

Bridging the gap between damaged infrastructures and disaster mortality

Arkabrabha Bhattacharyya  · Nazli Yonca Aydin · Tina Comes

Received: 8 January 2026 / Accepted: 16 September 2026

© The Author(s) 2026

Abstract

Driven by the lack of global empirical data, there is limited research that analyzed the relationship between infrastructure damage and disaster impact. In this research, we addressed this gap by scraping 79 Post Disaster Needs Assessment reports to collect disaster specific infrastructure damage data for 79 disaster events of this century. Then, we used the data in the Generalized Propensity Score method allowing us to reveal the real effect of infrastructure damage on disaster mortality by accounting for all other confounding factors. We derived an aggregate hazard agnostic response function indicating that damaged infrastructures exponentially increase disaster mortality. We also found that the impact of damaged infrastructures on disaster mortality is more profound among the low- and lower-middle-income countries as compared to overall impact. Lastly, we found that among different infrastructure sectors, the damage to energy, WASH (water, sanitation and hygiene), and health sectors lead to higher disaster mortality as compared to transport, communication, and education sectors. Through these empirical relationships, this research bridges the evidential gap between damaged infrastructures and disaster mortality that can help decision-makers forwarding infrastructure resilience agendas and prioritizing infrastructure sectors for resilience related investments.

Keywords Disaster mortality · Infrastructure damage · Vulnerability · Generalized propensity score · Post disaster needs assessment

Introduction

At the third UN world conference in Sendai, Japan in 2015, the Sendai Framework for Disaster Risk Reduction 2015–2030 was adopted by the stakeholders¹. The framework sets seven global targets that the stakeholders agreed to achieve by 2030. The first target is to *substantially reduce global disaster mortality*. However, disaster mortality is not distributed equally across the globe. A recent report by the United Nations Office for Disaster Risk Reduction (UNDRR) revealed that between 2000 and 2019, 67% of disaster related deaths happened in the low- and lower-middle-income countries, despite these countries experiencing only 43% of the global disaster during the same period². Not surprisingly, in academic literature, disaster mortality has been primarily associated with demographic conditions of the disaster affected populations^{3–5}. Researchers have found that socially

This Article in Press is shared early to give you faster access to new research. It is citable and carries a permanent DOI. The final edited version will replace it automatically.



vulnerable communities are often more severely affected by disasters due to their lack of coping capacities to deal with them^{6,7}.

Another target set by the Sendai framework is *reducing the disaster damage to critical infrastructures and basic services* particularly healthcare and education¹. Since infrastructures are essential for national security and the economic prosperity of a nation, understanding their vulnerability and resilience becomes directly relevant for developing effective DRR policies for informing governance and response for societal well-being. Therefore, academic literature has been focusing on assessing and analyzing how interdependent infrastructure systems perform under natural and man-made hazards for more than two decades aiming to provide insights into reducing disaster damage^{8–12}.

In addition to their importance to economic prosperity and national security, critical infrastructures like transport, communication, energy, water and sanitation also provide lifeline services to communities. When a critical infrastructure is disrupted, it can pose serious health risk to disaster affected communities as repeatedly witnessed in historical disaster events^{13–15}. In theory, it is known that damaged infrastructures influence the overall severity of disasters consequences. However, the magnitude of this influence remains underexplored. This is likely due to the limited availability of openly accessible disaster specific infrastructure damage data¹⁶.

Additionally, the disproportionate impact of disasters across global contexts necessitates a systematic investigation into heterogeneous effects. Theoretical framework such as the INFORM Risk Index suggests that disaster risk is the intersection of exposure to hazard, vulnerability, and lack of coping capacity¹⁷. In low- and lower-middle-income countries, this vulnerability is often compounded by limited institutional capacity, lack of redundant infrastructure, and inadequate enforcement of building codes^{18–20}. Consequently, the failure of a single critical asset in these regions can trigger a catastrophic cascade of human loss that is not observed in wealthier nations with higher built-in resilience^{21,22}. By analyzing the relationship between infrastructure damage and mortality across distinct country income groups, this study seeks to quantify how development status modulates the causal link between physical destruction and human life loss, which has largely remained underexplored in the existing literature.

To address the identified gaps, this study investigates the following two research questions: (1) What is the relationship between damaged infrastructures and disaster impact? We chose disaster mortality as a proxy of disaster impact as mortality reduction has been given the highest priority in the globally adopted Sendai Framework for Disaster Risk Reduction¹. (2) How does the relationship differ between countries belonging to different income groups and infrastructure sectors?

To answer these two research questions, we scraped infrastructure damage data from 79 openly accessible Post Disaster Needs Assessment (PDNA) reports and combined them exposure, vulnerability, and coping capacity data collected from multiple other sources to develop empirical models on how damaged infrastructures lead to disaster mortality. From these reports, we obtained disaster specific damage data to transport, communication, energy, water, sanitation, and hygiene (WASH), health, and education sectors for 79 disasters of this century caused by earthquakes, storms, and floods. Since we used observational data to investigate the effect of damaged infrastructure on disaster mortality, we adopted the Generalized Propensity Score method²³, which aims to approximate causal effects by taking into account confounding variables affecting disaster mortality and infrastructure damage. Furthermore, conventional statistical models often assume a linear relationship between physical destruction and human loss, disaster dynamics are frequently characterized by non-linear complexities and critical thresholds²⁴. To move beyond simple correlations and capture these dynamics, this study employs the GPS method. The primary motivation for adopting this framework is to reveal the specific dose–response function reflecting the causal link between infrastructure damage and disaster mortality. By utilizing a continuous treatment approach, we aim to highlight the potentially exponential nature of this relationship. Identifying such an exponential scale is crucial for understanding how mortality may accelerate disproportionately as infrastructure systems exceed their failure points. Through this research, we provide evidence and multi-country contexts on how damaged infrastructures lead to disaster mortality, which primarily existed in theory.

Results

Table 1 summarizes the relationship between infrastructure damage and disaster mortality based on a GPS weighted Generalized Linear Model (GLM) using Negative Binomial distribution. The model estimates the logarithm of disaster mortality per million population as a function of the total percentage damage to critical infrastructures including transportation, communication, energy, WASH, health, and education sectors relative to the country’s nominal GDP at the time of the disaster.

Weights for each sample were derived from the GPS, which adjusts for confounding by differentially weighting observations. This ensures that confounding variables do not bias the estimated causal effect of infrastructure damage on mortality. The coefficient for "% Damage to Infrastructures" measures the multiplicative increase in disaster mortality associated with each unit increase in infrastructure damage percentage. All coefficients in Table 1 are statistically significant (p values < 0.05), confirming the robustness of these causal estimates.

The Negative Binomial model intercept is 4.93 (p value < 0.001), and the slope coefficient for infrastructure damage is 18.18 (p value < 0.001), indicating a strong positive relationship. Specifically, each percent increase in infrastructure damage is associated with an exponential increase in disaster mortality. Based on these estimates, the expected fatalities per million population due to a disaster causing $x\%$ damage to infrastructures relative to nominal GDP can be calculated as $e^{(4.93+18.18x)}$.

The Cox-Snell pseudo- R^2 of 0.47 indicates that aggregate infrastructure damage as a percentage of GDP explains approximately 47% of the variation in deaths per million population, a notable result for a single-predictor model applied to cross-country disaster data where unobserved country-level heterogeneity is substantial.

Figure 1 visualizes the relationship between infrastructure damage and disaster mortality, using data from all countries in the sample. The horizontal axis measures total damage to infrastructures as a percentage of each country’s nominal GDP at the time of the disaster, while the vertical axis shows disaster deaths per million population. The figure demonstrates that higher infrastructure damage is associated with a sharply increasing (nonlinear) rise in disaster mortality. The prominent curve on the figure represents the Negative Binomial fit, which was used to model observed deaths per million at each level of infrastructure damage.

In Table 1, the Deviance/df ratio of 5.42 exceeds the target value of 1.0, indicating residual overdispersion beyond what the Negative Binomial family fully absorbs at the aggregate level. This is attributable to a small number of catastrophic events most notably Haiti (2010), Myanmar (2008), The Bahamas (2019), Libya (2023), etc., whose observed mortality substantially exceeds the model’s fitted values, as annotated in Fig. 1. These events represent structural outliers driven by factors beyond infrastructure damage alone, including pre-existing state fragility and near-total collapse of emergency response capacity. The elevated Deviance/df should therefore be interpreted as a reflection of the inherent heterogeneity of cross-country disaster mortality rather than a fundamental misspecification of the model’s mean function.

Historically, low- and lower-middle-income (L&LM) countries experienced more disaster mortality than the high- and upper-middle-income (H&UM) countries². Therefore, we analyzed if the influence of damaged infrastructures on disaster mortality depends on the country’s income groups. Table 2 presents the regression coefficients of the response functions for the two country groups. Like the aggregate response function in Table 1, here also the log-transformed disaster fatalities per million population were regressed on percentage damage to

Table 1 Regression coefficients for the aggregate response function (n=74).

	Coefficient	p value
Intercept	4.93	<0.001
% damage to infrastructures	18.18	<0.001
n	74	
Log-likelihood	−486.01	
AIC	976.02	
Pseudo R^2	0.47	
Deviance/df	5.42	

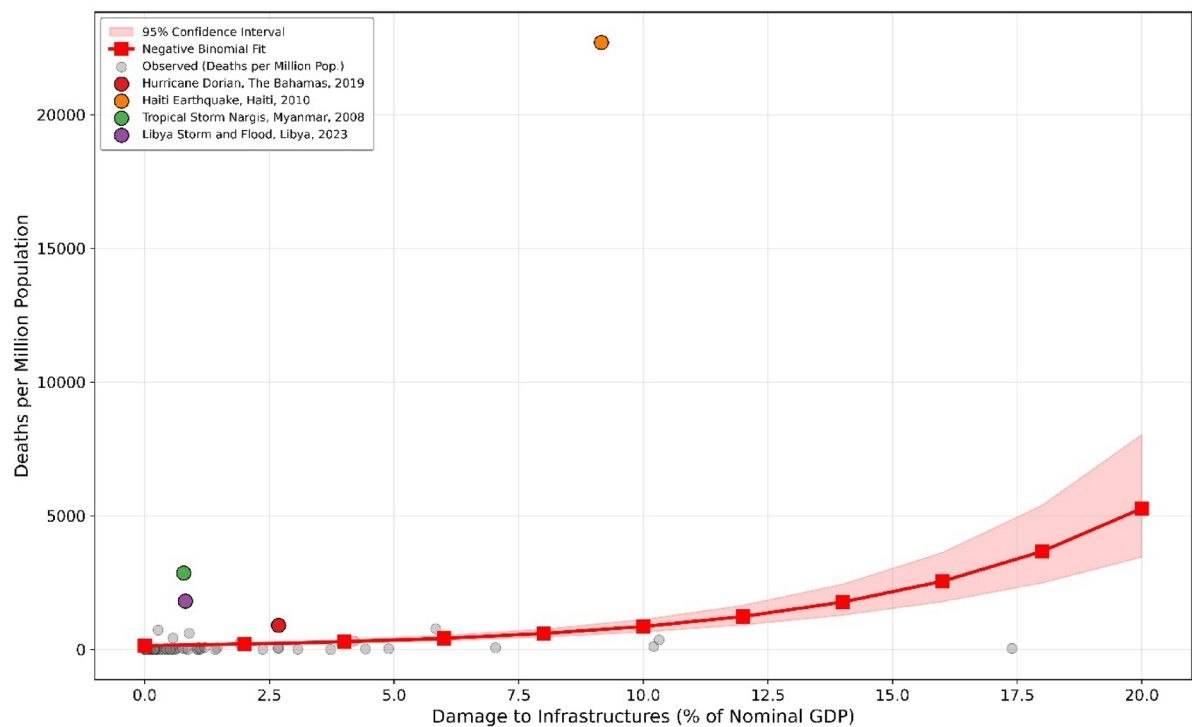


Fig. 1 Aggregate response functions for all countries.

Table 2 Regression coefficients for the two country groups.

	Low- and lower-middle-income countries (n=56)		High- and upper-middle-income countries (n=18)	
	Coefficient	<i>p</i> value	Coefficient	<i>p</i> value
Intercept	4.19	<0.001	5.30	<0.001
% damage to infrastructures	47.88	<0.001	1.45	0.366
n	56		18	
Log-likelihood	−318.20		−115.22	
AIC	640.40		234.44	
Pseudo R ²	0.89		0.07	
Deviance/df	4.09		4.42	

infrastructures using GPS weighted Negative Binomial regression model. First, it can be observed that the regression coefficients for the low- and lower-middle-income countries are both positive and statistically significant. Like the aggregate response function in Table 1, a positive coefficient corresponding to the percentage damage to infrastructures indicate that disaster mortality increases exponentially with higher infrastructure damage. Also, the regression coefficient corresponding to the percentage damage to infrastructures for low- and lower-middle-income countries in Table 2 is higher than that of in Table 1. This suggests that the impact of damaged infrastructures on disaster mortality is more severe among the low- and lower-middle-income countries. The Cox-Snell pseudo- R^2 of 0.89 indicates that aggregate infrastructure damage explains approximately 89% of the variation in disaster mortality within this group, reflecting a well-defined dose–response relationship.

In contrast, the impact of damaged infrastructures on disaster mortality is not statistically significant for the high- and upper-middle-income countries. This could be possibly due to the lack of data points for high- and upper-middle-income countries (n=18) compared to low- and lower-middle-income countries (n=56). Due to statistical insignificance, the results and insights for high- and upper-middle-income countries should only

be interpreted for exploratory purposes. No inference should be made for this country group due to statistical insignificance of the results. The insignificant regression coefficient for damaged infrastructures among the high- and upper-middle-income countries is also much smaller compared to the low- and lower-middle-income countries. The high- and upper-middle-income countries' response functions have higher intercept value than low- and lower-middle-income countries' response functions. This suggests that for lower levels of damage to infrastructures, high- and upper-middle-income countries suffered more disaster mortality compared to low- and lower-middle-income countries. However, disaster mortality increased more rapidly among the low- and lower-middle-income countries due to higher coefficient values corresponding to percentage damage to infrastructures. Hence, at higher levels of damage to infrastructures, disaster mortality experienced by low- and lower-middle-income countries was higher compared to high- and upper-middle-income countries.

The Deviance/df ratios of 4.09 (L&LM) and 4.42 (H&UM) both exceed the target value of 1.0, indicating residual overdispersion in both models. As discussed in relation to Table 1, this is attributable to a small number of catastrophic events whose observed mortality substantially exceeds the model's fitted values, rather than to fundamental misspecification of the mean function.

Next, we present the response function for low- and lower-middle-income countries in Fig. 2. There, the damage to infrastructures as a percentage of nominal GDP has been limited till 10% as more than 95% of the data points fell within 10%. Figure 2 shows that disaster mortality increases due to higher levels of damage to infrastructure sectors for low- and lower-middle-income countries. However, the rate of increase in disaster mortality due to higher infrastructure damage is much more profound in low- and lower-middle-income countries compared to aggregate response function in Fig. 1. Due to the statistical insignificance of regression coefficients for high- and upper-middle-income countries in Table 2, we have not developed the corresponding response function.

Next, we analyzed the influence of different infrastructure sectors on disaster mortality for the low- and lower-middle-income countries and high- and upper-middle-income countries separately. In addition to the five infrastructure sectors (transportation and communication, energy, WASH, health, and education), we also analyzed the influence of damaged buildings on disaster mortality. It is important to note that damaged buildings were not

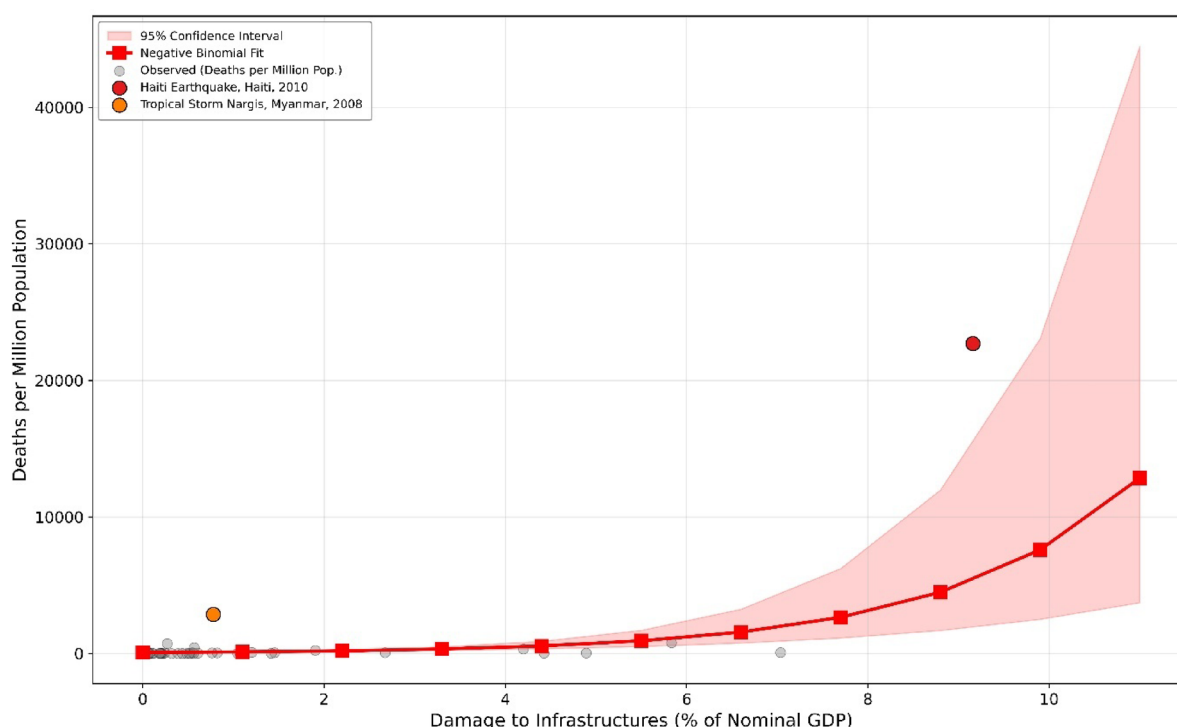


Fig. 2 Aggregate response functions for low- and lower-middle-income countries.

considered as part of the infrastructure sectors for the aggregated response functions shown in Figs. 1 and 2. Since most of the PDNA reports reported damage to transport and communication sectors together as one sector, they were considered collectively as one sector for this sectoral analysis.

First, we inspect the sectoral damages in our database, which are shown in Table 3. It presents the descriptive statistics of sectoral infrastructure damage as a percentage of nominal GDP for the two country income groups. Across all six sectors, H&UM countries report substantially higher damage-to-GDP ratios than L&LM countries, both in terms of mean and median values. This finding may appear counterintuitive at first glance, as wealthier countries might be expected to sustain lower relative losses. However, the H&UM subsample is dominated by small island developing states including Dominica, the Bahamas, Grenada, Saint Vincent and the Grenadines, and others whose GDP base is disproportionately small relative to their exposed built infrastructure stock. A single cyclone or earthquake damaging coastal buildings and transport networks in these nations generates a high damage-to-GDP ratio even when the absolute dollar loss is modest in comparison to larger L&LM economies such as Bangladesh or India.

For L&LM countries, the Building sector records the highest mean damage at 1.77% of GDP, followed by Transport & Communications at 0.76%, Education at 0.31%, Energy at 0.10%, Health at 0.10%, and WASH at 0.09%. The ordering is broadly similar for H&UM countries, where Buildings again dominates at 9.07% of GDP, followed by Transport & Communications at 6.32%, Education at 1.38%, Energy at 0.55%, WASH at 0.52%, and Health at 0.34%. Within L&LM countries, the WASH and Energy sectors show particularly compressed distributions, with 75th percentile values of 0.09% and 0.04% of GDP respectively, indicating that meaningful energy and sanitation damage is reported only in a small minority of events. Within H&UM countries, the Transport & Communications sector shows the widest dispersion, with a standard deviation of 14.79% against a mean of 6.32%, reflecting the outsized role of a few extreme cyclone events in small island states where road and port networks represent a large share of national assets.

Across both groups, all six sectoral distributions are heavily right-skewed, with standard deviations substantially exceeding the respective means. The gap between mean and median is especially pronounced in the Buildings and Transport & Communications sectors. For L&LM countries, Buildings damage has a mean of 1.77% but a median of only 0.49%, while Transport & Communications has a mean of 0.76% against a median of 0.15%. For H&UM countries, the same pattern is even more extreme: Buildings records a mean of 9.07% against a median of 3.94%, and Transport & Communications a mean of 6.32% against a median of just 0.31%. This skewness confirms that group-level averages are driven by a small number of catastrophic events rather than by the typical disaster in the sample.

For the intersectoral comparison, we present the results in Table 4. We showed the regression coefficients of the sector specific response functions for the six sectors (5 infrastructure sectors and buildings) for the two country groups—low- and lower-middle (L&LM) income and high- and upper-middle (H&UM) income in Table

Table 3 Descriptive statistics of sectoral damage.

Group	Sectors	Mean	Std	Min	25%	50%	75%	Max
L&LM countries (n = 56)	Buildings	1.77%	3.76%	0.00%	0.12%	0.49%	1.54%	19.67%
	Health	0.10%	0.28%	0.00%	0.00%	0.02%	0.07%	1.66%
	Education	0.31%	0.85%	0.00%	0.01%	0.05%	0.17%	5.04%
	Transport & Comm	0.76%	1.67%	0.00%	0.03%	0.15%	0.61%	9.87%
	Energy	0.10%	0.33%	0.00%	0.00%	0.01%	0.04%	2.22%
	WASH	0.09%	0.19%	0.00%	0.00%	0.01%	0.09%	0.89%
H&UM countries (n = 18)	Buildings	9.07%	16.73%	0.02%	0.56%	3.94%	7.95%	67.90%
	Health	0.34%	0.59%	0.00%	0.02%	0.07%	0.28%	2.09%
	Education	1.38%	3.45%	0.00%	0.02%	0.14%	0.63%	14.20%
	Transport & Comm	6.32%	14.79%	0.00%	0.10%	0.31%	2.63%	48.85%
	Energy	0.55%	1.48%	0.00%	0.02%	0.07%	0.34%	6.36%
	WASH	0.52%	1.25%	0.00%	0.02%	0.07%	0.22%	4.60%

Table 4 Sector specific regression coefficients for the two country groups.

Sector	Low- and lower-middle-income countries				High- and upper-middle-income countries			
	Coefficient	<i>p</i> value	Intercept	<i>p</i> value	Coefficient	<i>p</i> value	Intercept	<i>p</i> value
Transport & communication	94.49	<0.001	4.39	<0.001	1.49	0.360	5.40	<0.001
Energy	1955.27	<0.001	4.49	<0.001	33.13	0.353	5.45	<0.001
WASH	894.97	<0.001	4.65	<0.001	29.52	0.248	5.43	<0.001
Health	288.97	<0.001	4.56	<0.001	6.54	0.916	5.63	<0.001
Education	233.83	<0.001	4.21	<0.001	6.59	0.706	5.10	<0.001
Building	83.80	<0.001	3.72	<0.001	4.93	0.056	5.17	<0.001

4. From Table 4, it can be noticed that the sectoral influence on disaster mortality is statistically significant only for the low- and lower-middle-income countries as noticed in Table 2. Within the low- and lower-middle-income countries, damage to energy sector contributes the most to disaster mortality, which is followed by WASH, health, education, transport and communication, and buildings. On the other hand, for the high- and upper-middle-income countries, none of the sectoral influences are statistically significant. This is possibly due to the limited number of data points available to derive the response functions. Despite the statistical insignificance, the order of influence of different sectors on disaster mortality among the high- and upper-middle-income countries follow similar order as the low- and lower-middle-income countries. Energy sector has the highest influence on disaster mortality that is followed by WASH, education, health, building, and transport and communication. Lastly, if we compare the sectoral influence between the two country groups only for exploratory purposes, despite the statistical insignificance of the regression coefficients for high- and upper-middle-income countries, it can be noticed that influence of all the sectors on disaster mortality is more profound among the low- and lower-middle-income countries.

The sectoral regression coefficients reported in Table 4 must be interpreted in light of the damage scales documented in Table 3. All sectoral predictors are expressed as proportions of GDP and take near-zero values in the large majority of observations. The seemingly extreme coefficient magnitudes such as the Energy coefficient of 1955.27 and the WASH coefficient of 894.97 for L&LM countries do not imply astronomically large effects at realistic damage levels. At the 75th percentile of observed Energy damage for L&LM countries (0.04% of GDP, or 0.0004 in model units), the implied multiplicative increase in deaths per million population is $e^{1955.27 \times 0.0004} \approx e^{0.782} \approx 2.19$, representing an approximate doubling of expected mortality. At the same percentile for WASH damage (0.09% of GDP), the implied multiplier is $e^{894.97 \times 0.0009} \approx e^{0.805} \approx 2.23$. For Transport & Communications, whose 75th percentile damage for L&LM countries is 0.61% of GDP, the implied multiplier is $e^{94.49 \times 0.0061} \approx e^{0.576} \approx 1.78$, yielding a more moderate increase consistent with the sector's broader damage range. The large coefficient magnitudes therefore reflect the combination of a near-zero damage scale and a steep dose–response relationship concentrated in the small number of high-damage events. Readers are advised to evaluate all sectoral coefficients at the percentile values reported in Table 3 rather than at a theoretical one-unit increase, which would represent a damage level orders of magnitude beyond any observed event in the dataset.

Table 5 reports the goodness-of-fit statistics for the GPS-weighted negative binomial dose–response models estimated separately for each infrastructure sector and income group. The results reveal a consistent pattern of strong model performance for L&LM countries and substantially weaker fit for H&UM countries across all sectors.

For L&LM countries, the sectoral models achieve pseudo- R^2 values ranging from 0.73 (WASH) to 0.84 (Energy), indicating that individual sectoral damage explains between 73 and 84% of the variation in disaster mortality within this group. These values are broadly comparable to the aggregate model pseudo- R^2 of 0.89 (Table 2), confirming that each sector independently captures a substantial share of the mortality signal. The AIC values range from 575.28 (Education) to 675.44 (WASH), and each sectoral AIC must be interpreted against the aggregate baseline of 640.40. The Education (575.28), Health (615.60), Energy (628.16), and Buildings (633.66) sectoral models all achieve lower AIC than the aggregate specification, indicating superior fit relative to the single

Table 5 Goodness of fit for sectoral response functions.

Group	Sectors	n	Log-likelihood	AIC	Pseudo R ²	Deviance/df
L&LM countries (n=56)	Buildings	56	−314.83	633.66	0.81	4.08
	Health	53	−305.80	615.60	0.82	4.04
	Education	50	−285.64	575.28	0.80	3.81
	Transport & Comm	54	−320.80	645.60	0.77	4.40
	Energy	45	−312.08	628.16	0.84	14.33
	WASH	52	−335.72	675.44	0.73	5.65
H&UM countries (n=18)	Buildings	18	−116.03	236.05	0.14	4.83
	Health	16	−106.37	216.74	<0.001	4.98
	Education	15	−92.18	188.36	0.02	6.51
	Transport & Comm	17	−110.54	225.08	0.06	4.49
	Energy	16	−105.13	214.26	0.06	4.07
	WASH	17	−111.63	227.26	0.09	3.93

aggregate damage predictor. The Transport & Communications (645.60) and WASH (675.44) models show marginally higher AIC than the aggregate, suggesting these sectors alone are less efficient predictors of mortality than the composite infrastructure damage measure for L&LM countries.

The observation counts vary slightly across sectors within the L&LM group, ranging from 45 (Energy) to 56 (Buildings), reflecting the removal of zero-damage observations prior to model estimation as discussed in Sects. “[Sensitivity analysis](#)” and “[Methodology](#)”. This variation should be noted when comparing AIC values across sectors within the same group, as AIC is sensitive to sample size and direct comparisons are most reliable when n is equal. The Energy sector warrants particular attention. Despite achieving the highest pseudo-R² (0.84), it records the highest Deviance/df of 14.33 among sectoral models. This indicates substantial residual overdispersion concentrated in a small number of events where energy infrastructure damage co-occurs with catastrophic mortality outcomes, consistent with the structural outliers identified in Figs. 1 and 2.

For H&UM countries, the sectoral models show uniformly weak goodness-of-fit, with pseudo-R² values ranging from less than 0.001 (Health) to 0.14 (Buildings). None of the sectoral specifications achieved a pseudo-R² above 0.15, confirming that individual sectoral damage ratios are poor predictors of disaster mortality for this group at the aggregate level. The AIC values range from 188.36 (Education, n=15) to 236.05 (Buildings, n=18), all of which are lower than the H&UM aggregate model AIC of 234.44. However, given that observation counts vary between 15 and 18 across sectors and that pseudo-R² values are uniformly low, the lower AIC values reflect the reduced sample sizes rather than genuine improvement in explanatory power. The Deviance/df ratios for H&UM sectors range from 3.93 (WASH) to 6.51 (Education), indicating moderate to substantial overdispersion throughout. Taken together, the H&UM sectoral results reinforce the conclusion drawn from Table 2: the small and compositionally heterogeneous nature of the H&UM subsample limits the statistical power of any single-predictor dose–response specification, and the sectoral coefficients for this group reported in Table 4 should be interpreted with appropriate caution. As explained previously, the dose response functions for H&UM group should only be used for exploratory purposes and no inference should be made from them due to statistical insignificance.

Sensitivity analysis

We ran a sensitivity analysis to explore the effect of missing data imputation scheme on our response functions. Table 6 reports the number and percentage of missing values for each infrastructure sector across the two country income groups. Missing values here refer to observations where a disaster event was recorded in the dataset, but no damage estimate was available for a given sector in the original PDNA report.

Table 6 Number and percentages of missing values for each sector.

Sector	L&LM (n=56) missing (n)	L&LM (n=56) missing (%)	H&UM (n=18) missing (n)	H&UM (n=18) missing (%)
Buildings	0	0,00%	0	0,00%
Health	2	3,60%	2	11,10%
Education	5	8,90%	2	11,10%
Transport & Comm	0	0,00%	0	0,00%
Energy	11	19,60%	2	11,10%
WASH	4	7,10%	1	5,60%

Table 7 Regression coefficients without missing data imputation.

	All countries		L&LM countries		H&UM countries	
	Coefficient	<i>p</i> value	Coefficient	<i>p</i> value	Coefficient	<i>p</i> value
Intercept	5.32	<0.001	4.45	<0.001	5.73	<0.001
% damage to infrastructures	13.47	<0.001	45.34	<0.001	1.10	0.645
<i>n</i>	59		45		14	
Log-likelihood	−403.87		−269.24		−94.93	
AIC	811.74		542.48		193.86	
Pseudo R ²	0.33		0.89		0.02	
Deviance/df	5.36		4.10		4.46	

The Buildings and Transport & Communications sectors have no missing value in either group, reflecting the near-universal availability of damage estimates for physical infrastructure in post-disaster assessments. These two sectors are also the largest in absolute damage terms (Table 3), which is consistent with their systematic documentation across all disaster types and income contexts.

The remaining four sectors show varying degrees of missingness. The Energy sector records the highest rate of missing data overall, with 11 missing observations in the L&LM group (19.6%) and 2 in the H&UM group (11.1%). The Education sector follows with 5 missing observations in L&LM (8.9%) and 2 in H&UM (11.1%). WASH records 4 missing values in L&LM (7.1%) and 1 in H&UM (5.6%). Health has the lowest missingness among the four affected sectors, with 2 missing observations in each group (3.6% for L&LM and 11.1% for H&UM). The higher percentage of missing values for the H&UM group in Health and Education reflects the smaller absolute sample size (*n*=18) rather than a systematically greater data availability problem. In absolute terms, the number of missing observations is equal to or lower than in the L&LM group for every sector.

These missing observations are the direct reason why the sectoral model sample sizes reported in Table 5 differ from the group totals of 56 and 18. Rows with missing sectoral damage values were excluded listwise prior to sectoral response function estimation. So, the Energy model for L&LM is estimated on 45 observations, the Education model on 50, and the WASH model on 52. On the other hand, for aggregate response functions in Table 1 and 2, the missing values were imputed as zero.

To assess the robustness of the primary results to the imputation of missing sectoral damage values, a complete-case sensitivity analysis was conducted by re-estimating the GPS-weighted Negative Binomial dose–response models after deletion of all observations with missing values in any of the six infrastructure sectors. This reduced the analytical sample from 74 to 59 observations across all countries, from 56 to 45 for L&LM countries, and from 18 to 14 for H&UM countries. The response functions after removing the sectoral missing data are presented in Table 7.

For the aggregate response function model, the complete-case coefficient is 13.47 (*p*<0.001) compared to 18.18 (*p*<0.001) in the primary specification. The moderate reduction in coefficient magnitude is expected given that the complete-case sample excludes the 15 observations with missing sector values, several of which correspond to high-damage, high-mortality events that contribute substantially to the estimated slope. The pseudo-R²

decreases from 0.47 to 0.33, and the AIC changes from 976.02 to 811.74 noting that the latter reflects the smaller sample size ($n=74$ vs $n=59$) rather than a deterioration in model fit per observation. The positive direction and statistical significance of the aggregate dose–response relationship are nevertheless preserved.

The findings for L&LM countries are highly consistent with the primary analysis. The coefficient on infrastructure damage in the complete-case specification is 45.34 ($p<0.001$), compared to 47.88 ($p<0.001$) in the imputed dataset, i.e., a difference of less than 6% in magnitude with no change in direction or significance. The pseudo- R^2 remains 0.89 and the Deviance/df of 4.10 is virtually identical to the primary model value of 4.09, confirming that the strong dose–response relationship between infrastructure damage and disaster mortality in L&LM countries is not an artefact of the imputation procedure.

For H&UM countries, the complete-case coefficient is 1.10 ($p=0.645$), consistent with the primary result of 1.45 ($p=0.366$). In both specifications, the coefficient is small in magnitude, in the same direction, and statistically non-significant. The reduction in sample size from 18 to 14 further reduces statistical power.

Taken together, the sensitivity analysis confirms that the primary findings are robust to the treatment of missing data. The directional consistency, preservation of statistical significance patterns, and near-identical goodness-of-fit diagnostics across all three specifications provide reassurance that the imputation of missing sectoral damage values does not materially influence the substantive conclusions of the study.

Discussion

We found positive and statistically significant causal relationships between damaged infrastructures and disaster mortality. It is well-known that infrastructures provide lifeline services to communities. Therefore, disruption in those lifeline services evidently poses life threatening risks, which explains why damaged infrastructures lead to disaster mortality. However, the existing literature has not yet established which infrastructure sectors contribute most to disaster fatalities across countries. This study addresses that using historical multi-country contextual data.

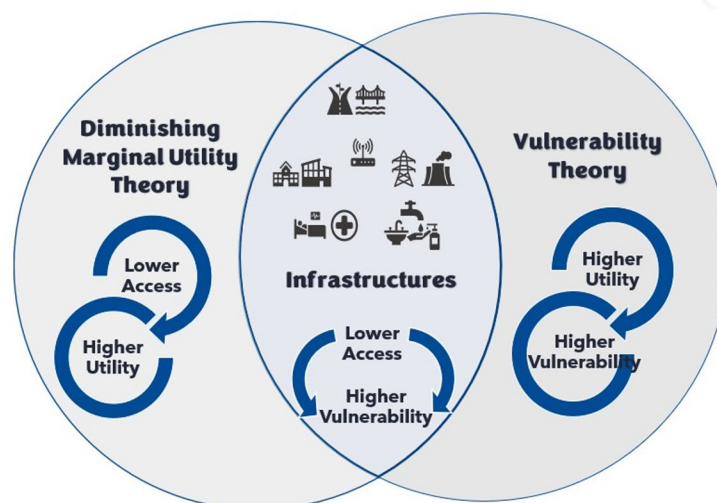
We found that disaster mortality increases more rapidly among the low- and lower-middle-income countries compared to high- and upper-middle-income countries for higher infrastructure damage. This could be due to the fact that in low- and lower-middle-income countries the infrastructure including healthcare, roads, electricity and WASH could already be fragile during pre-disaster conditions. When exposed to disasters, the knock-on effects on them are much more severe.

Additionally, poor quality infrastructures in low- and lower-middle-income countries also contribute to their vulnerability. Poorly maintained infrastructures fail more frequently during disasters²⁵. The Global Infrastructure Hub (GI Hub), which is the global platform of the World Bank's Public–Private Infrastructure Advisory Facility (PPIAF) rated the infrastructure quality among low-, lower-middle-, upper-middle-, and high-income country groups in 2019. The rating ranges between 1 and 100, where 100 is the best. The average infrastructure quality among countries in low-, lower-middle-, upper-middle-, and high-income groups were 41.4, 57.4, 69, and 84, respectively²⁶. Clearly, the quality of infrastructures in low- and lower-middle-income countries is inferior compared to high- and upper-middle-income countries, which further explains the difference in the influence of damaged infrastructures on disaster mortality between these country groups.

Arguably, upper-middle- and high-income country groups have better emergency management and response systems, and/or early warning systems, which are indications of higher coping capacity. Therefore, if the damage magnitude is constant at both groups, the low- and lower-middle-income countries with pre-existing vulnerabilities such as high poverty rates, less coping capacity, weaker health systems will lead to worse outcomes.

This disproportionate impact of infrastructure damage on disaster mortality could be further explained through a combination of two theories as shown in Fig. 3. The first theory is the law of diminishing marginal utility, i.e., a theory popularized in microeconomics. It states that the additional satisfaction from consuming goods or services decreases as consumption increases. Based on this theory, it can be claimed that the utility or criticality

Fig. 3 Theoretical framework explaining why damaged infrastructures lead to more disaster mortality in low- and lower-middle-income countries.



of infrastructures is higher in countries that have traditionally lower access to them. For instance, if community A only has one hospital that is working, the utility of that hospital is higher in that community than a similar community B that has two or more hospitals that are working. On the other hand, vulnerability theories claim that higher dependence on a single infrastructure increases the vulnerability of the users to its failure^{27,28}. If the only hospital in community A is damaged and fails to provide the essential services, it will cause more plights to community A compared to the failure of one of the hospitals in community B as it has more redundancies from having two or more hospitals.

Figure 4 shows the differences in access to different infrastructure sectors among low- and lower-middle (L&LM) income and high- and upper-middle (H&UM) income countries in the data used for this research. It can be noticed that the pattern is consistent for the six sectors in Fig. 4. In all of them, the median access to infrastructures is lower in low- and lower-middle-income countries compared to high- and upper-middle-income countries. The lower access rate combined with lack of redundancy in infrastructures, where the communities rely on a single hospital or water supply leads to steep increase in disaster fatalities in these countries. This explains why low- and lower-middle-income countries suffer more in terms of disaster mortality due to damaged infrastructures.

Methodology

The methodological flowchart is shown in Fig. 5. To derive the relationship between damaged infrastructures and disaster mortality, we adopted the Generalized Propensity Score (GPS) method. The method focuses on quantifying the causal estimates between a treatment variable (damaged infrastructure) and an outcome variable (disaster mortality) while balancing the effects of covariates from observational data. Due to its effectiveness, propensity score-based methods have gained popularity in disaster risk reduction and resilience research^{29–32}.

The GPS method balances the effects of confounding variables or covariates that influence both the treatment and response variable. Hence, neutralizing their effects is essential to realize the true causal relationship between the treatment and outcome variable. In the GPS method, the relationship between the treatment and outcome variable is presented as a response function that shows the variation in the outcome variable for various levels of treatment variable. These variables have been explained in further detail in the Data section.

The method—Generalized Propensity Score for continuous treatment was initially proposed by Hirano and Imbens²³. They defined GPS as the conditional density of the continuous treatment based on underlying covariates. The definition is shown in Eq. 1.

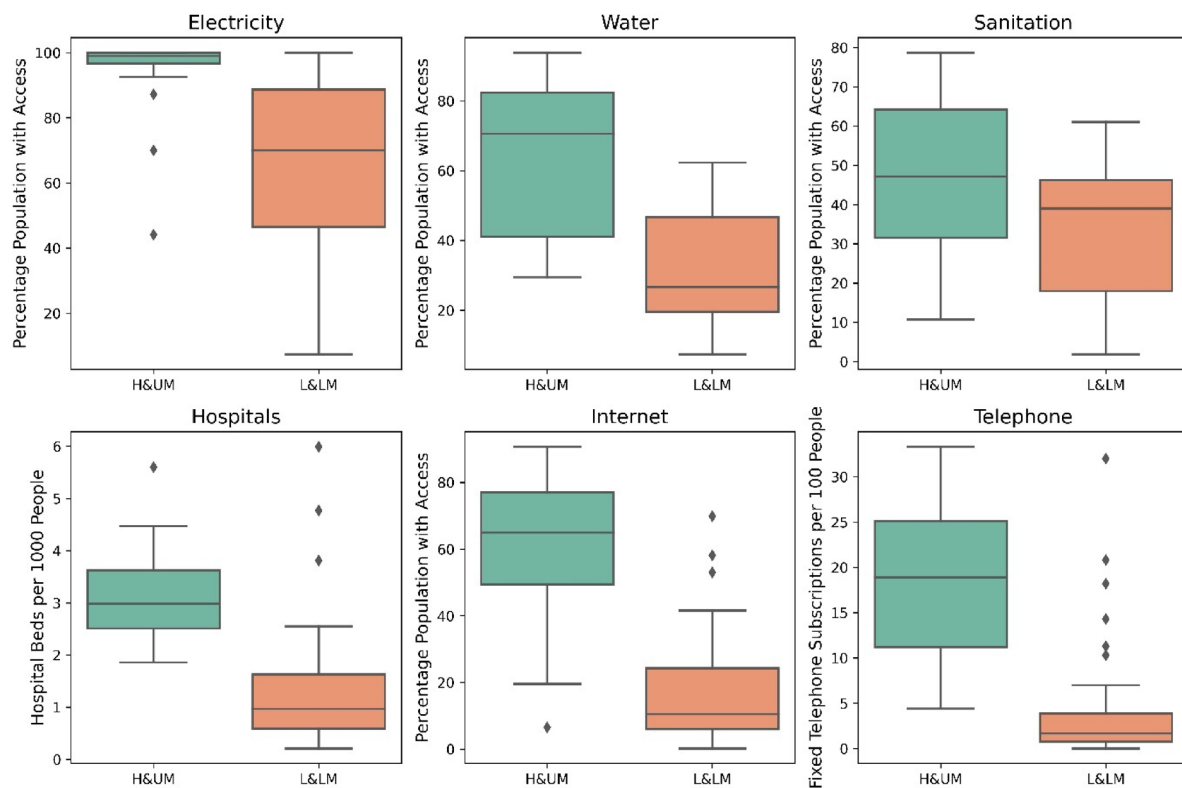


Fig. 4 Differences in access to infrastructure sectors between the country groups.

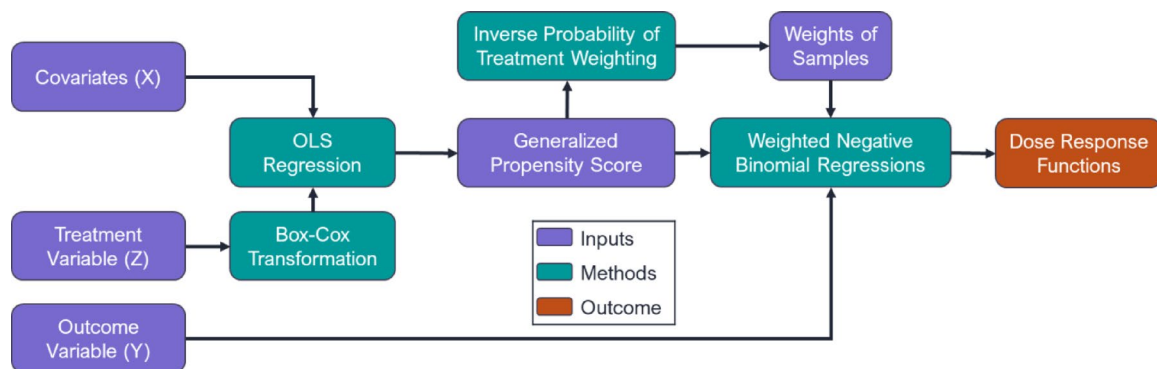


Fig. 5 Methodological flowchart.

$$r(z, x) = f_{Z|X}(z|x) \quad (1)$$

where, Z is the treatment variable and X is the set of measured baseline covariates. The GPS is defined as $R = r(Z, X)$. Imai and Van Dyk³³ refers to the conditional density function $f_{Z|X}$ as the propensity function, which is derived based on the methodological flowchart shown in Fig. 5. There, it can be noticed that the process starts with establishing an ordinary least square (OLS) regression between the treatment variable and the covariates. This OLS regression is used to derive the propensity function for computing the GPS. The GPS is calculated as the density of the residuals in the OLS regression as shown in Eq. 2,

$$GPS = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(z - \beta^T x)^2}{2\sigma^2}} \quad (2)$$

where, β (regression coefficients) and σ^2 (variance of random error) are estimated using OLS regression. It is worth mentioning that the calculation of GPS using OLS regression assumes that the random error follows a normal distribution. To ensure this assumption, we conducted Box-Cox transformation of the treatment variable before implementing the OLS regression. The residuals of the OLS regression model were also tested using Shapiro–Wilk normality test to ensure the assumption is validated.

GPS ensures conditional independence between the treatment variable and the covariates. This independence of covariates and the treatment variable conditional on GPS has been tested using the method suggested in Imai and Van Dyk³³. The process to test conditional independence, as described in Imai and Van Dyk³³, involves verifying that each covariate is independent of the treatment given the generalized propensity score (GPS). It is done by examining the t-statistics of the treatment coefficient in regression models of each covariate on the treatment and the estimated GPS. If these t-statistics are close to zero, it supports the conditional independence assumption needed for valid causal inference between treatment and outcome variables.

Figure 6 presents the Q-Q plots of the t-statistics from the conditional independence test before and after GPS adjustment. Prior to GPS adjustment (left panel), the t-statistics deviate substantially from the theoretical normal quantiles, with the upper tail extending to values exceeding 10, indicating that several covariates retain a statistically significant association with the treatment variable in the unadjusted sample. Following GPS adjustment (right panel), the t-statistics collapse to a range of approximately -3×10^{-14} to 3×10^{-14} , i.e., approximately zero. This near-perfect alignment confirms that conditioning on the estimated GPS removes the systematic association between the treatment variable and all ten covariates, satisfying the conditional independence assumption required for valid causal dose–response estimation.

Once the conditional independence is tested, the derived GPS is used in the next step to derive the dose response function $\mu(z)$ as Eq. 3, where $Y_i(z)$ denotes the outcome of the i th sample if it receives a treatment of $Z=z$. To produce the dose response function, the conditional expectation of Y_i given Z_i , where Z_i is the treatment of the i th sample, is calculated. This is done by regressing the outcome variables on the treatment variable through a weighted regression. Here, we used weighted Negative Binomial regression for deriving the dose response functions. Negative binomial is suited exponentially distributed discrete data like fatality count, where the standard deviation is higher than the mean unlike Poisson distribution.

In the weighted regressions, the weights of the samples are derived based on Inverse Probability of Treatment Weighting (IPTW) method, where the weights are inversely proportional to the GPS of the sample^{34,35}. The weight of a sample is calculated as Eq. 4, where $w(Z_i)$ is a function that is included to stabilize the weights. Zhang, Zhou³⁵ have suggested that a reasonable choice for W is an estimate of the marginal density function of Z

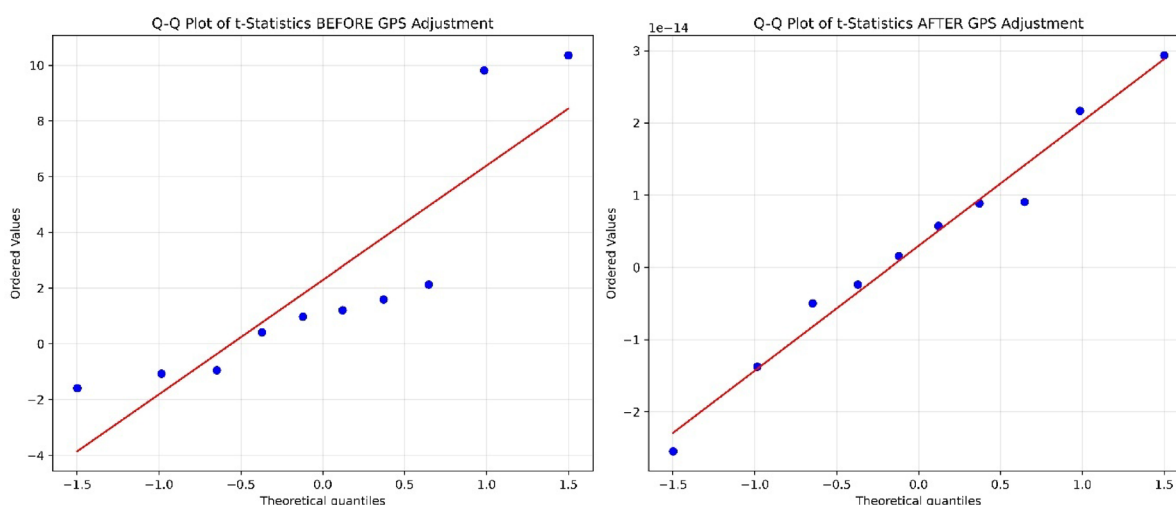


Fig. 6 Outcomes of conditional independence test.

as shown in Eq. 5. Additionally, to improve stability of the final model, we trimmed extreme weights (at the 5th and 95th percentiles) and normalized them to have a mean of 1.

$$\mu(z) = E[Y_i(z)] \quad (3)$$

$$\text{Weight of sample } i = \frac{W(Z_i)}{r(Z_i|X_i)} \quad (4)$$

$$W(Z_i) = \frac{1}{\sqrt{2\pi\sigma_{\text{sample}}^2}} e^{-\frac{(Z_i - \mu_{\text{sample}})^2}{2\sigma_{\text{sample}}^2}} \quad (5)$$

Data

We collected data for the treatment, outcome, and confounding variables. Here we explain each of these variables.

Treatment variable

Treatment variable is the variable whose impacts are measured on the outcome variable, which in this research is the damage to the infrastructure. Infrastructures get damaged during disasters due to natural hazards. But that damaged data is not readily available among popular public databases. Therefore, we had to rely on a non-conventional data source. We scraped the damage information from publicly available Post Disaster Needs Assessment (PDNA) reports. The PDNA tool was developed collectively by UN Development Group (UNDG), the World Bank (WB) and the European Union (EU) to facilitate a standard, harmonized, and coordinated approach that enables objective, comprehensive and government-led assessment of the post disaster damages, losses and recovery needs, so that a consolidated post-disaster recovery framework can be planned³⁶. These assessments have been made about multiple disasters in this century, and the reports are publicly available. We downloaded these reports for 79 disasters of this century, which happened in 52 different countries. Figure 7 shows the spatial distribution of these countries. It can be noticed that most of the countries in the dataset belong to Asia and Africa. The two countries that had the highest number of datapoints are India and Haiti.

Figure 8 shows the distribution of country income groups and hazards in the collected data. It can be noticed that most of the countries belonged to the low- (L) and lower-middle- (LM) income groups. The high- (H) and

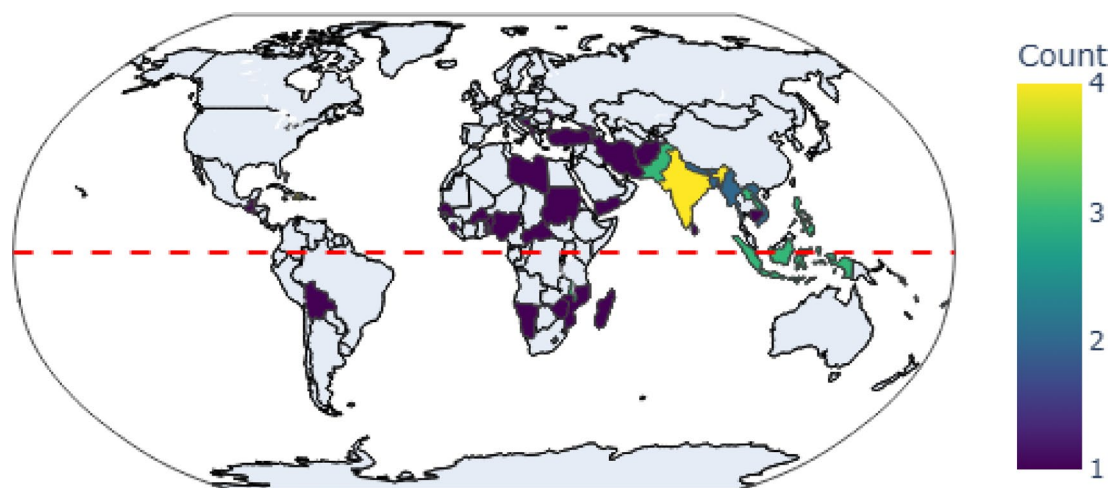


Fig. 7 Spatial distribution of countries in the dataset.

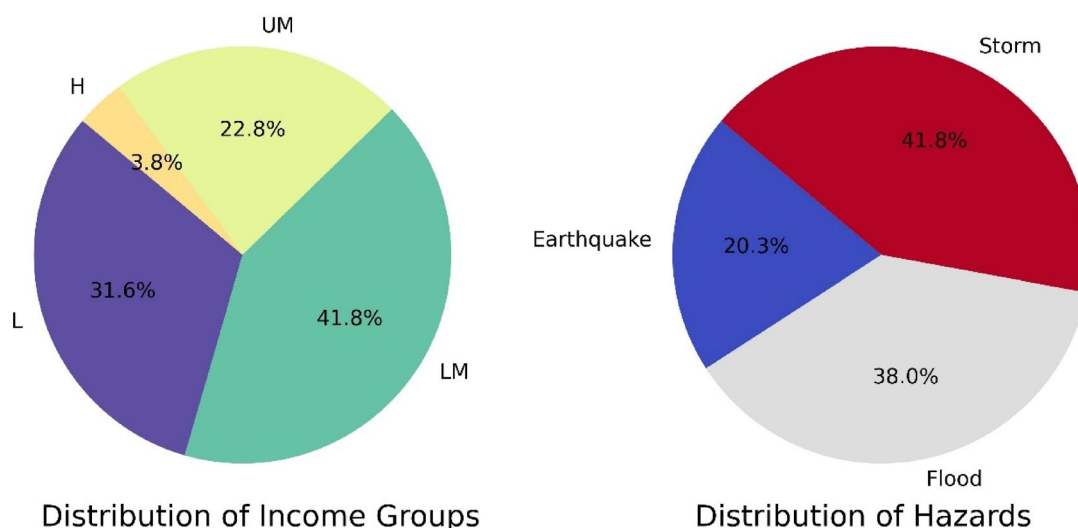


Fig. 8 Distribution of country income groups and hazards.

upper-middle- (UM) income countries together only represented approximately 25% of the data points. This skewed representation of country income groups is due to using PDNA reports as our primary data source since these assessments have historically been done primarily for the low- and lower-middle-income countries. Figure 8 also shows the distribution of hazards in the dataset. It can be seen that most of the assessments have been done for disasters caused by storms, which were followed by floods and earthquakes.

We manually scraped through these 79 reports to find the damage information for six infrastructure sectors—transport, communication, energy, WASH (water, sanitation, and hygiene), healthcare, and education. The majority of the reports combined transport and communication as one sector. Hence, we considered them collectively as one sector. The damage information is expressed in monetary values in the PDNA reports. To neutralize the effects of the spatial and temporal differences of the currencies of different countries in different time periods, we normalized the damage values with the nominal GDP of the country of that year to calculate the damage to each sector. The total damage to the infrastructure sector is the sum of the damage to the sectors normalized with respect to the nominal GDP. As explained in Sect. “[Sensitivity analysis](#)”, damage information for all the sectors was not available in all the reports. For deriving the aggregate response functions, we used the total damage to all infrastructure sectors. There, we assumed the missing values in a sector as zero. However, for sector specific response functions, the missing values were not imputed. The datapoints that did not contain sector specific damage data were not used in the response function derivation of that sector.

Outcome variable

The outcome variable is the disaster mortality, which is expressed in deaths per million population in the countries where the disasters took place. The fatality data was normalized with respect to population to neutralize its effects. This data was collected from the EM-DAT database³⁷. From this database, we could extract the fatality information for 74 events and therefore, the research was conducted using these 74 events only. The distribution of the outcome variable, treatment variable, and their correlations can be noticed in Fig. 9, where it can be seen that both the outcome and treatment variables have very long tails. Since the outcome variable is right skewed with a ratio of standard deviation to mean approximately 5.7 (i.e., higher than 1), the choice of exponential distribution, i.e., negative binomial for deriving the response functions is justified. The correlation coefficient between the treatment and outcome variables was found to be 0.10, i.e., positive but low.

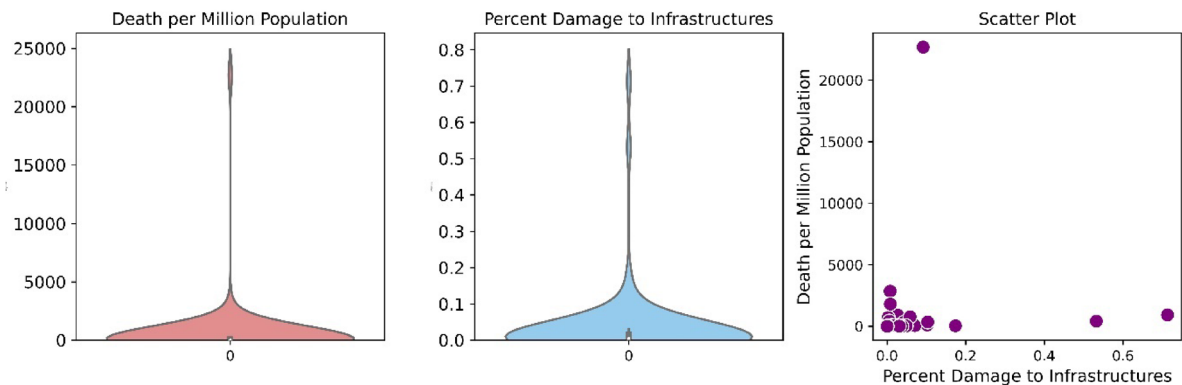


Fig. 9 Distributions of outcome and treatment variables and their scatter plot.

Table 8 Descriptive statistics of outcome and treatment variables.

	All countries (n = 74)		L&LM countries (n = 56)		H&UM countries (n = 18)	
	Outcome	Treatment	Outcome	Treatment	Outcome	Treatment
Mean	464	3.20%	519	1.37%	294	9.10%
Std	2655	10.40%	3045	2.87%	491	19.83%
Min	0.04	0.002%	0.04	0.002%	0.25	0.10%
25%	2.51	0.11%	2.55	0.07%	3.39	0.48%
50%	14.53	0.54%	13.21	0.41%	30.98	1.63%
75%	60.54	1.45%	52.69	1.09%	408.72	3.57%
Max	22,700	71.30%	22,700	17.39%	1807	71.32%

Table 8 provides descriptive statistics of treatment and outcome variables. It can be seen that among the low- and lower-middle-income countries, the range of infrastructure damage, i.e., the difference between maximum and minimum, is lower than high- and upper-middle- countries. However, the range for fatality per million population is higher among the low- and lower-middle-income countries. Among the low- and lower-middle-income countries, the average infrastructure damage was 1.37% and the average fatality per million population was 519. Whereas, among the high- and upper-middle-income countries, the average infrastructure damage was 9.1% but the average fatality per million population was 294. It reflects that low- and lower-middle-income countries suffered more fatalities per million population despite lower damage to infrastructure sectors compared to high- and upper-middle-income countries.

Confounding variables or covariates

Confounding Variables or covariates are the factors that influence both the treatment and outcome variables. Therefore, these variables' effects should be controlled to get the accurate causal estimate between the treatment and outcome variables. For selecting the covariates, we have relied on the popular INFORM risk index that expresses disaster risk as a function of hazard and exposure, vulnerability, and lack of coping capacity¹⁷. We have selected several variables representing each of these dimensions of disaster risk. However, it should be noted that the list of covariates is not exhaustive, and our selection of covariates was restricted due to relatively low number of datapoints. The list of variables along with their definition and data sources are shown in Table 9.

For the hazard and exposure dimension, we used hazard as a categorical variable. As shown in Fig. 8, we had three hazards in our dataset. They were used as covariates. For exposure, we used the number of people affected per million population due to the disaster event as a representative variable. This variable also captured the severity of the hazard event, which influenced both the treatment and outcome variables. We collected this data from the EM-DAT database³⁷.

Table 9 List of confounding variables.

Dimension	Indicator	Definition	Source
Hazard & exposure	Hazard type	Categorical variable identifying the hazard types (Flood, Storm, Earthquake)	EM-DAT
Hazard & exposure	People affected per million population	Number of people affected by the disaster event per million population capturing population exposure and hazard severity	EM-DAT
Vulnerability	Human development index (HDI)	Composite index combining life expectancy, mean years of schooling, and gross national income per capita reflecting country-level socioeconomic development	UNDP/World Bank
Vulnerability	Share of population in extreme poverty	Percentage of the national population living below the international extreme poverty line reflecting socioeconomic vulnerability	World bank
Vulnerability	Damage to buildings (% of GDP)	Monetary value of building damage due to the disaster event, normalized by nominal GDP capturing the vulnerability of the built environment	PDNA reports
Coping capacity	Disaster precedence	Binary variable equal to 1 if the country had previously experienced a disaster of the same hazard type with higher fatalities than the current event capturing historical preparedness and foresight	EM-DAT
Coping capacity	Government effectiveness	World Bank's composite index capturing the quality of public services, civil service, policy formulation and implementation, and government's credibility	World bank
Coping capacity	Civil society participation index (CSPI)	Composite index measuring the strength of civil society, women's participation, policy consultation, and decentralization of legislative candidate nomination	V-Dem
Coping capacity	ODA as share of GDP	Official Development Assistance (ODA) received by the country in the disaster year as a percentage of GDP serving as a proxy for post-disaster financial aid capacity	OECD

For the vulnerability dimension, we considered three variables. For socio-economic vulnerability, we used the Human Development Index (HDI) and share of population living in extreme poverty in the country. HDI was developed by the United Nations Development Program (UNDP) and combines life expectancy, mean years of schooling, and gross national income per capita for assessing the levels of development in a country³⁸. These two datasets were collected from the World Bank's database. We also considered the vulnerability of the built environment by considering the damage to buildings due to the disaster event. This data was collected from the scraped 79 PDNA reports. The damages are expressed in monetary values and therefore were normalized with respect to the current GDPs of the countries like it was done for the infrastructure sectors.

For the coping capacity dimension, we considered four variables. We introduced a variable that looked at the precedence of disasters in that country. This binary variable was given a value of 1, if the country had previously experienced another disaster event due to same hazard, where the fatality was higher than the event in our dataset. We used EM-DAT data for this precedence analysis. This variable was constructed based on the insight that disasters in the past provide historical basis for foresight and preparedness³⁹. In fact, when we compared the mortality between the events with and without a precedence in our dataset, we found that events without a precedence caused on average 1067 fatalities per million people compared to 26 fatalities per million people for events with a precedence.

The second coping capacity variable is another composite index produced by the World Bank named government effectiveness, which “captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies”⁴⁰. This estimate is available annually at the country level and it ranges between -2.5 to 2.5. The data was collected from the World Bank's database. The next coping capacity variable is another composite index named Civil Society Participation Index (CSPI), which measures the strength of civil society, women participation in it, if it is consulted in policy making, and

decentralization of legislative candidate nomination⁴¹. This data was obtained from V-Dem⁴². This variable is introduced as a measure of community engagement that greatly enhances the coping capacity of a community^{43,44}. Lastly, we have considered the financial aid received by a country in the year, when a disaster happened. This variable is used as a proxy of the post-disaster financial aid that is often provided to low, lower middle, and upper-middle-income countries by OECD countries. The data was obtained from OECD⁴⁵.

Limitations

This research contains a number of limitations. The dataset is restricted to disasters documented via Post-Disaster Needs Assessment reports. These reports often reflect events where international support was actively sought. Hence, the proportion of samples belonging to L&LM countries is much higher than H&UM countries. For that, the aggregate response function may not be an ideal representation of how damaged infrastructures influence disaster mortality across all countries. The sample size for high- and upper-middle-income countries is particularly small. Thus, findings for this specific group must be treated as exploratory and no inference should be made from them. Methodologically, the Generalized Propensity Score model relies on a finite set of confounding variables. It may not capture localized factors like community resilience or early warning effectiveness. The Deviance/df ratios across all models exceed 1.0, indicating residual overdispersion beyond what the Negative Binomial (NB) family absorbs. This is attributable to a small number of structurally anomalous disaster events that include the 2010 Haiti earthquake, 2008 Myanmar cyclone, 2023 Libya floods, etc., whose mortality substantially exceeds model predictions due to near-total collapse of state institutions and emergency response capacity. The NB model's coefficient estimates, and significance levels remain the primary inferential basis of this study. The elevated Deviance/df ratio should be interpreted as a measure of the data's inherent complexity rather than model failure. High coefficients in the sectoral models stem from the very small decimal values of infrastructure damage relative to GDP. Cross-country comparison between income groups should be made with caution due to the differences in sample size and country characteristics. The findings may not generalize to all disaster contexts or rare hazard types. Larger datasets are required to confirm the sectoral trends observed in wealthier nations. In other words, the sectoral ranking reported in Table 4 should be interpreted as indicative or relative importance rather than precise causal estimates.

Conclusion

This research bridges the gap between damaged infrastructures and disaster mortality by developing data-driven models demonstrating how damaged infrastructures contribute to disaster related deaths, which previously mostly existed in theory. We scraped 79 post-disaster needs assessments reports to collect infrastructure damage data for 79 disaster events of this century and used them in a Generalized Propensity Score method to derive response functions that show how different levels of infrastructure damage led to disaster mortality. We found damaged infrastructures exponentially increased disaster mortality. We also explored context dependency of this impact and found that effect of damaged infrastructures on disaster mortality was more profound among the low- and lower-middle-income countries that had limited access to infrastructures. We attributed this disproportionate impact to lower access and poor quality of infrastructures among the low- and lower-middle-income countries. Additionally, we found that disaster mortality increases more rapidly for higher damage in energy, WASH, and health sectors compared to transport and communication, education infrastructures and buildings. Therefore, safeguarding energy, WASH, and health infrastructures should be prioritized to reduce disaster related deaths, which has been globally accepted as the first goal of disaster risk reduction. This research was primarily limited by a relatively small number of data points. As more data becomes available, the relationships derived in this

research should be verified or adjusted periodically. Also, advanced methodologies can be adopted that can provide insights into how infrastructure damage and their cascading effects can lead to disaster related deaths.

Acknowledgements This research is funded by the European Union's Horizon Europe and the UK Research and Innovation (UKRI) programme under the Horizon Europe grant agreement n°101121356 and the UK government's Horizon Europe funding guarantee n°10062626. The funders played no role in study design, data collection, analysis and interpretation of data, or the writing of this manuscript. The authors are thankful to Dr. Martijn Warnier, Professor of Complex Systems Design at TU Delft for his insightful comments in revising the article.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Arkaprabha Bhattacharyya, Nazli Yonca Aydin, and Tina Comes. The first draft of the manuscript was written by Arkaprabha Bhattacharyya, and all authors commented on previous versions of the manuscript. All authors read and approved of the final manuscript.

Funding Horizon 2020 Framework Programme, 101121356, 101121356, 101121356.

Data availability All data and Python scripts used to conduct this study are available on request from the corresponding author.

Declarations

Competing interests The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

1. Nations, U., *Sendai framework for disaster risk reduction 2015–2030*. (2015).
2. Reduction, U.O.f.D.R., *The human cost of disasters: An overview of the last 20 years (2000–2019)*. 2020, UN office for disaster risk reduction Geneva, Switzerland.
3. Ward, P. S. & Shively, G. E. Disaster risk, social vulnerability, and economic development. *Disasters* **41**(2), 324–351 (2017).
4. Flanagan, B. E. et al. A social vulnerability index for disaster management. *J. Homeland Secur. Emerg. Manag.* <https://doi.org/10.2202/1547-7355.1792> (2011).
5. Cutter, S. L., Boruff, B. J. & Shirley, W. L. Social vulnerability to environmental hazards. *Soc. Sci. Q.* **84**(2), 242–261 (2003).
6. Han, Y., Ye, X. & Zhu, C. The unequal impact of disasters: Assessing the interplay between social vulnerability, public assistance, flood insurance, and migration in the US. *Urban Informatics* **3**(1), 30 (2024).
7. Choong, J. J. et al. Shared hazards, unequal outcomes: Income-driven inequities in disaster risk. *NPJ Nat. Hazards* **2**(1), 33 (2025).
8. Bhattacharyya, A., Yoon, S. & Hastak, M. Economic impact assessment of severe weather-induced power outages in the US. *J. Infrastruct. Syst.* **27**(4), 04021038 (2021).
9. Rinaldi, S. M., Peerenboom, J. P. & Kelly, T. K. Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Syst. Mag.* **21**(6), 11–25 (2001).
10. Aydin, N. Y. et al. Framework for improving the resilience and recovery of transportation networks under geohazard risks. *Int. J. Disaster Risk Reduct.* **31**, 832–843 (2018).
11. Comes, T. & Van de Walle, B. A. Measuring disaster resilience: The impact of hurricane Sandy on critical infrastructure systems. *ISCRAM* **11**(May), 195–204 (2014).
12. Santos, J. R. & Haimes, Y. Y. Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures. *Risk Anal.* **24**(6), 1437–1451 (2004).

13. Cavalieri, F. et al. Quantitative assessment of social losses based on physical damage and interaction with infrastructural systems. *Earthq. Eng. Struct. Dyn.* **41**(11), 1569–1589 (2012).
14. Inagaki, M. Exploring of the factors behind disaster-related deaths. *J. Disaster Res.* **19**(1), 173–181 (2024).
15. Bhattacharyya, A. & Hastak, M. Indirect cost estimation of winter storm-induced power outage in Texas. *J. Manag. Eng.* **38**(6), 04022057 (2022).
16. Nirandjan, S. et al. Physical vulnerability database for critical infrastructure multi-hazard risk assessments—A systematic review and data collection. *Natural Hazards Earth Sys. Sci. Discuss.* **2024**, 1–38 (2024).
17. De Groeve, T., K. Poljansek, & L. Vernaccini, *Index for risk management-INFORM*. JRC science for policy reports (Brussels: European Commission), (2015).
18. Aydin, N. Y. et al. Rebuilding Antakya: Cultivating urban resilience through cultural identity and education for post-disaster reconstruction in Turkey. *Int. J. Disaster Risk Reduct.* **117**, 105196 (2025).
19. Augustinus, N., et al., Reformative recovery for resilience in disaster risk management: A scoping review and analytical framework. *Int. J. Dis. Risk Reduct.* 106152 (2026).
20. Bhattacharyya, A. & Hastak, M. Empirical causal analysis of flood risk factors on US flood insurance payouts: Implications for solvency and risk reduction. *J. Environ. Manage.* **352**, 120075 (2024).
21. Cutter, S. L., Ash, K. D. & Emrich, C. T. The geographies of community disaster resilience. *Glob. Environ. Change* **29**, 65–77 (2014).
22. Cutter, S. L., Boruff, B. J. & Shirley, W. L. Social vulnerability to environmental hazards. In *Hazards vulnerability and environmental justice* 143–160 (Routledge, 2012).
23. Hirano, K. & Imbens, G. W. The propensity score with continuous treatments. In *Applied Bayesian modeling and causal inference from incomplete-data perspectives* 73–84 (2004).
24. Hallegatte, S., et al., *Unbreakable: building the resilience of the poor in the face of natural disasters*. (World Bank Publications, 2016).
25. Escaleras, M. & Register, C. The high cost of low quality infrastructure when natural disasters strike. *J. Dev. Areas* **50**(1), 103–122 (2016).
26. PPIAF, P.-P.I.A.F., *Analyse country*. (2025).
27. Oh, E. H., Deshmukh, A. & Hastak, M. Criticality assessment of lifeline infrastructure for enhancing disaster response. *Nat. Hazards Rev.* **14**(2), 98–107 (2013).
28. Deshmukh, A., Oh, E. H. & Hastak, M. Impact of flood damaged critical infrastructure on communities and industries. *Built Environ. Proj. Asset Manag.* **1**(2), 156–175 (2011).
29. Bhattacharyya, A., Wang, H. H. & Hastak, M. Impact of post-disaster federal assistance on the national flood insurance program. *Int. J. Disaster Risk Reduct.* **102**, 104290 (2024).
30. Giffin, A. et al. Generalized propensity score approach to causal inference with spatial interference. *Biometrics* **79**(3), 2220–2231 (2022).
31. Sarabia, M. M. et al. The challenges of impact evaluation: Attempting to measure the effectiveness of community-based disaster risk management. *Int. J. Disaster Risk Reduct.* **49**, 101732 (2020).
32. Endendijk, T. et al. Enhancing resilience: Understanding the impact of flood hazard and vulnerability on business interruption and losses. *Water Resour. Econ.* **46**, 100244 (2024).
33. Imai, K. & Van Dyk, D. A. Causal inference with general treatment regimes: Generalizing the propensity score. *J. Am. Stat. Assoc.* **99**(467), 854–866 (2004).
34. Imbens, G. W. The role of the propensity score in estimating dose-response functions. *Biometrika* **87**(3), 706–710 (2000).
35. Zhang, Z. et al. Causal inference with a quantitative exposure. *Stat. Methods Med. Res.* **25**(1), 315–335 (2016).
36. GFDRR, *Post-disaster needs assessment guidelines, Volume A*. (2013).
37. CRED, *Disasters in numbers*. Brussels: CRED, 2024. (2023).
38. UNDP, *Human development report 2025*. UNDP (United Nations Development Programme, 2025).
39. Alexander, D. *Disaster and crisis preparedness* (Oxford University Press, 2021).
40. Group, W.B. *Metadata glossary government effectiveness: Estimate*. 2025 [cited 2025 July 16, 2025]; Available from: <https://databank.worldbank.org/metadataglossary/worldwide-governance-indicators/series/GE.EST>.
41. Coppedge, M., John Gerring, Carl Henrik Knutsen, Staffan I. Lindberg, Jan Teorell, David, et al., *V-Dem codebook v15*. 2025, varieties of democracy (V-Dem) Project.
42. V-Dem, *Civil society participation index – V-Dem*. V-Dem, “Democracy report v15” [original data]. Our World in Data, (2025).
43. Aldrich, D. P. *Building resilience: Social capital in post-disaster recovery* (University of Chicago Press, 2012).
44. Aldrich, D. P. & Meyer, M. A. Social capital and community resilience. *Am. Behav. Sci.* **59**(2), 254–269 (2015).
45. OECD, *Foreign aid received—Official donors*. OECD, “OECD official development assistance (ODA)—DAC2A: Aid (ODA) disbursements to countries and regions. (2025).

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Arkaprabha Bhattacharyya¹  · Nazli Yonca Aydin² · Tina Comes³

✉ Arkaprabha Bhattacharyya
A.Bhattacharyya@tudelft.nl

¹ Engineering Systems and Services, Faculty Technology, Policy, and Management, TU Delft, Delft, The Netherlands

² Multi-Actor Systems, Faculty Technology, Policy, and Management, TU Delft, Delft, The Netherlands

³ Decision Theory & ICT, Faculty of Technology, Policy, and Management, TU Delft, Delft, The Netherlands