed a highly significant positive coefficient ($p < 2e{-}16$), indicating that greater road connectivity is associated with an increase in the incidence of disasters. This may reflect greater exposure to areas with developed infrastructure or more frequent reporting of events in these regions. In contrast, road density (RD) had a significant negative coefficient ($p = 0.006375$), suggesting that greater road density could be related to better disaster response or mitigation capacity.

Furthermore, population density (PD) was also positively associated with DIS ($p < 0.001$), implying that more densely populated areas face a higher risk of disasters, possibly due to a higher concentration of vulnerable people and infrastructure. The Human Development Index (HDI) showed a strong significant positive effect ($p < 2e{-}16$), which may reflect that regions with higher human development are more exposed to or better record disasters, highlighting the complexity in the interaction between development and risk. On the other hand, Land Use Categorization (LUC) presented a highly significant negative effect ($p < 2e{-}16$), which could indicate that certain types of land use are associated with lower disaster rates, perhaps due to more effective land management practices. Variables such as POB (total population) and GDP (gross domestic product per capita) were not statistically significant, suggesting that their influence on disaster occurrence is less direct or is moderated by other factors.

The most important variable in the Random Forest model is POB (total population), with an IncNodePurity value of 474,913.203 (Table 3). This indicates that total population has the largest impact on reducing node impurity in the forest, suggesting that it is a key predictor of total disasters. This is consistent with the idea that areas with a higher population are more exposed to disasters, due to a higher concentration of susceptible people and assets.

The second most influential variable is RT (total road distance), with a value of 418,280.876. This could imply that the extent of the road network is a significant factor, possibly related to access to areas and disaster response capacity. HDI (Human Development Index) also shows a significant contribution (145,523.374), suggesting that regions with higher human development experience more disasters, perhaps due to better documentation or more exposed infrastructure. On the other hand, variables such as GDP (gross domestic product per capita) and LUC (Land Use Categorization) have lower IncNodePurity values, indicating that they have a lower impact on predicting total disasters in this model.

Based on the results from the linear regression, Poisson regression, and Random Forest models (Fig. 8; Table 4), key variables emerge as significant predictors of disaster totals (DIS) at the municipal level. Across all three models, population total (POB) consistently stands out as a highly relevant factor. The linear regression indicates a strong positive relationship, suggesting that higher population levels increase the likelihood and impact of disasters, likely due to greater exposure and the concentration of vulnerable assets. The Random Forest model further supports this, ranking POB as the most important variable, with the highest IncNodePurity, emphasizing its critical role in disaster occurrence. This highlights the need for disaster risk management strategies to prioritize highly populated areas to reduce potential impacts effectively (Table 5).

Table 3 Random forest increasy node purity (IncNodePurity)

RT	RD	POB	PD	GDP	LUC	HDI
418,280.876	83,614.173	474,913.203	110,727.876	33,532.893	2856.474	145,523.374

Table 4 Statistically significant predictors across three modeling approaches: linear regression, Poisson regression, and random forest

Variable	Multiple regression (Estimate, *p*)	Poisson regression (Estimate, *p*)	Random forest (IncNodePurity)
RT	−0.03736, $p = 0.000564$***	+0.001626, $p < 2e{-}16$***	418,280,876
PD	−0.02006, $p = 0.000547$***	+0.0001454, $p = 5.78e{-}07$***	110,727,876
HDI	+118.2, p = 0.000697***	+2.996, $p < 2e{-}16$***	145,523,374
POB	+0.0008401, $p < 2e{-}16$***	–	474,913,203
RD	–	−0.03156, $p = 0.006375$**	83,614,173
LUC	–	−0.03521, $p < 2e{-}16$***	2856,474

Variables: *RT* road distance, *RD* road density, *POB* population total, *PD* population density, *GDP* gross domestic product per capita, *HDI* Human Development Index related to *DIS* disaster totals

Table 5 Summarize of the key quantitative findings to clarify main causal pathways

Variable	Linear regression	Poisson regression	Random forest	Interpretation
Road distance (RT)	↓ Disasters (negative)	↑ Disasters (positive)	High importance	Fewer roads = delayed response (higher impact); more roads = greater exposure and reporting
Road density (RD)	–	↓ Disasters	Moderate importance	Denser networks may reduce local impacts but show variability
Population total (POB)	↑ Disasters	–	Very high importance	More people = higher exposure and potential losses
Population density (PD)	↓ Disasters	↑ Disasters	High importance	Rural/isolated areas suffer more impact; urban areas have more reporting
Human Development Index (HDI)	↑ Disasters	↑ Disasters	High importance	Developed areas: higher exposure and better reporting
Land use (LUC)	–	↓ Disasters	Low importance	Certain land uses amplify hazard susceptibility

In the linear regression, RT shows a negative association with disaster totals; however, this relationship should be interpreted cautiously, as road infrastructure may also reflect exposure and reporting capacity rather than solely enhanced connectivity or response. However, the Poisson regression and Random Forest models reveal a more nuanced relationship. The Random Forest model ranks RT second in importance, indicating its strong influence, possibly reflecting the complex interplay between infrastructure development and disaster risk, where extensive road networks could also expose more areas to hazards.

Human Development Index (HDI) also emerges as a significant variable, especially in the Poisson and Random Forest models. The positive association observed in both models suggests that regions with higher development levels may experience more reported disasters, potentially due to better documentation and greater exposure of critical infrastructure. Conversely, variables such as GDP (Gross Domestic Product per capita) and land use category (LUC) appear less influential across the models, indicating that their impact on disaster totals is either limited or moderated by other factors. These findings collectively underline the multifaceted nature of disaster risk and the importance of integrating population density, infrastructure, and socioeconomic indicators into comprehensive risk assessment and management frameworks.

4 Discussion

4.1 Historical disaster spatiotemporal trends

Guatemala has historically suffered significant disaster impacts, primarily due to its geological and climatic conditions (Fig. 7). The country's position along active fault lines makes it prone to frequent earthquakes, while its volcanic landscape increases the risk of eruptions, lahars, and ashfall. The 1902 Great Western Earthquake (8.2 magnitude on the Richter scale) devastated San Marcos and Quetzaltenango, while the 1976 Great Earthquake (7.5 magnitude on the Richter scale) impacted 17 out of 22 departments, destroying 66% of homes and causing USD 200 million in losses [28]. These events underscore the persistent seismic risk, as evidenced by 4,283 seismic events recorded by INSIVUMEH in 2024 (https://conred.gob.gt/sismos-registrados-en-el-pais-durante-el-2024/. In addition, Guatemala's volcanic hazards remain significant; for instance, the 2018 Volcán de Fuego eruption lasted over 16 h, affected 1.7 million people, and caused 114 fatalities [61]. These disasters highlight the urgent need for risk mitigation strategies, particularly in densely populated urban and rural areas. It is important also to consider that the relative increase in the disasters counting during both periods may reflect improved monitoring rather than an actual rise in events, this fact represents a restriction of the technical ability to mitigate the negative impacts of different natural hazards [5, 30, 46].

Hydrometeorological hazards have also left lasting impacts on Guatemala. Hurricane Mitch (1998) accounted 268 deaths in the country [12]; Hurricane Stan (2005) resulted in 669 deaths and 338,000 affected people, while Tropical Storm Agatha (2010) caused 193 fatalities and worsened poverty by 18%, demonstrating the cascading socioeconomic effects of extreme weather events [7]. More recently, Hurricanes Eta and Iota (2020) impacted 16 departments, causing 60 deaths and USD 127 million in agricultural losses [8]. These storms, despite not making direct landfall, triggered intense floods and landslides, exacerbated by Guatemala's high deforestation rates and steep topography. Many of these disasters correlate with strong La Niña events (ONI between −1.5 and −1.9 °C), such as those recorded in 2010–2011, which contributed to extreme rainfall patterns, crop failures, and infrastructure damage. Given these historical trends, strengthening climate adaptation and disaster preparedness efforts is imperative for reducing vulnerability.

Many of these hydrometeorological hazards are expected to intensify their impacts and damage in a developing climate change [36]. As it can be seen from the obtained results droughts also have a significant impact on Guatemala, in specific at an agricultural level [13]. Droughts are considered as slow onset events, because they are not noticeable until several damages, such as famine and malnutrition, affect people. Both conditions increase other disasters' impacts and they can accelerate damage in a multi-hazard environment.

It is important to note that the spatio-temporal patterns discussed in this section reflect the complementary nature of the disaster databases used. EM-DAT emphasizes high-impact, nationally significant events, which explains the prominence of major earthquakes and hurricanes in the long-term national profile, while smaller-scale, recurrent disasters are underrepresented. In contrast, DesInventar captures localized and lower-impact events at finer spatial and temporal resolutions, particularly at the municipal level. This methodological distinction partly explains differences in observed disaster frequencies across scales and underscores the importance of combining both databases for a multi-scale interpretation of disaster processes in Guatemala.

4.2 Statistical analysis implications and parallels

The analysis revealed that road length (RT), population density (PD), and the Human Development Index (HDI) consistently emerged as statistically significant predictors across the three modeling approaches. In the multiple linear regression model, RT showed a negative association with disaster occurrence, which may suggest that areas with limited road infrastructure—often rural or isolated—face delayed emergency responses and higher disaster impacts. This pattern has been documented in remote Andean regions, where road inaccessibility has been linked to elevated disaster vulnerability [44, 50]. Conversely, RT showed a positive relationship in the Poisson model, pointing to a possible exposure effect, where areas with denser road networks, such as urban centers, may register more disasters due to higher reporting rates and infrastructure concentration. Similar dual effects have been observed in other Central American areas, where urban sprawl has increased both exposure and disaster documentation [27, 56, 58, 62].

PD and HDI were strongly and positively associated with disaster frequency across all models, suggesting that more densely populated and socioeconomically developed areas are more exposed to hazards and may also benefit from better data collection systems. This is consistent with studies in Asia, where disaster records are often denser in developed, populated municipalities [39, 68]. Notably, total population (POB) was highly significant in the linear regression and important in the random forest model, reinforcing its value as an exposure proxy. Although not significant in the Poisson model, the influence of population on disaster occurrence aligns with global findings indicating that population size is a core factor in impact magnitude, particularly for hydrometeorological hazards [3, 6, 54].

Road density (RD) and land use category (LUC) showed selective significance—only appearing in the Poisson and random forest models. This variability is not uncommon and may reflect the influence of model structure and variable interactions. Land use, for example, has been identified as a key factor in flood and landslide risks in countries where urbanization and deforesation have drastically altered hazard patterns [1, 38, 72]. Overall, these findings highlight the importance of integrating infrastructural and sociodemographic dimensions in disaster risk assessments, echoing calls for more granular, locally contextualized models in line with the Sendai Framework for Disaster Risk Reduction.

4.3 Future disaster risk considerations

From the perspective of the risk triangle (hazard, exposure, and vulnerability), Guatemala's vulnerability to multiple hazards demands a comprehensive disaster risk reduction (DRR) framework. However, institutional preparedness remains reactive rather than preventive [28]. Strengthening early warning systems (EWS) for hydrological, seismic, and volcanic hazards is crucial [67], particularly in municipalities where high disaster occurrence coincides with elevated population exposure (POB and PD). Guatemala was recently selected for the UN's "Early Warnings for All" initiative (2022), emphasizing the importance of hazard monitoring, risk communication, and emergency preparedness [14]. Beyond hydrometeorological monitoring, Guatemala's early warning system has progressively incorporated additional pillars, including institutional coordination, community-based preparedness, communication protocols, and response capacity, mainly through the roles of INSIVUMEH and CONRED at national and local levels. Although progress has been made in hazard detection and information dissemination, challenges remain in ensuring territorial coverage, inter-institutional integration, and systematic monitoring of EWS effectiveness, particularly in rural and highly vulnerable municipalities [16, 21, 37, 40]. However, significant gaps remain in the lack of basic services (such as electricity, energy, water, communication, sanitation, among others) and infrastructure resilience, particularly in rural regions, where the statistical results indicate higher vulnerability despite lower infrastructure density (RT and RD [45]). The Los Chorros landslide (2009), in San Cristóbal Verapaz, in the department of Alta Verapaz, which destroyed 1.2 km of roadway and disrupted regional connectivity, exemplifies the vulnerability component of risk in municipalities with limited redundancy in critical infrastructure.

Droughts, identified in this study as a key hydrometeorological hazard, though not directly causing high mortality (e.g. 41 deaths in Chiquimula were attributed to droughts in 2001 [66], significantly impact food security and economic stability, thereby increasing vulnerability rather than exposure, especially in subsistence farming communities. Maize and beans, Guatemala's staple crops, are particularly susceptible to delayed or prolonged dry spells caused by climate variability. The El Niño-Southern Oscillation (ENSO) plays a crucial role in these variations, with prolonged droughts reducing agricultural yields and increasing food insecurity [13]. The situation is particularly critical in indigenous communities with rain-fed agricultural practices, where low HDI values identified in the Results amplify vulnerability, and corn-based diets dominate, and malnutrition rates severely affect children, as reported by the Ministry of Public Health and Social Assistance (MSPAS, in Spanish), accounting for 46.5% of minors under five years of age living with chronic malnutrition [71]. Nature-based solutions (NbS) and Ecosystem-based Adaptation (EbA) measures, which primarily target the vulnerability component of disaster risk, such as agroforestry and crop diversification, could enhance climate resilience and reduce the socio-economic vulnerability of smallholder farmers [59].

In Guatemala, successful EbA measures that were successfully proven for the diversity of agroecological, and cultural contexts are the ones related to soil and water conservation, particularly in municipalities identified in this study as having high disaster frequency and low development indicators, for example, the integration of dispersed trees in maize fields [32], agroforestry systems with hedgerows, conservation tillage with mulch, contour ditches and crop rotation in maize and bean fields [63],scattered trees, home gardens, live fences in Guatemala and Honduras [15], among others. Other EbA measures suitable to the Guatemalan traditional and ancestral knowledge, which strengthen adaptive capacity rather than modifying hazards, such as the implementation of sustainable production models and water resources management governance efforts [48], like Watershed Councils', have been successfully accepted by local people.

To improve national disaster planning, the statistical identification of exposure- and vulnerability-driven disaster patterns highlights the need to address local and regional disparities, considering Guatemala's diverse topography, microclimates, and indigenous worldviews on disasters. Disaggregated risk assessments are needed to prioritize at-risk areas where high population exposure coincides with low infrastructure redundancy and ensure culturally appropriate disaster response mechanisms. Furthermore, financial mechanisms such as the Conditional Cash Transfer (CCT) program, which aids disaster-affected families, should be expanded to improve economic resilience [9], particularly in municipalities where low HDI emerged as a compounding vulnerability factor.

Disaster risk reduction must be integrated into broader development policies, ensuring resilience-building strategies in housing, infrastructure, agriculture, and energy sectors [2, 8, 41]. Economic losses from disasters—including USD 56 million in tourism losses from Hurricanes Eta and Iota is—underscore the role of exposure concentration in economically active municipalities, reinforcing the need for cross-sectoral risk management approaches. Stakeholders should leverage early warning data to develop proactive policies, preventing avoidable deaths and economic disruptions from future disasters [35]. By prioritizing vulnerability reduction in highly exposed municipalities, Guatemala can reduce socio-economic inequalities and enhance community resilience in the face of escalating disaster threats.

Beyond statistical interpretation, the use of multiple modeling approaches has direct implications for disaster risk policy. Traditional regression models allow explicit identification of exposure and vulnerability drivers, offer interpretable coefficients that allow policymakers to trace clear, causal-like relationships (e.g., how population or infrastructure relate to disaster occurrence), which can guide targeted interventions. In contrast, machine learning approaches such as random forests capture non-linear interactions across hazard, exposure, and vulnerability components, identifying municipalities where multiple risk drivers converge. Using both approaches in parallel strengthens the operational relevance of the results, supporting policies that are both analytically robust and spatially actionable.

The results of this study must be interpreted considering limitations related to disaster database structure, reporting thresholds, and temporal coverage. EM-DAT prioritizes high-impact events, which can lead to strong magnitude bias, whereby a small number of extreme disasters dominate long-term statistics; for example, a single flood event in 1949 accounts for approximately 97% of all flood-related fatalities recorded in Guatemala between 1900 and 2020. This issue has been documented in regional analyses and may bias cumulative indicators if not explicitly acknowledged [20]. In contrast, DesInventar captures recurrent, low- to medium-impact events at finer spatial scales, resulting in higher event counts but lower per-event impacts. For this reason, the statistical analyses do not directly correlate EM-DAT and DesInventar time series,instead, they rely on internally consistent datasets and interpret correlations as associative rather than causal, acknowledging uncertainty arising from differing data resolutions and reporting practices.

5 Conclusions

Hydrometeorological disasters, including hurricanes, tropical storms, and recurrent droughts, have intensified food insecurity and economic instability, particularly in urban areas but also in rural and indigenous communities of Guatemala where rainfed, subsistence agriculture is the main livelihood. Many of these disasters are associated with ENSO-driven climate fluctuations, especially strong La Niña phases that trigger extreme rainfall, floods, and landslides. The statistical findings of this research confirm that municipal disaster occurrence is significantly influenced by population density (POB), road infrastructure (RT), and human development levels (HDI), with more developed and densely populated municipalities reporting a higher frequency of recorded disasters. However, these data also reflect structural disparities, as rural regions often face underreporting and delayed emergency response, despite being among the most vulnerable.

As a future exercise, it will be valuable to obtain a correlation measure between both categories (hydrometeorological and other events like explosions), because deforestation, human errors, behaviors and deterioration of the environment are related activities that lead to anthropogenic climate change and will further increase the disasters reported by hydrometeorological events. In addition, this research has a limitation regarding municipal data coverage, because there is potential underreporting, specifically in rural areas. These data gaps could hide part of the reality of vulnerability and exposure in areas such as the Guatemalan highlands, coastal regions and valleys. Strategies such as consulting other sources, e.g. results of implemented projects in the country, lessons learned and improvement proposed measures by a diversity of actors, in addition to qualitative field validation and remote sensing can help to address underreporting in future efforts. The results of this work show its associative nature with the observational data from EM-DAT and DesInventar because they show temporal sequence, strength and consistency. Otherwise, the results obtained will obey a causal relationship [29].

Even though the obtained results are robust for Guatemala, this methodology may not be applicable to other countries. The performance of the methods used here depends on the availability of data and the capacity of an in-situ validation. This was possible in Guatemala due to the diversity of initiatives that are being implemented in the country. This approach can be implemented in other settings after developing a complete mapping of actors, policies and projects. Once this mapping is developed, the results of applying the methodology presented in this research can be contrasted so, historical drivers of DRR can be unveiled.

As referred by the IPCC [36] climate change enhances the impacts of observed hazards around the world and Guatemala is not an exception. Impacts on ecosystems (coastal and terrestrial), food and human health will be severely affected in Central America. In this context, the creation of regional policies for local and inclusive development [24] is a powerful tool to diminish the vulnerability and impacts of extreme events. However, this study has some limitations, for example, it does not use climate scenarios as a source of data, or surveys at a municipal level. Further efforts should be made to include these sources and employ other methodologies such as prospective modeling or an action-network [25] approach to identify drivers explicitly.

To strengthen resilience and address the spatial and social inequities revealed by this study, Guatemala must adopt a multilevel, differentiated approach to DRR. While urban centers require improved land-use planning, drainage, and risk-informed development, rural and indigenous regions demand targeted interventions grounded in local realities. First, the expansion and localization of EWS for seismic, volcanic, and climate-related hazards should be prioritized, particularly in underserved areas, integrating real-time data and hazard mapping with community-based communication in indigenous languages. Second, risk assessments must incorporate ancestral knowledge and traditional coping mechanisms to ensure culturally appropriate and trusted interventions. Third, infrastructure investments should focus on enhancing road access, disaster-resilient housing, and basic services in remote areas where emergency delays significantly heighten disaster impacts. Fourth, NbS and EbA measures—such as agroforestry, soil conservation, and crop diversification—can improve food security and reduce environmental degradation in drought-prone and erosion-sensitive zones. Finally, DRR must be embedded in national development planning, encouraging cross-sectoral coordination among state agencies, scientific institutions, and local communities to foster an inclusive, adaptive, and risk-informed society.

Supplementary Information

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Supplementary file 1.

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Author contributions

All authors contributed to the study's conception, design, data analysis, and manuscript preparation. All authors read and approved the final manuscript.

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Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Also, there is the supplementary material.

Clinical trial number

Not applicable.

Declarations

Ethics approval and consent to participate

Not applicable.

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