

Spatiotemporal reorganization of global earthquake impacts within coupled human-Earth systems

Zekang Zhang¹, Yingqiao Qiu^{2,3}, Yanjun Ye¹, Chaoran Xuan¹

¹School of Earth Science and Engineering, Hebei University of Engineering, Handan 056038, China.

²Hebei Key Laboratory of Agricultural Water-Saving, Center for Agricultural Resources Research, Institute of Genetics and Developmental Biology, Chinese Academy of Sciences, Shijiazhuang 050022, China.

³School of Advanced Agricultural Sciences, University of Chinese Academy of Sciences, Beijing 100049, China.

Correspondence: Yanjun Ye (yeyanjun@hebeu.edu.cn)

Abstract. Understanding how earthquake impacts reorganize across space and time is essential for interpreting seismic hazards within coupled human-earth systems. Using global disaster records from EM-DAT spanning 1980–2024, this study examines multi-scale spatiotemporal patterns of earthquake impacts and their socio-environmental associations at global and national scales. Temporal analyses show a pronounced decoupling between seismic occurrence and event consequences: while earthquake frequency, exposed population, and cumulative economic losses increased overall, mortality rates declined markedly after the early 2000s. Spatial analyses reveal strong heterogeneity across continents, countries, and major tectonic plates. Asia accounts for a substantial share of global earthquake occurrences, affected populations, fatalities, and economic losses, yet national-level impacts vary considerably across countries and regions. Unweighted centroid analyses indicate a multi-stage directional migration pattern of recorded earthquake occurrences over time, whereas population-, fatality-, and economic loss-weighted centroid analyses reveal substantial spatial differentiation among different impact dimensions.. Standard deviation ellipse and centroid analyses further indicate an eastward to southeastward migration of the global earthquake disaster centroid over time, accompanied by relatively stable orientation and a modest contraction in spatial dispersion. To explore factors associated with national differences in fatalities, a Geographical Detector model is applied using cumulative fatalities as the dependent variable and a set of natural, climatic, socioeconomic, governance, infrastructure, and health-related variables as explanatory factors. Results show that population density and development- and governance-related indicators exhibit relatively high explanatory power, while interactions among factors generally strengthen spatial associations through bilinear or nonlinear enhancement. Overall, the findings suggest that global disparities in earthquake impacts reflect the spatial co-configuration of hazard exposure, development conditions, and institutional capacity, contributing to a system-level understanding of how seismic impacts evolve within coupled human-earth systems.

1 Introduction

Earthquake disasters remain among the most destructive natural hazards worldwide, causing profound human, economic, and infrastructural losses each year ([United Nations Office for Disaster Risk Reduction \(Undrr\), 2023](#); [Daniell et al., 2017](#)). Despite notable advances in seismology, engineering design, and emergency response systems, global earthquake losses have not declined uniformly. Instead, rapid urban expansion, population concentration in seismic belts, and intensified development in tectonically active landscapes continue to elevate exposure and reinforce event vulnerability ([Cutter, 2021](#); [Aksha and Khanal, 2019](#); [Düzgün et al., 2023](#)). This

39 persistent rise in event impacts—despite improved monitoring and hazard science—illustrates a central paradox
40 in contemporary earthquake risk: events increasingly emerge from the interaction between geophysical
41 processes and evolving social–environmental conditions, with event risk becoming most visible through its
42 realized impacts on populations and economies.

43 A human–environment systems perspective, widely adopted in event risk research, is essential for
44 understanding these patterns because it situates earthquakes within the broader spatial processes that shape risk
45 production (Gall et al., 2011; Lee et al., 2022). Geophysically, seismic hazards are structured by plate
46 interactions, strain accumulation, and lithospheric deformation, forming persistent seismic belts such as the
47 Pacific Ring of Fire and the Alpine–Himalayan arc (Bird, 2003a; Kagan and Jackson, 2016). Yet similar
48 earthquakes often produce vastly different outcomes depending on demographic exposure, infrastructure quality,
49 governance effectiveness, and environmental fragility (Anbarci et al., 2005; Keefer et al., 2011; Wyss et al.,
50 2023). These disparities underscore a growing recognition that earthquake events arise not solely from tectonic
51 forces, but from the coupled operation of natural hazards and socially mediated vulnerability across space
52 (Cohen and Werker, 2008; Reid, 2013; Ismail-Zadeh, 2024).

53 Decades of empirical research highlight the importance of governance, inequality, institutional capacity,
54 and land-use change in shaping event risk. Weak governance and corruption undermine building-code
55 enforcement and response capacity, significantly amplifying earthquake mortality (Escaleras et al., 2007;
56 Anbarci et al., 2005). Health system capacity and social capital influence post-event survival, particularly in
57 high-density or resource-constrained regions (Flanagan et al., 2011). Environmental degradation—through
58 deforestation, unregulated construction, and slope instability—magnifies secondary hazards such as landslides
59 and debris flows (Cannon et al., 2003; De Ruiter et al., 2021). Together, these findings reinforce that earthquake
60 impacts reflect interacting natural, demographic, environmental, and governance processes within coupled
61 human–environment systems (Lapietra et al., 2024).

62 Despite substantial progress in regional seismic hazard studies, global-scale analyses of earthquake events
63 impacts, as distinct from seismicity alone, remain limited. Most global assessments rely on instrumental
64 catalogs to evaluate earthquake occurrence, magnitude–frequency patterns, or aftershock clustering (Zaliapin
65 and Ben-Zion, 2013; Kagan and Jackson, 2016). While crucial for characterizing physical processes, these
66 studies do not explain why comparable earthquakes generate disproportionate losses across countries (Noy,
67 2016; Li et al., 2021; Guo et al., 2020). Recent global models of seismic exposure and vulnerability (Xofi et al.,
68 2022) represent important advances but underrepresent governance, environmental change, and socio-economic
69 inequality-factors identified by the Sendai Framework as root causes of escalating event risk (United Nations
70 Office for Disaster Risk Reduction (Undrr), 2023).

71 Moreover, the interaction effects among multiple drivers remain poorly understood at the global scale.
72 Traditional regression approaches frequently assume linearity and overlook spatial stratification, non-linear
73 amplification, and synergistic interactions, such as those between population density and governance quality or
74 between basic public infrastructure, precipitation, and topography (Wang et al., 2010; Hu et al., 2011; Ansari et
75 al., 2025). Yet multi-factor interactions increasingly determine where event hotspots emerge within rapidly
76 changing socio-ecological systems (Burton, 2015; Aksha and Khanal, 2019). Addressing these analytical
77 limitations requires tools capable of detecting spatial heterogeneity and quantifying both independent and
78 interactive effects within complex, coupled systems.

79 To address these gaps, this study integrates EM-DAT global event records (1980–2024), GIS-based spatial
80 analysis, and the Geographical Detector model to examine the spatiotemporal dynamics and associated drivers
81 of earthquake impacts at the global scale. Specifically, we address four interrelated scientific questions:

(1) How have global earthquake events evolved over time? We analyze long-term temporal trends in earthquake frequency, mortality, population affected, and economic losses.

(2) How do earthquake impact patterns vary spatially across continents, countries, and tectonic plates?

(3) How have global and plate-level earthquake impact patterns reorganized over time, as reflected in unweighted and weighted centroid migration trajectories and directional patterns?

(4) Which natural, demographic, environmental, and governance factors—independently and interactively—shape global earthquake fatalities?

By situating earthquake impacts within a multi-scale human–Earth system perspective, this study provides a globally comparable assessment of earthquake impact patterns over four decades, clarifies the spatial processes impact differentiation and reorganization, and identifies priority regions where governance, healthcare, and land-use interventions can most effectively reduce seismic risk.

2 Data sources and processing

2.1 Data sources

This study used earthquake event records from the Emergency Events Database (EM-DAT), covering reported events with magnitudes ranging from 3.0 to 9.5 during the period 1980–2024 (Cred, 2024). EM-DAT is widely adopted in global event risk research because it systematically documents event impacts—including fatalities, affected populations, and economic losses—rather than focusing solely on physical seismicity, and has been extensively used in the international community (Rosvold and Buhaug, 2021; Peduzzi and Herold, 2005). The global national administrative boundaries data were from the Resource and Environmental Sciences Data Platform (Igsnrr and Cas), and the plate boundary data were from the global plate boundary dataset (Bird, 2003b). To enhance data consistency, all EM-DAT earthquake event entries from 1980 to 2024 were extracted using the event subtype “Earthquake” and cross-checked to remove duplicate entries and records with incomplete impact information. To improve temporal comparability, reported economic losses were converted to constant 2020 USD using World Bank deflators (World Bank, 2025), thereby reducing the influence of inflation and interannual reporting inconsistencies.

2.2 Data processing

The EM-DAT database provides information including occurrence time, epicenter coordinates (latitude and longitude), affected countries (with ISO codes), affected population, fatalities, and economic losses. Based on these raw records, we constructed a harmonized national-level dataset through spatial matching and attribute aggregation. For each country, the following indicators were calculated: cumulative earthquake frequency, cumulative fatalities, cumulative affected population, and cumulative economic losses. To better capture event severity and normalized impacts, four per-event indicators were further derived: (1) Average number of affected people per event, (2) Average fatalities per event, (3) Average economic loss per event, and (4) Mortality rate (defined as fatalities relative to affected population). Considering that this study mainly focuses on comparisons across three aggregated study periods (1980–1994, 1995–2009, and 2010–2024), these indicators were used as supplementary metrics to reflect relative event-level impact characteristics within each period under a broadly consistent reporting framework. Although the completeness and precision of earthquake records may have improved over time, particularly for lower-impact events, the event-normalized indicators remain broadly comparable at the period scale and are mainly intended to support relative comparisons among different stages and regions.

3 Methods

3.1 Temporal variability analysis method

To characterize the temporal evolution of major global earthquake events from 1980 to 2024, with an emphasis on event impacts rather than seismic activity alone, linear regression and the Mann-Kendall (MK) trend test were employed. These methods are widely applied in event risk and climate-related research to identify long-term trends in impact-related indicators under non-normal distributions and reporting uncertainty (Wang et al., 2021). The MK test, a non-parametric approach robust to outliers and missing values, was used to evaluate monotonic trends in eight earthquake event indicators, including frequency, fatalities, affected population, and economic losses. The MK statistic S was computed following standard procedures, as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (1)$$

Where x_i and x_j represent two observations in the time series. The sign function returns 1, 0, or -1 depending on whether the difference is positive, zero, or negative.

The standardized Z-value was then derived to assess trend significance:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} & \text{if } S < 0 \end{cases} \quad (2)$$

A positive Z-value indicates an upward trend, while a negative value indicates a downward trend. Significance thresholds were set at $|Z| = 1.28$ (90%), 1.64 (95%), and 2.33 (99%) (Casella and Berger, 2002). By combining linear regression slopes with MK significance testing, this approach captures both the magnitude and robustness of long-term changes in earthquake impacts.

3.2 Spatial variability analysis method

3.2.1 Standard deviation ellipse (SDE)

Standard Deviation Ellipse (SDE) is widely used to quantify the directional tendency and dispersion of geographic phenomena (Wu et al., 2021; Xiong et al., 2019). In the context of earthquake-related studies, SDE provides an effective means to identify large-scale spatial patterns and directional characteristics of event distributions. In this study, the SDE method was applied to analyze the directional pattern and spatial dispersion of recorded global earthquake events. The SDE is defined by three parameters: (1) rotation angle (θ), (2) standard deviation along the major axis (δ_x), and (3) standard deviation along the minor axis (δ_y). The relative coordinates of each point with respect to the regional centroid were computed as follows:

$$\tilde{x} = (x_i - \bar{x}), \quad \tilde{y} = (y_i - \bar{y}) \quad (3)$$

Where $(\bar{x}, \bar{y})$ represents the spatial mean center of all earthquake events.

To ensure consistency with the centroid analysis, both unweighted and weighted formulations are considered. The general weighted mean center is defined as:

$$\bar{x}^{(k)} = \frac{\sum_{i=1}^n w_i^{(k)} x_i}{\sum_{i=1}^n w_i^{(k)}}, \quad \bar{y}^{(k)} = \frac{\sum_{i=1}^n w_i^{(k)} y_i}{\sum_{i=1}^n w_i^{(k)}} \quad (4)$$

where $w_i^{(k)}$ represents the weight assigned to each event under scheme k . In this study:

$$w_i^{(0)}=1, \quad w_i^{(F)}=F_i, \quad w_i^{(A)}=A_i, \quad w_i^{(L)}=L_i \quad (5)$$

corresponding to unweighted events, fatalities, affected population, and economic losses, respectively.

In the SDE analysis presented in this study, equal weights ($w_i^{(0)}=1$) are adopted, such that the ellipse reflects the spatial distribution of recorded earthquake events rather than impact magnitude. The weighted formulations are used in centroid analysis to characterize the spatial concentration of different impact dimensions.

The rotation angle is defined as the clockwise angle between the positive north direction and the major axis of the ellipse, capturing the dominant spatial orientation of earthquake distribution. The tangent of the rotation angle θ was computed as:

$$\tan \theta = \frac{\sum_{i=1}^n W_i^2 \tilde{x}_i^2 - \sum_{i=1}^n W_i^2 \tilde{y}_i^2 + \sqrt{(\sum_{i=1}^n W_i^2 \tilde{x}_i^2 - \sum_{i=1}^n W_i^2 \tilde{y}_i^2)^2 + 4(\sum_{i=1}^n W_i^2 \tilde{x}_i \tilde{y}_i)^2}}{2 \sum_{i=1}^n W_i^2 \tilde{x}_i \tilde{y}_i} \quad (6)$$

δ_x and δ_y denote the semi-major axis and semi-minor axis of the SDE:

$$\delta_x = \sqrt{\frac{\sum_{i=1}^n (W_i \bar{x}_i \cos \theta - W_i \bar{y}_i \sin \theta)^2}{\sum_{i=1}^n W_i^2}}, \quad \delta_y = \sqrt{\frac{\sum_{i=1}^n (W_i \bar{x}_i \sin \theta + W_i \bar{y}_i \cos \theta)^2}{\sum_{i=1}^n W_i^2}} \quad (7)$$

where δ_x _major and δ_y _minor denote the semi-major and semi-minor axes of the SDE. A larger contrast between the two axes indicates a stronger directional structure, while variations in the minor axis reflect changes in spatial dispersion of earthquake event distributions.

3.2.2 Geometric centroid shift analysis

Geometric centroid shift analysis is a widely used method for examining the spatial evolution of geographic phenomena over time. In this study, it is applied to characterize the spatial displacement of recorded earthquake events and their associated impacts. The centroid coordinates for each period are calculated using a weighted mean approach:

$$\bar{X}_t^{(k)} = \frac{\sum_{i=1}^{n_t} w_i^{(k)} X_i}{\sum_{i=1}^{n_t} w_i^{(k)}}, \quad \bar{Y}_t^{(k)} = \frac{\sum_{i=1}^{n_t} w_i^{(k)} Y_i}{\sum_{i=1}^{n_t} w_i^{(k)}} \quad (8)$$

where n_t is the number of earthquake events in period t ; i denotes the i -th event; X_i and Y_i are the longitude and latitude of the event, respectively; and $w_i^{(k)}$ represents the weight assigned to each event under different schemes. Four weighting schemes are considered in this study. For the unweighted centroid, all weights are set to unity ($w_i^{(0)}=1$), representing the spatial position of recorded earthquake events. In addition, three impact-weighted centroids are calculated using fatalities ($w_i^{(F)}=F_i$), affected population ($w_i^{(A)}=A_i$), and economic losses ($w_i^{(L)}=L_i$) as weights. These weighted centroids represent the spatial concentration of different dimensions of earthquake disaster impacts. The centroid shift distance between two consecutive periods is calculated as:

The Geometric Centroid shift distance D is calculated by the formula:

$$D=C\sqrt{(\bar{X}_{t+1}^{(k)}-\bar{X}_t^{(k)})^2+(\bar{Y}_{t+1}^{(k)}-\bar{Y}_t^{(k)})^2} \quad (9)$$

where C is a constant used to convert geographic coordinates into planar distance. This approach allows for distinguishing between the spatial displacement of recorded earthquake events and the spatial concentration of different impact dimensions. It also avoids overinterpreting unweighted centroids as representing impact intensity.

3.3 Geographical detector

3.3.1 Single-factor detector

The Geographical Detector model (Geodetector) is a statistical method grounded in spatial stratification heterogeneity theory, designed to quantify the influence intensity of different factors on geographical phenomena and to reveal the underlying mechanisms driving spatial heterogeneity (Wang et al., 2010). Because it does not assume linearity or normality, the method is well suited for analyzing event impacts shaped by coupled natural and social processes. In this study, the factor detector was applied to assess the independent spatial explanatory power of multiple natural, socioeconomic, governance, infrastructure, and health-related factors on cumulative earthquake fatalities at the national scale. Explanatory strength was quantified using the q -statistic, which ranges from 0 to 1, with higher values indicating stronger spatial explanatory ability (Wang et al., 2016). The formula is as follows:

$$q=1-\frac{\sum_{h=1}^L N_h \sigma_h^2}{N\sigma^2} \quad (10)$$

Where q denotes the explanatory power quantifying the extent to which the independent variable X accounts for the spatial heterogeneity of the dependent variable Y , with a value range of [0,1]. L represents the number of strata, defined by the categorization of the independent variable X based on its attribute values. N_h denotes the number of samples within the h -th stratum, and σ_h^2 represents the variance of the h -th stratum, reflecting the dispersion degree of the dependent variable Y within the h -th category.

3.3.2 Interaction detector

To investigate the interaction effects between driving factors, the interaction detector was applied to calculate the joint explanatory power of two factors and determine their interaction type. The formula is as follows:

$$q(X_1 \cap X_2)=1-\frac{\sum_{h=1}^{L_{12}} N_{h12} \sigma_{h12}^2}{N\sigma^2} \quad (11)$$

Where $q(X_1 \cap X_2)$ denotes the interaction explanatory power, measuring the joint influence of factors X_1 and X_2 on Y . L_{12} represents the number of joint strata formed by the overlay of factors X_1 and X_2 . h_{12} is the joint stratum index, indicating the h_{12} -th combined category. N_{h12} denotes the sample size in the joint stratum, i.e., the number of observations in the h_{12} -th combination. σ_{h12}^2 represents the variance of Y that joint stratum. Based on the comparison between $q(X_1 \cap X_2)$ and the individual q -values of X_1 and X_2 , factor interactions can be identified as independent, bilinear enhancement ($q(X_1 \cap X_2) > \max(q_1, q_2)$), or nonlinear enhancement ($q(X_1 \cap X_2) > q_1 + q_2$). By comparing interaction q -values with individual q -values, interactions were classified as independent, bilinear enhancement, or nonlinear enhancement. This analysis characterizes statistical associations arising from the spatial co-occurrence of exposure, vulnerability, and institutional conditions, without implying causal relationships.

4 Spatiotemporal characteristics analysis of global earthquake events

4.1 Temporal trends of global earthquake events

4.1.1 Inter-annual trend analysis of global earthquake events

Inter-annual variability in global earthquake impacts from 1980 to 2024 reveals distinct and contrasting trends across different indicators (Figure 1). The number of earthquakes shows a clear upward trend (slope = 0.15), reflecting a gradual increase in event frequency. Cumulative affected population exhibits only a slight upward trend with substantial year-to-year fluctuations, while the average affected population per event shows only a marginal increase over time. Several pronounced peaks in affected population, fatalities, and economic losses correspond to major catastrophic earthquakes, including the 2004 Sumatra earthquake and Indian Ocean tsunami, the 2008 Wenchuan earthquake, the 2010 Haiti earthquake, the 2011 Tohoku earthquake, and the 2023 Türkiye–Syria earthquake. These events substantially influenced short-term fluctuations in multiple indicators.

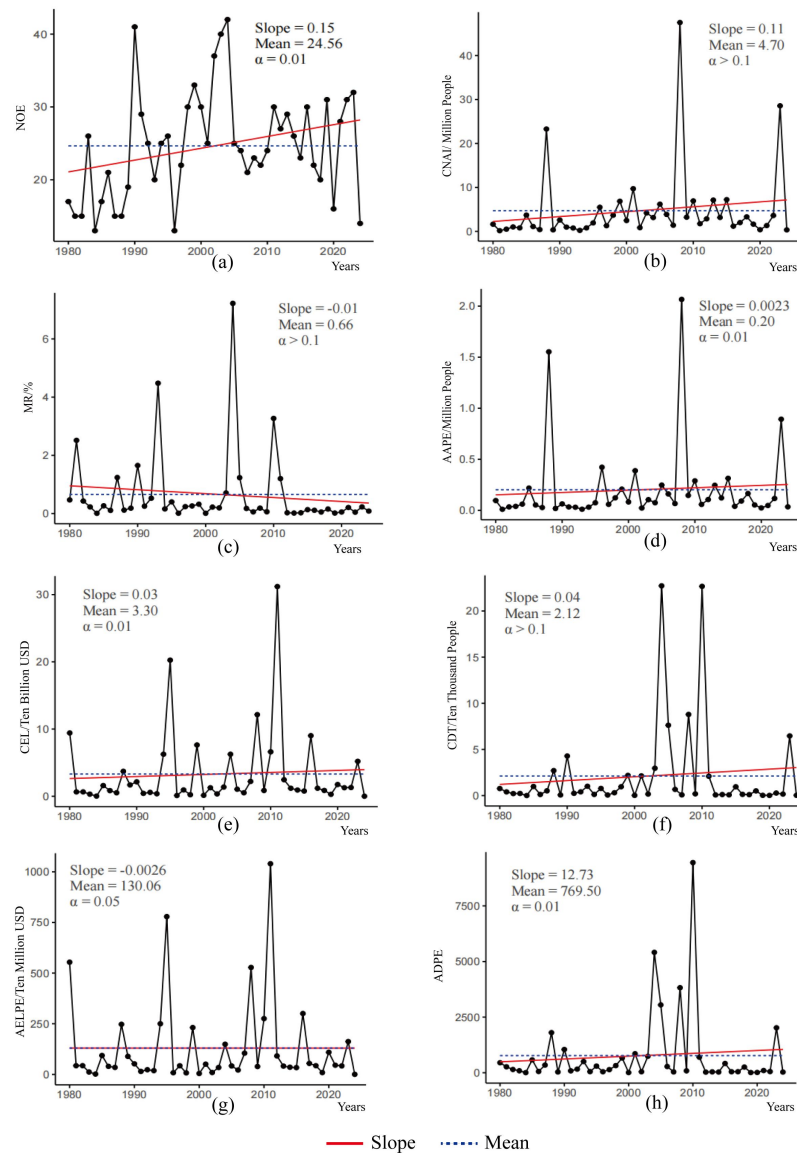


Figure 1. Temporal trends of major global earthquake event indicators in 1980-2024. a) Number of Earthquakes; b) Cumulative Number of Affected People ; c) Mortality Rate ; d) Average Number of Affected People per Event; e)

Cumulative Economic Losses; f) Cumulative Number of Fatalities; g) Average Economic Loss per Event; h) Average Number of Fatalities per Event.

The mortality rate displays a mild downward trend, corresponding to a decline in fatalities relative to exposed populations. Cumulative economic losses also show a slight but statistically insignificant upward tendency, whereas average economic loss per event demonstrates a weak declining trend. In contrast, average deaths per event reveal a strong upward trend (slope = 12.73), associated with a limited number of high-impact catastrophic events, while cumulative fatalities fluctuate considerably without a statistically significant long-term trend. Overall, the inter-annual analysis reveals a temporal decoupling between earthquake occurrence and event consequences, characterized by increasing event frequency, declining mortality rates, and contrasting behaviors between cumulative and per-event impact indicators.

4.1.2 Multi-period trend analysis based on three 15-year time windows

To examine longer-term shifts in earthquake impacts, a multi-period trend analysis was conducted using three consecutive 15-year time windows, allowing comparison of event severity across different development stages. Eight earthquake event indicators were examined across three consecutive 15-year periods (Figure 2). Most indicators—including mortality rate, cumulative deaths, average deaths per event, cumulative affected population, and average affected population per event—reached their highest levels during the second period (1995–2010). In contrast, economic indicators showed a slightly different pattern: although cumulative and per-event economic losses remained high during the third period (2011–2024), their values were slightly lower than those of the second period. Earthquake frequency also increased markedly in the second period and then declined slightly in the third, while remaining above the level observed in the first period. In the most recent period, substantial reductions in cumulative and per-event fatalities and affected populations led to a pronounced decline in mortality rates. These results indicate a recent reduction in the lethality of global earthquake events, occurring alongside persistently high—though slightly reduced—levels of economic exposure.

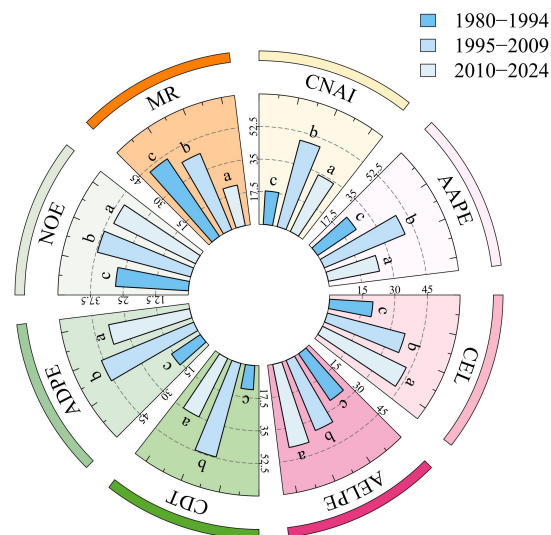


Figure 2. Analysis of changes in global earthquake event indicators from 1980 to 2024. NOE represents number of earthquakes, CNAI represents cumulative number of affected people, CEL represents cumulative economic losses, CDT represents cumulative number of fatalities, AAPE represents average number of affected people per event, AELPE represents average economic loss per event, ADPE represents average number of fatalities per event, MR represents mortality rate.

By integrating inter-annual variability with multi-period trend analysis, this section captures both short-term fluctuations and longer-term shifts in global earthquake impacts. These temporal patterns provide a descriptive baseline for interpreting the spatial heterogeneity and associated drivers of earthquake events examined in subsequent sections.

4.2 Multi-scale spatial patterns of global major seismic events

The spatial distribution of global earthquake events is shaped by the combined configuration of tectonic settings, population exposure, and socio-economic conditions, rather than by seismicity alone. To describe spatial heterogeneity in a manner that is comparable across both administrative and geophysical units, the analysis is conducted at three complementary scales. At the continental scale, aggregated indicators provide a first-order overview of where earthquake impacts concentrate globally. At the national scale, spatial mapping and trend testing characterize cross-country differences in event impacts and their temporal directions. At the tectonic-plate scale, centroid migration and standard deviation ellipse analyses are used to trace the spatial reorganization of earthquake event hotspots over time. Together, these analyses describe where event impacts are concentrated, how those concentrations shift through time, and how spatial patterns differ across tectonic contexts.

4.2.1 Continental differences of global major seismic events

Continental-scale comparison provides a first-order description of spatial heterogeneity in global earthquake events, reflecting broad contrasts in tectonic environments, population exposure, and development conditions.. Across 1980-2024, the composition of event indicators differs markedly by continent ([Figure 3](#)). Asia accounts for the largest shares of most indicators—including earthquake frequency, cumulative affected population, cumulative economic losses, and cumulative fatalities—consistent with the coexistence of extensive seismic belts and large exposed populations.. In contrast, the Americas contribute the largest shares of mortality rate and average deaths per event, indicating that per-event mortality metrics are strongly influenced by a limited number of high-impact catastrophic events. Europe shows comparatively low earthquake frequency but ranks second in average economic loss per event, corresponding to high-value built environments and concentrated economic assets. Africa and Oceania represent small proportions for most indicators; however, Africa exhibits relatively elevated mortality-related shares relative to event counts, implying heightened vulnerability in specific national contexts rather than higher seismic activity.

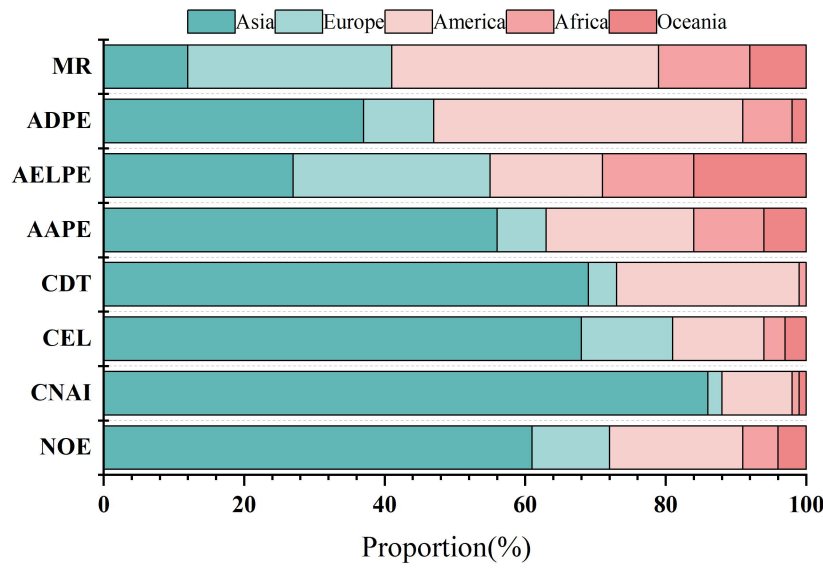


Figure 3. Continental disparities in the composition of global earthquake event indicators (1980–2024). NOE represents number of earthquakes, CNAI represents cumulative number of affected people, CEL represents cumulative economic losses, CDT represents cumulative number of fatalities, AAPE represents average number of affected people per event, AELPE represents average economic loss per event, ADPE represents average number of fatalities per event, MR represents mortality rate.

4.2.2 Spatiotemporal variability analysis of global seismic events at the national scale

Pronounced spatial differences are observed in the national-level trends of eight seismic event indicators during 1980–2024. Seismic frequency (Figure 4.a) exhibits predominantly non-significant temporal variation ($-1.64 \leq Z \leq 1.64$) across most countries, while significant increases ($Z > 1.64$) appear mainly in parts of East and Southeast Asia, where absolute earthquake counts are also high. Significant decreases ($Z < -1.64$) occur sporadically without forming coherent regional clusters. Mortality-related indicators (Figure 4.(b , f)) display widespread significant declines across Asia, Africa, and Oceania, whereas significant upward trends are restricted to a small number of countries in Eastern Europe, Central America, and South Asia. Cumulative and per-event affected populations (Figure 4.(c , d)) show high values in China, India, Indonesia, and parts of South Asia, with significant increases along the western coast of South America, South Asia, and the Indonesian archipelago, while many other regions exhibit non-significant temporal changes. Cumulative fatalities (Figure 4.e) are concentrated in a limited group of countries (e.g., China, India, Iran, Turkey, and Haiti), but trend directions vary, with both increases and decreases observed across different subregions.

Economic-related indicators demonstrate another layer of spatial heterogeneity. High cumulative economic losses (Figure 4.g) are concentrated in the United States, Japan, China, Italy, and Turkey, with significant upward trends present in East Asia, the Mediterranean region, and parts of South America. By contrast, many countries in Africa, Central Asia, and Eastern Europe show limited or statistically non-significant temporal variation. Average economic loss per event (Figure 4.h) is highest in high-income countries, including Japan, New Zealand, Italy, and the United States, although trend directions vary across national contexts. Overall, national-scale results emphasize that statistically significant trends are spatially clustered for certain indicators—particularly economic losses—whereas non-significant trends dominate large portions of the Global South.

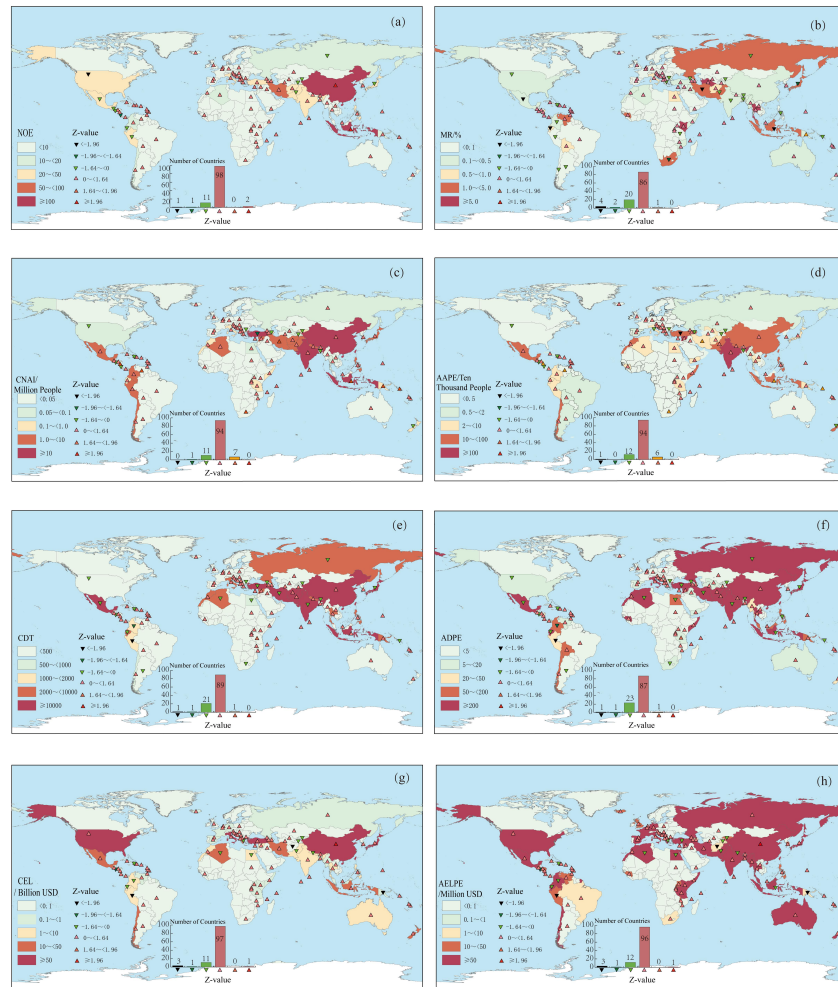


Figure 4. Spatial heterogeneity and temporal trends of eight earthquake event indicators at the national scale (1980–2024).
a) Earthquake occurrence; b) Mortality rate; c) Cumulative affected population; d) Average affected population per event; e) Cumulative fatalities; f) Average fatalities per event; g) Cumulative economic losses; h) Average economic loss per event.

4.2.3 Spatiotemporal evolution of global seismic event centroids across tectonic plates

At the plate scale, centroid trajectories display pronounced regional heterogeneity under different weighting schemes (Figure 5). The Pacific and Indian Ocean plates exhibit the largest centroid displacements and the most dynamic migration trajectories, particularly around Southeast Asia and adjacent subduction zones. In contrast, centroid movements on the Eurasian and American plates are comparatively more stable, reflecting relatively persistent spatial distributions of earthquake impacts. The African Plate shows substantial directional variability, consistent with its dispersed seismic activity and heterogeneous impact distribution.

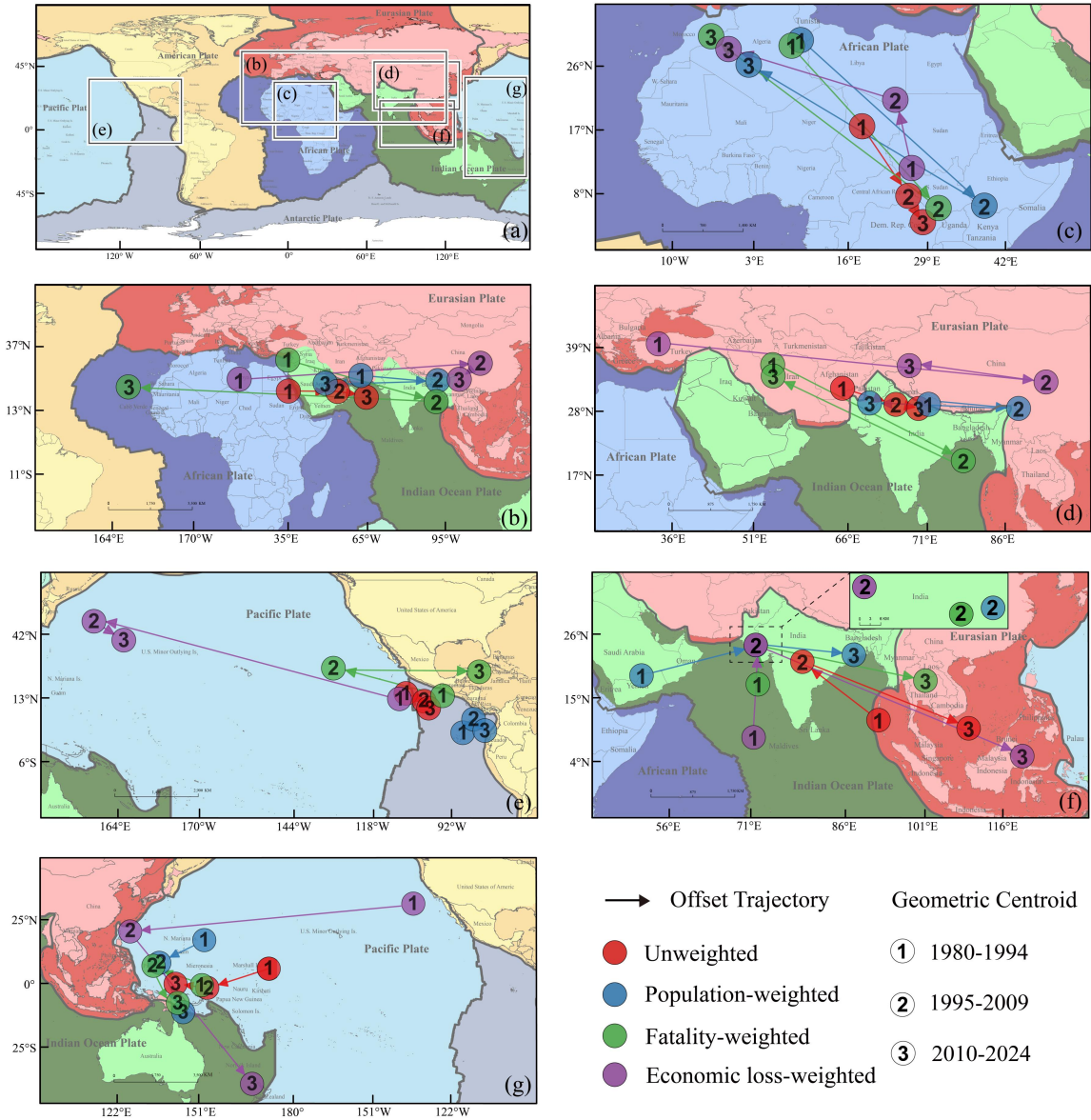


Figure 5. Spatiotemporal evolution of global and plate-scale seismic event centroids and spatial dispersion patterns from 1980 to 2024. a) Global standard deviation ellipses and centroid trajectories of seismic events across four periods; b) Global centroid displacement trajectory; c) Centroid shifts on the American Plate; Centroid shifts on the d) African Plate, e) Eurasian Plate, f) Indian Ocean Plate, and g) Pacific Plate.

Weighted centroid patterns further reveal differences between impact dimensions across tectonic regions. Fatality-weighted centroids are more concentrated in densely populated developing regions, whereas economic loss-weighted centroids are more closely associated with economically developed and infrastructure-intensive areas. These results indicate that tectonic settings provide the physical framework for earthquake occurrence, while differences in exposure, vulnerability, and economic concentration strongly influence the spatial organization of earthquake impacts.

The unweighted centroid of global earthquake impacts exhibits a multi-stage migration pattern over the study period. It was located in northeastern Africa west of the Red Sea during 1980-1990, shifted northeastward toward the Arabian Peninsula in 1991-2000 (~909 km), moved southeastward to the central Arabian Peninsula in 2001-2010 (~1,476 km), and then adjusted northeastward during 2011-2024 (~433 km), ultimately

positioning it in the Arabian Sea region (Table 1). This trajectory reflects a sequence of directional shifts rather than a strictly monotonic trend. Changes in spatial dispersion provide additional context for this pattern. The semi-major axis of the standard deviation ellipse decreases over time, indicating a contraction in the longitudinal extent of the distribution, while the semi-minor axis shows relatively small and alternating variations. The dominant orientation remains stable, consistent with the alignment of major global seismic belts (Table 1). Overall, based on unweighted centroid location and spatial dispersion characteristics, the spatial position of global earthquake disaster impacts shows a gradual shift.

Table 1. Temporal evolution of the location and displacement of the global seismic event unweighted centroid (1980–2024).

Analysis period	Unweighted centroid location	Displacement distance (km)	Dominant shift direction	Change in semi-major axis (km)	Change in semi-minor axis (km)
1980–1990	31.49°E, 21.28°N	-	-	-	-
1991–2000	40.48°E, 23.92°N	908	Northeastward	-732	-217
2001–2010	53.94°E, 20.27°N	1,476	Southeastward	-419	180
2011–2024	57.91°E, 20.68°N	433	Northeastward	-203	-91

At the plate scale, unweighted centroid trajectories display pronounced regional heterogeneity (Figure 5.c–g; Table 2). On the American Plate, unweighted centroid movements are relatively short and primarily oriented southeastward, corresponding to localized adjustments in the spatial concentration of event impacts. The African Plate shows more pronounced unweighted centroid displacements, generally trending eastward and southeastward, reflecting its broad spatial extent and dispersed seismic activity. The Eurasian Plate exhibits comparatively limited unweighted centroid movement despite its extensive geographic coverage, indicating a spatially expansive but relatively stable impact distribution. In contrast, unweighted centroid trajectories on the Indian Ocean and Pacific Plates are more dynamic, with alternating directional shifts concentrated around Southeast Asia, Indonesia, and adjacent subduction zones, highlighting localized but active reorganization of event hotspots.

Table 2. Plate-specific unweighted centroid locations, displacement distances, and dominant shift directions of global seismic events during 1980–2024.

Tectonic plate	Analysis period	Unweighted centroid location	Displacement distance (km)	Dominant shift direction
Pacific Plate	1980–1990	179.26°E, 5.48°N	-	-
	1991–2000	161.43°E, 11.28°N	2039	Northwestward
	2001–2010	161.03°E, 1.60°S	1433	Southwestward
	2011–2024	137.57°E, 1.98°N	2576	Northwestward
Indian Ocean Plate	1980–1990	118.45°E, 3.23°S	-	-
	1991–2000	96.75°E, 1.39°N	2433	Northwestward
	2001–2010	103.00°E, 3.69°S	834	Southeastward
	2011–2024	119.96°E, 1.86°S	1887	Northeastward
Eurasian Plate	1980–1990	61.27°E, 35.30°N	-	-
	1991–2000	69.54°E, 35.69°N	716	Northeastward
	2001–2010	75.86°E, 33.20°N	685	Southeastward
	2011–2024	79.95°E, 31.56°N	458	Southeastward
African Plate	1980–1990	15.77°E, 14.38°N	-	-
	1991–2000	21.33°E, 14.11°N	605	Southeastward
	2001–2010	34.89°E, 6.96°N	1487	Southeastward
	2011–2024	22.57°E, 3.80°N	1385	Southwestward
American Plate	1980–1990	83.67°W, 8.95°N	-	-

Tectonic plate	Analysis period	Unweighted centroid location	Displacement distance (km)	Dominant shift direction
	1991–2000	70.13°W, 8.65°N	1477	Southeastward
	2001–2010	82.97°W, 6.12°N	1435	Southwestward
	2011–2024	77.32°W, 4.22°N	658	Southeastward

Overall, the combined global and plate-scale results indicate that unweighted earthquake occurrence centroids exhibit coherent large-scale migration trajectories, while the weighted centroid patterns presented in [Figure 5](#) further reveal substantial differences among population exposure, fatality impacts, and economic losses across tectonic regions. However, it should be noted that the 1980-2024 observation period remains substantially shorter than the recurrence intervals of major earthquakes along many global fault systems. Therefore, the centroid migration patterns identified in this study primarily reflect the spatiotemporal organization of recorded earthquake impacts within the study period, rather than complete long-term seismic cycles or persistent tectonic evolution.

4.3 Drivers of global earthquake impacts

The temporal and spatial analyses above reveal a clear decoupling between the physical occurrence of earthquakes and the severity of their impacts. While tectonic plate boundaries structure the global pattern of seismicity, earthquake consequences vary substantially across countries even under broadly comparable hazard settings. This spatial heterogeneity indicates that variations in event impacts cannot be accounted for by seismicity alone and are closely associated with differences in exposure and vulnerability conditions. Building on the multi-scale patterns identified in Sections 3.1 and 3.2, this subsection examines national-scale statistical associations between earthquake mortality and multiple socio-environmental factors the Geographical Detector model. Cumulative fatalities are used as the dependent variable, and explanatory factors ([Table 3](#)) are grouped into (i) tectonic–locational context (proximity to plate boundaries), (ii) hydro-climatic and environmental conditions, (iii) socioeconomic development and the built environment, and (iv) governance and health-system capacity ([Abatzoglou et al., 2018](#); [World Bank, 2025](#); [Sims et al., 2022](#); [World Health Organization, 2025](#)). All explanatory variables were derived from globally consistent cross-sectional datasets for the year 2021, aiming to capture the contemporary socio-environmental conditions associated with present-day earthquake impacts. Focusing on the most recent stage provides more direct implications for current disaster risk reduction and resilience-oriented governance. The analysis quantifies the degree of spatial correspondence between fatalities and individual factors (q-statistics), as well as the extent to which paired factors jointly enhance spatial differentiation in fatalities. In doing so, we address which factors—and which combinations of factors—are most strongly associated with cross-national disparities in earthquake impacts, rather than attempting to infer causal relationships.

388 **Table 3.** Explanatory variables used in the geographical detector analysis of national earthquake fatalities and data sources.

Driver category	Indicator	Data source	Representation
Hydro-climatic and environmental conditions	Precipitation	Terraclimate (Abatzoglou et al., 2018)	Represents hydro-climatic conditions that may influence secondary earthquake hazards such as landslides and debris flows.
Hydro-climatic and environmental conditions	Soil Moisture	Terraclimate (Abatzoglou et al., 2018)	Indicates ground saturation conditions that can amplify slope instability and earthquake-triggered environmental damage.
Tectonic–locational context	Distance from Earthquake to Nearest Plate Boundary	EM-DAT (Cred, 2024)	Serves as a proxy for tectonic exposure and proximity to active seismic sources.
Hydro-climatic and environmental conditions	Diurnal Temperature Variation	C-LSAT (Wei et al., 2025)	Reflects short-term climatic stress that may affect environmental vulnerability and human health conditions.
Hydro-climatic and environmental conditions	Composite Environmental Quality Index	Figshare (Tu, 2025)	Integrates multiple environmental attributes to characterize overall ecological and land-surface conditions.
Socioeconomic development and the built environment	GDP	Zenodo (Kummu et al., 2025)	Represents national economic development level and the concentration of exposed economic assets.
Socioeconomic development and the built environment	Commercial Facility Density	Figshare (Tu, 2025)	Captures the intensity of economic activity and built-environment concentration.
Socioeconomic development and the built environment	GDP Growth Rate	ESG (World Bank, 2025)	Reflects economic dynamics and development trajectories influencing exposure and recovery capacity.
Socioeconomic development and the built environment	Population Density	LandScan (Sims et al., 2022)	Represents human exposure intensity in seismically active areas.
Socioeconomic development and the built environment	Level of Social Infrastructure	Figshare (Tu, 2025)	Indicates the availability of basic public services and urban support capacity.
Governance and health-system capacity	Government Effectiveness Estimate	ESG (World Bank, 2025)	Represents institutional capacity for regulation enforcement, emergency response, and event governance.
Governance and health-system capacity	Physicians per 10,000 Population	GHO (World Health Organization, 2025)	Serves as a proxy for health system capacity and post-event medical response potential.

389

390 **4.3.1 Individual drivers of spatial variation in earthquake mortality**

391 The factor detector results show pronounced spatial heterogeneity in the associations between individual factors
392 and cumulative earthquake fatalities (Figure 6.a). Population density (Factor 1) yields the highest explanatory
393 power ($q = 0.41$), indicating that cross-national differences in exposure are closely aligned with the spatial

differentiation of cumulative fatalities at the national scale. Development-related indicators, including GDP (Factor 2; $q = 0.39$) and the level of social infrastructure (Factor 3; $q = 0.36$), also exhibit relatively high explanatory power, suggesting that fatality patterns co-vary with development level and built-environment conditions across countries.

A second group of factors shows moderate explanatory power, including physicians per 10,000 population (Factor 8; $q = 0.21$) and governance-related indicators (Factors 7–9; $0.22 \geq q \geq 0.12$). These results indicate that health-system capacity and institutional conditions are statistically associated with part of the observed spatial differentiation in fatalities. By contrast, the tectonic–locational proxy distance to the nearest plate boundary (Factor 12; $q = 0.05$) shows comparatively low explanatory power when considered alone, implying that proximity to active plate margins has limited ability to differentiate national-level fatality outcomes in isolation.

Overall, the single-factor results indicate that no individual variable fully accounts for the observed spatial heterogeneity in earthquake fatalities. Instead, higher q -values are concentrated among exposure- and development-related indicators, providing a basis for examining whether combinations of factors further strengthen spatial differentiation.

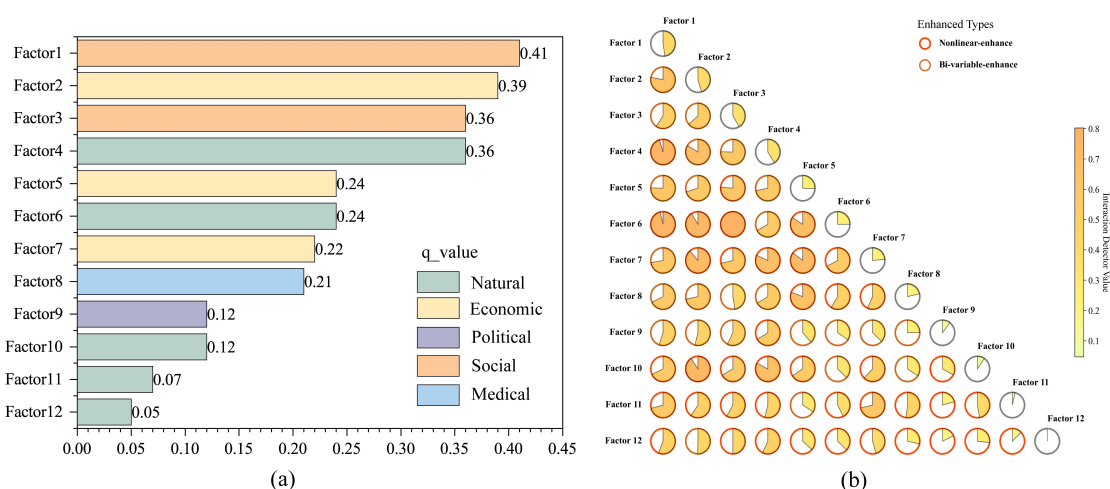


Figure 6. Spatial drivers of cumulative earthquake fatalities and their interaction effects at the global scale. a) Individual explanatory power of drivers based on the factor detector; b) Interaction effects among drivers identified by the interaction detector. Factors include: Factor 1 (Population density); Factor 2 (Gross domestic product (GDP)); Factor 3 (Level of social infrastructure); Factor 4 (Diurnal temperature variation); Factor 5 (Commercial facility density); Factor 6 (Composite environmental quality index); Factor 7 (GDP growth rate); Factor 8 (Physicians per 10,000 population); Factor 9 (Government effectiveness estimate); Factor 10 (Precipitation); Factor 11 (Soil moisture); Factor 12 (Distance to the nearest tectonic plate boundary).

4.3.2 Multi-factor interactions shaping earthquake mortality patterns

Interaction detector results indicate that earthquake fatality patterns are characterized by widespread multi-factor coupling (Figure 6.b). For nearly all factor pairs, joint explanatory power exceeds the corresponding single-factor q -values, and most interactions are classified as bi-variable enhancement or nonlinear enhancement, indicating that spatial differentiation in fatalities strengthens when factors are considered jointly. Interactions that involve high- q exposure and development indicators (e.g., population density with GDP or infrastructure) generally yield stronger joint effects, implying that spatial differentiation in fatalities becomes more pronounced when multiple factors are considered jointly.

Interactions involving high-q exposure and development indicators (e.g., population density combined with GDP or social infrastructure) generally yield stronger joint effects, suggesting that the spatial imprint of exposure is conditioned by national development and capacity contexts. Notably, factors with relatively low independent explanatory power—such as distance to the nearest plate boundary—often exhibit substantially higher explanatory power when combined with exposure- or capacity-related indicators. This pattern suggests that locational hazard context becomes more informative for understanding fatality patterns when evaluated together with where people, assets, and response capacity are distributed.

Overall, the interaction results reinforce that cross-national disparities in earthquake fatalities are associated with overlapping gradients of exposure, development, institutional capacity, and environmental conditions, rather than isolated single drivers.

4.3.3 A coupled human–environment interpretation of event impacts

Taken together, the Geographical Detector results support an interpretation of earthquake impacts as outcomes emerging from the spatial co-location of hazard context, exposure, and vulnerability. Tectonic structures define the global backdrop of seismic hazard, but cross-national variation in fatalities is more strongly aligned with population exposure and differences in development conditions, governance capacity, healthcare availability, and environmental context. The widespread enhancement and frequent nonlinear interactions observed in Figure 6.b further indicate that the association between any single factor and fatalities depends on the configuration of other factors, consistent with a multi-dimensional view of event risk.

Importantly, these results describe statistical associations at the national scale and do not imply causal relationships between individual drivers and earthquake fatalities. Nevertheless, they complement the preceding spatiotemporal analyses by clarifying why broadly similar tectonic settings can be associated with markedly different mortality outcomes across countries. In applied terms, the findings suggest that earthquake risk reduction may benefit from integrated intervention strategies that jointly address exposure management and capacity building (e.g., infrastructure and healthcare), rather than relying on single-sector measures. These associations are identified at the national scale and may mask subnational heterogeneity in exposure and vulnerability.

5 Discussion

5.1 Synthesis of key findings

This study provides a multi-scale synthesis of how global earthquake impacts have reorganized in space and time from 1980 to 2024. The temporal analyses reveal a distinct decoupling between seismic occurrence and event consequences: although earthquake frequency, human exposure, and cumulative economic losses increased over the study period, mortality rates declined steadily, especially after 2009. Similar findings have been reported globally and regionally, showing that while direct economic losses exhibit significant upward trends, mortality and human vulnerability have generally decreased due to advances in building resilience, governance, and risk management (Daniell et al., 2011; He et al., 2018; Formetta and Feyen, 2019). By integrating long-term interannual trends with period-based comparisons, our results further show that this decoupling varies markedly across regions and national contexts, highlighting the importance of socio-environmental conditions in shaping event outcomes. By explicitly combining long-term temporal trends with multi-scale spatial reorganization metrics and interaction-based attribution at the global scale, this study extends existing global earthquake assessments beyond patterns of hazard occurrence toward a comparative

understanding of event impacts across countries.

Spatial analyses show persistent clustering of earthquake occurrences and impacts along major tectonic boundaries—most prominently the Pacific Ring of Fire and the Alpine–Himalayan belt—yet with strong national-level disparities in event severity (Silva et al., 2019). The unweighted centroid analysis reveals coherent large-scale migration trajectories of recorded earthquake occurrences, while weighted centroid analyses based on affected population, fatalities, and economic losses demonstrate substantial spatial differentiation among different impact dimensions. Rather than indicating fundamental changes in global seismicity, these migration patterns primarily reflect changes in the spatial organization of recorded earthquake impacts. Attribution analysis using the Geographical Detector shows that population density, level of public infrastructure, economic level, governance quality, and healthcare capacity, together with their interaction effects, are strongly associated with cross-national variation in earthquake mortality (Peduzzi, 2019).

These integrated findings illustrate that earthquake impact outcomes are shaped not only by tectonic processes but also by evolving exposure patterns and socio-environmental vulnerability embedded within human-earth systems (Izquierdo-Horna and Yopez, 2022). Taken together, the spatiotemporal and interaction-based results reinforce the view that global earthquake impacts emerge through the interaction of tectonic processes, population exposure, socioeconomic vulnerability, and economic concentration across multiple spatial scales.

5.2 Mechanisms behind the spatiotemporal patterns

5.2.1 Human–Earth interactions shaping earthquake disaster impacts

The weighted centroid analyses reveal clear differences in the spatial organization of earthquake disaster impacts under different impact dimensions. While the unweighted centroids generally follow the distribution of major tectonic belts, the population-weighted, fatality-weighted, and economic loss-weighted centroids exhibit distinct spatial trajectories, indicating that earthquake impacts are shaped not only by seismic occurrence itself, but also by differences in population exposure, socioeconomic vulnerability, and economic concentration.

The population- and fatality-weighted centroids are mainly concentrated in South Asia, Southeast Asia, and the western Pacific margin, where dense populations and rapidly urbanizing settlements overlap with tectonically active regions. In particular, the fatality-weighted centroids show stronger clustering in developing regions with comparatively limited disaster resilience capacity. These patterns are consistent with the Geographical Detector results in Section 4.3, which indicate significant spatial associations between earthquake fatalities and socioeconomic, governance, and health-related factors. This suggests that contemporary earthquake disaster impacts are increasingly influenced by the interaction between physical hazard patterns and human-system characteristics, including urbanization, infrastructure concentration, governance capacity, and socioeconomic vulnerability (Cutter et al., 2003; Turner et al., 2003; IPCC, 2022).

By contrast, the economic loss-weighted centroids exhibit a relatively stronger concentration toward economically developed and asset-intensive regions, particularly around the western Pacific and trans-Pacific margins. This pattern indicates that countries with highly concentrated infrastructure and economic assets may experience substantial economic losses even when mortality impacts are comparatively lower. The divergence between fatality-weighted and economic loss-weighted patterns therefore reflects the uneven distribution of different dimensions of earthquake risk across global regions.

Overall, the observed spatiotemporal variations are more appropriately interpreted as changes in the spatial distribution and consequences of recorded earthquake disaster impacts under coupled human–Earth systems, rather than as fundamental changes in global tectonic processes.

5.2.2 Robustness and uncertainty assessment

Although EM-DAT is currently one of the most widely used global disaster databases, potential temporal variations in reporting completeness remain an important source of uncertainty, particularly for lower-impact earthquake events. Improvements in seismic monitoring systems, disaster reporting mechanisms, and international data integration since the 1980s may have increased the completeness and precision of recorded events over time. Such variations may particularly influence indicators normalized by the number of recorded earthquake events.

However, several aspects of the present study help reduce the influence of this uncertainty on the main conclusions. First, the temporal analysis was conducted using three aggregated study periods (1980–1994, 1995–2009, and 2010–2024), which reduces the influence of short-term fluctuations and year-to-year inconsistencies in event reporting. Second, the event-normalized indicators were mainly used as supplementary metrics to compare relative event-level impact characteristics among different stages and regions, rather than as primary indicators for inferring long-term changes in seismic activity or disaster severity. The principal conclusions of this study are primarily based on cumulative indicators, mortality-rate metrics, and spatial analyses, which are comparatively less sensitive to variations in event counts.

To further evaluate robustness, sensitivity analyses were conducted using different fatality thresholds (≥ 10 , ≥ 50 , and ≥ 100 deaths) and by excluding the top 1% deadliest earthquake events (Table 4). The results show that the principal temporal patterns remain broadly consistent across different sample specifications, suggesting that the observed trends are not solely driven by incomplete reporting of low-impact events or by a few catastrophic earthquakes.

Table 4. Sensitivity and robustness analyses of temporal trends under different event-selection criteria

Sample specification	NOE	MR	CDT	ADPE	CNAI	AAPE	CEL	AELPE	Conclusion
Full sample	↑*	↓*	↓n.s.	↓n.s.	↑*	↑n.s.	↑n.s.	↑n.s.	Baseline
Deaths ≥ 10	↓n.s.	↓**	↓n.s.	↓n.s.	↑*	↑*	↓n.s.	↓n.s.	Mostly consistent
Deaths ≥ 50	↓n.s.	↓*	↓n.s.	↓n.s.	↑n.s.	↑n.s.	↓n.s.	↓n.s.	Mostly consistent
Deaths ≥ 100	↓n.s.	↓*	↓n.s.	↓n.s.	↑n.s.	↑n.s.	↓n.s.	↓n.s.	Mostly consistent
Excluding top 1% deadliest events	↑*	↓**	↑n.s.	↓n.s.	↑***	↑**	↑*	↑*	Consistent

Notes: n.s. = not significant; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ↑ = increasing trend, ↓ = decreasing trend.

5.2.3 Implications for dynamic earthquake risk governance

The differentiated spatial patterns identified in this study highlight the importance of integrating physical hazard information with socioeconomic and exposure conditions in earthquake disaster governance. The increasing availability of near-real-time seismic observations, remote sensing products, and socio-environmental datasets provides new opportunities for dynamic earthquake risk assessment and rapid impact evaluation (Allen et al., 2009; Jaiswal et al., 2010). Integrating rapidly updated seismic information with population exposure and infrastructure datasets may improve the timely identification of high-risk regions and support emergency response and post-disaster decision-making.

However, many vulnerability-related factors identified in this study, including urban structure, infrastructure concentration, governance conditions, and demographic exposure, generally evolve more slowly than seismic observations themselves. Consequently, near-real-time monitoring is more suitable for short-term situational awareness and emergency support, whereas medium- and long-term disaster risk reduction strategies remain essential for improving structural resilience, land-use planning, and governance capacity. Dynamic risk

monitoring and long-term resilience-oriented planning should therefore be regarded as complementary approaches in future earthquake disaster governance.

5.2.4 Implications for dynamic earthquake risk governance

To further evaluate the relative economic burden of earthquake disasters, we calculated GDP-normalized losses for each study period using the ratio of total earthquake economic losses to total global GDP within the same period:

$$REL_t = \frac{\sum L_{oss_t}}{\sum GDP_t} \quad (12)$$

This aggregation-based approach was adopted because it is more stable for cross-period comparison and avoids the disproportionate influence of small economies that may occur when averaging country-level loss-to-GDP ratios. The results show that although absolute earthquake losses increased from US\$291.72 billion in 1980–1994 to US\$640.35 billion in 2010–2024, GDP-normalized losses declined from 0.1784% to 0.0576%. This indicates that the relative macroeconomic burden of earthquake losses decreased over time, despite the continued growth of absolute economic exposure.

5.2.5 Limitations

Several limitations should be acknowledged. EM-DAT underreports small and moderate events, which may affect frequency-related indicators (Cvetković et al., 2024). National-scale spatial analysis simplifies complex local fault geometries and intra-country heterogeneity. Geographical Detector identifies spatially stratified associations but cannot determine causal direction (Peduzzi, 2019). Additionally, socioeconomic variables are often static or infrequently updated, limiting the ability to model rapid socio-economic transitions.

5.2.6 Future research directions

Future work should incorporate near-real-time seismic and socio-environmental data, develop dynamic models to track evolving risk landscapes, and examine compound hazards involving interactions between seismic activity and climatic extremes. Integrating machine learning with physical models may further enhance predictive capability (Silva et al., 2019). Expanding high-resolution exposure and vulnerability datasets will support more detailed subnational risk assessments (Ma et al., 2023). Ultimately, advancing global earthquake risk research will require closer integration of physical seismology, spatial analysis, and socio-institutional vulnerability studies, in order to better support event risk reduction and resilience planning. The analytical framework adopted here demonstrates how global event databases can be combined with spatial reorganization and interaction analyses to inform comparative risk assessment and policy-relevant interpretation.

6 Conclusion

This study analyzed the spatiotemporal evolution of global earthquake impacts from 1980 to 2024 and examined national-scale factors associated with cross-country differences in event impacts. By integrating long-term temporal analysis, multi-scale spatial assessment, centroid-based spatial metrics, and factor interaction analysis, the study addresses four interrelated research questions.

First, with respect to long-term temporal change, global earthquake events exhibit a persistent decoupling between occurrence and consequences. While earthquake frequency, affected population, and cumulative

economic losses increased overall, mortality rates declined substantially after the early 2000s, reflecting an overall improvement in life protection relative to growing exposure rather than a reduction in hazard occurrence.

Second, in terms of spatial heterogeneity, earthquake impacts are unevenly distributed across continents and countries. Asia accounts for a large share of global earthquake events in terms of frequency, affected population, fatalities, and economic losses, yet the severity of impacts differs markedly among countries, indicating that broadly comparable tectonic settings are associated with highly divergent event outcomes.

Third, regarding spatial reorganization, the unweighted centroid of recorded earthquake occurrences exhibits a multi-stage directional migration pattern over the study period, while weighted centroid analyses based on affected population, fatalities, and economic losses reveal substantial spatial differentiation among different impact dimensions. Plate-level comparisons further reveal differentiated centroid migration patterns across major tectonic plates, reflecting the regional heterogeneity of the spatial organization of global earthquake impacts. Meanwhile, differences among population-weighted, fatality-weighted, and economic loss-weighted centroid trajectories suggest that regional economic structures, population distributions, and disaster prevention and response capacities have jointly reshaped the spatial patterns of earthquake impacts.

Finally, with respect to spatial disparities in fatalities, the Geographical Detector results indicate that population density and development-related factors exhibit relatively strong explanatory power. More importantly, interactions among socioeconomic, governance, health, environmental, and hazard-related variables consistently enhance explanatory strength beyond single-factor effects, highlighting that observed fatality patterns are statistically associated with coupled natural–social conditions rather than with tectonic context alone.

Overall, the findings underscore that global earthquake impacts are shaped by the spatial convergence of hazard exposure, development pathways, and institutional capacity. By identifying where event impacts diverge under similar hazard conditions and how multiple factors co-vary spatially, this study provides comparative, globally consistent evidence that can inform risk assessment, preparedness planning, and resilience-oriented decision-making, particularly in regions experiencing rapid exposure growth alongside persistent social and institutional vulnerability.

Code and Data Availability

The earthquake event data used in this study were obtained from the Emergency Events Database (EM-DAT). Socioeconomic, environmental, governance, and health-related datasets were collected from publicly accessible international databases, including the World Bank and the World Health Organization. Processed data and analysis code supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions

Zekang Zhang: formal analysis, data curation, visualization, writing—original draft preparation, manuscript formatting; Yingqiao Qiu: methodology; Yanjun Ye: conceptualization, writing—review and editing, supervision; Chaoran Xuan: data curation. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

References

- Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., and Hegewisch, K. C.: TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015, *Scientific Data*, 5, 170191, <https://doi.org/10.1038/sdata.2017.191>, 2018.
- Aksha, S. K. and Khanal, S.: An analysis of social vulnerability to natural hazards in Nepal, *International Journal of Disaster Risk Science*, 10, 310–324, <https://doi.org/10.1007/s13753-018-0192-7>, 2019.
- Allen, T. I., Wald, D. J., Earle, P. S., Marano, K. D., Hotovec, A. J., Lin, K., and Hearne, M. G.: An Atlas of ShakeMaps and population exposure catalog for earthquake loss modeling, *Bulletin of Earthquake Engineering*, 7, 701–718, <https://doi.org/10.1007/s10518-009-9120-y>, 2009.
- Anbarci, N., Escaleras, M., and Register, C. A.: Earthquake fatalities: The interaction of nature and political economy, *Journal of Public Economics*, 89, 1907–1933, <https://doi.org/10.1016/j.jpubeco.2004.08.002>, 2005.
- Ansari, A., Al-Awadhi, T., Al-Rawas, G., and Al-Busaidi, A.: Integrated GIS–AHP based assessment of earthquake vulnerability and risk in residential areas of Al-Seeb, Muscat Governorate (Oman), *Scientific Reports*, 15, 17618, <https://doi.org/10.1038/s41598-025-17618-6>, 2025.
- Bird, P.: An updated digital model of plate boundaries, *Geochemistry, Geophysics, Geosystems*, 4, 1027, <https://doi.org/10.1029/2001gc000252>, 2003a.
- Bird, P.: PB2002: Plate Boundary and Tectonic Data (2003) [dataset], 2003b.
- Burton, I.: Understanding risk in a changing world, *Natural Hazards*, 78, 1951–1968, <https://doi.org/10.1007/s11069-015-1950-3>, 2015.
- Cannon, S. H., Ellen, S. D., and Wieczorek, G. F.: Landslide hazard associated with earthquakes: A global review, *Engineering Geology*, 70, 1–15, [https://doi.org/10.1016/S0013-7952\(03\)00057-2](https://doi.org/10.1016/S0013-7952(03)00057-2), 2003.
- Casella, G. and Berger, R. L.: *Statistical Inference*, Duxbury Press, Pacific Grove, CA2002.
- Cohen, M. and Werker, E.: The political economy of “natural” disasters, *Journal of Conflict Resolution*, 52, 795–819, <https://doi.org/10.1177/0022002708321421>, 2008.
- CRED: EM-DAT - The International Disaster Database (2024) [dataset], 2024.
- Cutter, S. L.: Facing global environmental change: Piecing together the human exposure mosaic, *Annals of the American Association of Geographers*, 111, 897–903, <https://doi.org/10.1080/24694452.2021.1881107>, 2021.
- Cutter, S. L., Boruff, B. J., and Shirley, W. L.: Social vulnerability to environmental hazards, *Social Science Quarterly*, 84, 242–261, <https://doi.org/10.1111/1540-6237.8402002>, 2003.
- Cvetković, V. M., Renner, R., Aleksova, B., and Lukić, T.: Geospatial and Temporal Patterns of Natural and Man-Made (Technological) Disasters (1900–2024): Insights from Different Socio-Economic and Demographic Perspectives, *Applied Sciences*, 14, 8129, 2024.
- Daniell, J. E., Khazai, B., Wenzel, F., and Vervaeck, A.: The CATDAT damaging earthquakes database, *Nat. Hazards Earth Syst. Sci.*, 11, 2235–2251, <https://doi.org/10.5194/nhess-11-2235-2011>, 2011.
- Daniell, J. E., Vervaeck, A., Wenzel, F., and Khazai, B.: The worldwide economic impact of earthquake disasters, *International Journal of Disaster Risk Reduction*, 21, 261–271, <https://doi.org/10.1016/j.ijdrr.2016.11.002>, 2017.

- De Ruiter, M. C., Couasnon, A., Ward, P. J., Daniell, J. E., and Aerts, J. C. J. H.: The asynergies of structural disaster risk reduction: Building-level DRR measures for earthquake vs flood vulnerability, *Earth's Future*, 9, e2020EF001531, <https://doi.org/10.1029/2020ef001531>, 2021.
- Düzgün, H. Ş., Güney, A. B., Özkan, Ö., and Taşeli, B. B.: A spatial framework for assessing urban earthquake vulnerability, *Natural Hazards*, 117, 891-908, <https://doi.org/10.1007/s11069-023-05841-8>, 2023.
- Escaleras, M., Anbarci, N., and Register, C. A.: Public sector corruption and major earthquakes: A potentially deadly interaction, *Public Choice*, 132, 209-230, <https://doi.org/10.1007/s11127-007-9148-y>, 2007.
- Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., and Lewis, B.: A social vulnerability index for disaster management, *Journal of Homeland Security and Emergency Management*, 8, Article 3, <https://doi.org/10.2202/1547-7355.1792>, 2011.
- Formetta, G. and Feyen, L.: Empirical evidence of declining global vulnerability to climate-related hazards, *Global Environmental Change*, 57, 101920, <https://doi.org/10.1016/j.gloenvcha.2019.05.004>, 2019.
- Gall, M., Borden, K. A., and Cutter, S. L.: When do losses count? Six fallacies of natural hazards loss data, *Bulletin of the American Meteorological Society*, 92, 835-840, <https://doi.org/10.1175/2010bams3090.1>, 2011.
- Guo, X., Xu, Y., and Li, H.: Assessing social vulnerability to earthquake disaster using county-level data: A case study in Hanzhong City, China, *International Journal of Disaster Risk Reduction*, 49, 101632, <https://doi.org/10.1016/j.ijdr.2020.101632>, 2020.
- He, X., Wu, J., Wang, C., and Ye, M.: Historical Earthquakes and Their Socioeconomic Consequences in China: 1950-2017, *Int J Environ Res Public Health*, 15, <https://doi.org/10.3390/ijerph15122728>, 2018.
- Hu, Y., Wang, J., Li, X., Ren, D., and Zhu, J.: Geographical detector-based risk assessment of under-five mortality in the 2008 Wenchuan Earthquake, China, *PLoS ONE*, 6, e21427, <https://doi.org/10.1371/journal.pone.0021427>, 2011.
- Resource and Environmental Science Data Platform: <https://www.resdc.cn/>, last access: 2024/11/10.
- IPCC: Climate Change 2022: Impacts, Adaptation and Vulnerability, Cambridge University Press, Cambridge, 10.1017/9781009325844, 2022.
- Ismail-Zadeh, A.: Earthquakes yes, disasters no, *npj Natural Hazards*, 1, Article 46, <https://doi.org/10.1038/s44304-024-00049-0>, 2024.
- Izquierdo-Horna, L. and Yepez, Y.: Dimensions of seismic vulnerability and resilience: A review, *International Journal of Disaster Risk Reduction*, 68, 102737, <https://doi.org/10.1016/j.ijdr.2021.102737>, 2022.
- Jaiswal, K., Wald, D., and Porter, K.: A Global Building Inventory for Earthquake Loss Estimation and Risk Management, *Earthquake Spectra*, 26, 731-748, <https://doi.org/10.1193/1.3450316>, 2010.
- Kagan, Y. Y. and Jackson, D. D.: Global earthquake forecasting: Seismicity models and hazard assessment, *Annual Review of Earth and Planetary Sciences*, 44, 109-137, <https://doi.org/10.1146/annurev-earth-060115-012225>, 2016.
- Keefer, P., Neumayer, E., and Plümpert, T.: Earthquake propensity and the politics of mortality prevention, *World Development*, 39, 1530-1541, <https://doi.org/10.1016/j.worlddev.2011.03.006>, 2011.
- Kummu, M., Kosonen, M., and Masoumzadeh Sayyar, S.: Downscaled gridded global dataset for gross domestic product (GDP) per capita PPP over 1990-2022, *Scientific Data*, 12, 178, <https://doi.org/10.1038/s41597-025-04487-x>, 2025.
- Lapietra, I., Bonasia, M., and Pelligra, V.: Unveiling social vulnerability to natural hazards in the European Economic Area, *International Journal of Disaster Risk Reduction*, 102, 103651, <https://doi.org/10.1016/j.ijdr.2023.103651>, 2024.

- Lee, S., Dodge, J., and Chen, G.: The cost of social vulnerability: An integrative conceptual framework for assessing financial risks in natural disasters, *Natural Hazards*, 114, 691-712, <https://doi.org/10.1007/s11069-022-05408-6>, 2022.
- Li, Y., Zhou, Y., and Wang, L.: Impact of economic development levels on the mortality rates of Asian earthquakes, *International Journal of Disaster Risk Reduction*, 62, 102409, <https://doi.org/10.1016/j.ijdrr.2021.102409>, 2021.
- Ma, M., Zhang, Y., Wang, J., and Liu, H.: Spatial assessment of social vulnerability to earthquakes using multi-criteria decision analysis, *Scientific Reports*, 13, 21489, <https://doi.org/10.1038/s41598-023-48430-4>, 2023.
- Noy, I.: The economics of natural disasters: A survey, *International Review of Environmental and Resource Economics*, 9, 71-108, <https://doi.org/10.1561/101.00000068>, 2016.
- Peduzzi, P.: Drivers of risk: Exposure, vulnerability and hazard, *Progress in Disaster Science*, 2, 100030, <https://doi.org/10.1016/j.pdisas.2019.100030>, 2019.
- Peduzzi, P. and Herold, H. D. C.: Mapping Disastrous Natural Hazards Using Global Datasets, *Natural Hazards*, 35, 265-289, <https://doi.org/10.1007/s11069-004-5703-8>, 2005.
- Reid, P.: Disasters and social inequalities, *Sociology Compass*, 7, 878-894, <https://doi.org/10.1111/soc4.12080>, 2013.
- Rosvold, E. L. and Buhaug, H.: GDIS, a global dataset of geocoded disaster locations, *Scientific Data*, 8, 61, <https://doi.org/10.1038/s41597-021-00846-6>, 2021.
- Silva, V., Amo-Oduro, D., Calderon, A., Costa, C., Dabbeek, J., Despotaki, V., Martins, L., Pagani, M., Rao, A., Simionato, M., Vigano, D., Yepes-Estrada, C., and Crowley, H.: Assessing seismic hazard and risk globally for an earthquake resilient world, United Nations Office for Disaster Risk Reduction (UNDRR), Contributing Paper to GAR 2019, 2019.
- Sims, K., Reith, A., Bright, E., McKee, J., and Rose, A.: LandScan Global 2021 (2021), Oak Ridge National Laboratory [dataset], 10.48690/1527702, 2022.
- Tu, Y.: infrastructure_access_inequality, 10.6084/m9.figshare.28424639.v2, 2025.
- Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., and Schiller, A.: A framework for vulnerability analysis in sustainability science, *Proceedings of the National Academy of Sciences*, 100, 8074-8079, <https://doi.org/10.1073/pnas.1231335100>, 2003.
- United Nations Office for Disaster Risk Reduction (UNDRR): Global Assessment Report on Disaster Risk Reduction 2023 (GAR2023), United Nations Office for Disaster Risk Reduction, Geneva: UNDRR, 2023.
- Wang, J. F., Zhang, T. L., and Fu, B. J.: A measure of spatial stratified heterogeneity, *Ecological Indicators*, 67, 250-256, <https://doi.org/10.1016/j.ecolind.2016.02.052>, 2016.
- Wang, J. F., Li, X. H., Christakos, G., Liao, Y. L., Zhang, T., Gu, X., and Zheng, X. Y.: Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China, *International Journal of Geographical Information Science*, 24, 107-127, <https://doi.org/10.1080/13658810802443457>, 2010.
- Wang, X., Xia, J., Dong, B., Zhou, M., and Deng, S.: Spatiotemporal distribution of flood disasters in Asia and influencing factors in 1980–2019, *Natural Hazards*, 108, 2721-2738, <https://doi.org/10.1007/s11069-021-04798-3>, 2021.
- Wei, S., Li, Q., Xu, Q., Li, Z., Zhang, H., and Lin, J.: Updates to C-LSAT 2.1 and the development of high-resolution land surface air temperature and diurnal temperature range datasets, *Earth System Science Data*, 17, 4985-5005, <https://doi.org/10.5194/essd-17-4985-2025>, 2025.

Environmental, social, and governance (ESG) data:
[https://databank.worldbank.org/source/environment-social-and-governance-\(esg\)-data](https://databank.worldbank.org/source/environment-social-and-governance-(esg)-data), last access:
 2025/7/22.

Global Healthcare Statistics 2025: <https://www.who.int/data/gho/whs-annex/>, last access: 2025/7/22.

Wu, S., Hu, Z., Wang, Z., Cao, S., Yang, Y., Qu, X., and Zhao, W.: Spatiotemporal variations in extreme precipitation on the middle and lower reaches of the Yangtze River Basin (1970–2018), *Quaternary International*, 592, 80-96, <https://doi.org/10.1016/j.quaint.2021.04.010>, 2021.

Wyss, M., Speiser, M., and Tolis, S.: Earthquake fatalities and potency, *Natural Hazards*, 119, 1091-1106, <https://doi.org/10.1007/s11069-022-05627-x>, 2023.

Xiong, J., Li, J., Cheng, W., Zhou, C., Guo, L., Zhang, X., Wang, N., and Li, W.: Spatial-temporal distribution and the influencing factors of mountain flood disaster in southwest China, *Acta Geographica Sinica*, 74, 1374-1391, <https://doi.org/10.11821/dlxb201907008>, 2019.

Xofi, M., Gkimisi, A., and Karatza, M.: Exposure and physical vulnerability indicators to assess seismic risk, *GeoRisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, 16, 209-226, <https://doi.org/10.1080/19475705.2022.2068457>, 2022.

Zaliapin, I. and Ben-Zion, Y.: Earthquake clusters in Southern California I: Identification and stability, *Journal of Geophysical Research: Solid Earth*, 118, <https://doi.org/10.1002/jgrb.50179>, 2013.