**Young Scientists Summer Program**

# Understanding the role of climate change in disaster mortality: Empirical evidence from Nepal

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**Mentor signature:**

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## Abstract

*The impacts associated with climate-related disasters have been rising globally. Several studies argue that this upward trend is due to rapid growth in population and wealth exposed to hazardous events. Others argue that increased frequency, intensity, and duration of extreme weather events due to climate change are responsible for the rise. While disaster impacts, such as loss of human life as its most severe consequence, are felt more acutely in low-income countries, existing studies focus mostly on developed countries or at the cross-country level. Our paper addresses this impact attribution question in the context of the Global South. It assesses the attribution of disaster mortality to indicators of climatic hazards, exposure, and vulnerability in Nepal. We employ disaster-specific mixed effects zero-inflated negative binomial regression model to study the causality of observed 30-year (1992-2021) landslide and flood mortality at the scale of 753 local units of Nepal. As explanatory variables, we use mean and extreme precipitation indices; population density; and per capita income and a social vulnerability index as indicators of hazards, exposure, and vulnerability. The spatiotemporal trends of disaster mortality closely follow the precipitation extremes trends. A one standardized unit increase in maximum 1-day precipitation and heavy rain days increase flood mortality by 33% and landslide mortality by 45%, respectively. A one-unit increase in per capita income decrease landslide and flood mortality by 30% and 45%, respectively. Population exposure does not show significant effects. Hence, we propose that the observed rise in climate-related disaster mortality, mainly in western Nepal, is attributable primarily to the increased precipitation extremes in these regions due to climate change.*

## About the author

**Dipesh Chapagain** is a PhD candidate at the Center for Development Research at the University of Bonn, Germany. In his PhD project, Dipesh studied the detection and attribution of spatiotemporal trends of climate-related disaster impacts and vulnerability in the context of the Global South taking Nepal as a case study. He participated in the IIASA Young Scientists Summer Program 2022. Previously, he completed the Humboldt research fellowship in Climate Analytics in Berlin. Dipesh has published several peer-reviewed articles in international journals. He is also a co-lead author of the UNEP Adaptation Gap Report 2021 and 2022. Moreover, Dipesh holds a decade-long experience in disaster risk reduction and climate change adaptation research and project management in international organizations in Nepal, Germany, and Austria.

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# 1. Background

Weather and climate-related disasters have caused 23,144 deaths and 118.3 billion USD economic losses annually on average between 2001-2020 worldwide (CRED, 2021). Moreover, climate-related disaster occurrences, as well as loss of life and property, are also on the rise globally (Formetta & Feyen, 2019; Hoeppe, 2016; Hu et al., 2018; UNDRR, 2022). These observed impacts have been increasingly attributed to the anthropogenic climate change (Bouwer, 2019; Huggel et al., 2013; IPCC, 2022). The latest report of the Intergovernmental Panel on Climate Change (IPCC) has confirmed the fact that the frequency and intensity of weather and climate extremes have increased since pre-industrial times due to anthropogenic greenhouse gas (GHG) emissions (Seneviratne et al., 2021). There is also high confidence that even a small additional increase in global warming will intensify temperature and precipitation extremes. Nevertheless, empirical evidence of the rise in climate extremes leading to a rise in disaster impacts is still limited and primarily focuses on the global North.

Several studies argue that the rapid growth in population and wealth exposed to disaster events has mainly caused the rise in disaster impacts, and a role of climate change is not evident (Bouwer, 2011; McAneney et al., 2019; Pielke, 2021; Visser et al., 2014). These studies focusing on socio-economic impact attribution use the predominant loss normalization approach first to normalize the impacts by exposure and check for any residual trend in the normalized losses that can be attributed to climate change. However, vulnerability is often not, or incompletely, accounted for in this literature, potentially resulting in the false attribution of disaster impact trends given the dynamic nature of the vulnerability (Botzen et al., 2021; Mechler & Bouwer, 2015). Estrada et al. (2015) proposed a regression-based approach to appropriately account for the change in exposure and vulnerability. As one of the only studies, they found an upward trend in the economic losses from the US hurricane that cannot be explained by the exposure variable. The effect of climatic hazard variables in explaining the trend of disaster impacts is much higher if the vulnerability is also controlled (Estrada et al., 2015; Forzieri et al., 2017).

In the past two decades, 90% of global disaster mortality has occurred in low- and middle-income countries (UNISDR, 2018). The economic losses due to disasters in low- and lower-middle-income countries are 0.8-1% of the gross domestic product (GDP) compared to 0.1-0.3% in high- and upper-middle-income countries (UNDRR, 2022). Moreover, almost 90% of the about 1.5 billion people exposed to flood risk and a large part of 3.6 billion people highly vulnerable to climate change live in low- and middle-income countries (IPCC, 2022; Rentschler & Salhab, 2020). Therefore, a better understanding of the disaster impacts trends and the role of climatic hazards, exposure, and vulnerability in developing countries is essential to plan and implement climate change adaptation and disaster risk reduction (DRR) measures. Otherwise, achieving the Sendai Framework for Disaster Risk Reduction, the adaptation goal associated with the Paris Agreement, and the Sustainable Development Goals will be extremely difficult. Similarly, more evidence from attribution science is essential for avoiding and managing loss and damage (L&D) through international mechanisms (James et al., 2019; R. Mechler et al., 2020).

However, most of the existing climate-related disaster impact attribution studies are from the United States, Europe, or other developed countries (Bouwer, 2019; Pielke, 2021).To address these scientific and policy-relevant issues in a Global South context, we present an empirical example of the attribution of climate-related disaster mortality to indicators of climatic hazards, exposure, and vulnerability in a low-income country. Nepal has been among the top ten countries worldwide most affected by climate-related disasters in the past two decades (Eckstein et al., 2021). Over ten thousand people lost their lives due to climate-related disasters in the past thirty years, and landslides and floods together account for almost 70% of the total climate-related disaster mortality (Chapagain et al., 2022). The INFORM Risk Index 2022 also categorized Nepal as a high-disaster risk country, and a significant increase in disaster risk and vulnerability by 2050 is projected due to climatic, demographic, and socio-economic changes (Inter-Agency Standing Committee and the European Commission, 2022). Hence, Nepal well serves as a case study of a low-income and highly disaster-vulnerable country.

In our study, we focus on the loss of human life as a measure of disaster impact as it is the most extreme impact of a disaster. Mortality data for Nepal (and in general) are also better recorded than other impacts, making it an appropriate proxy for the attribution study. We first studied the spatiotemporal trends of the past 30 years (1992-2021) of flood and landslide mortality in Nepal. Second, we studied the spatiotemporal trends of six mean and extreme precipitation indices in a climate change context. Third, we employed disaster-specific mixed effects zero-inflated negative binomial (ZINB) regression models to study the attribution of disaster mortality to climatic hazards, exposure, and vulnerability. We used mean and extreme precipitation indices as indicators of climatic hazards, population density as indicator of exposure, and per capita income (PCI) and social vulnerability index (SoVI) as indicators of vulnerability. Finally, we synthesized the observed spatiotemporal trends of disaster mortality with climatic hazards, exposure, and vulnerability indicators together with their statistical association to draw a conclusion on the attribution of disaster mortality.

# 2. Methodology

## 2.1. Study Location

Nepal is a mountainous country in South Asia located between 26° 22′ to 30° 27′ N and from 80° 04′ to 88° 12′ E (fig. 1). This landlocked country has a total area of 147,516 $km^2$ and is divided into five physiographic regions namely Tarai, Siwalik, Hills, Middle Mountains, and High Mountains (MoFE, 2021). The Tarai is a low-lying flatland in the South with the lowest point of 60 m above sea level (m.a.s.l.) and a tropical climate (Karki et al., 2015). Within 193 km width from South to North, the altitude increases up to 8,849 m.a.s.l at Mount Everest with the permanently snow-covered polar climate in the high Mountains (DOS, 2021). Such dramatic variation in altitude within the small area reflects the country's topographic and climatic heterogeneity, leading to highly localized extreme precipitation and disaster events (Pokharel et al., 2019). Hills and mountains are prone to landslides due to the steep slopes, whereas the deep river valleys and the low-lying flat lands are at risk of floods and flash floods.

Administratively, Nepal is divided into seven provinces and 753 local administrative units (MoFAGA, 2019). The local administrative units are the smallest sub-national units and are categorized into metropolitan cities, sub-metropolitan cities, municipalities as urban units, and rural municipalities as rural units. According to the 2021 census, the country's total population is almost 30 million, of which 66% live in urban units and 34% in rural units (CBS, 2022). Nepal is one of the lowest-income countries in the world, with only 1,222 USD per capita GDP (World Bank, 2022).

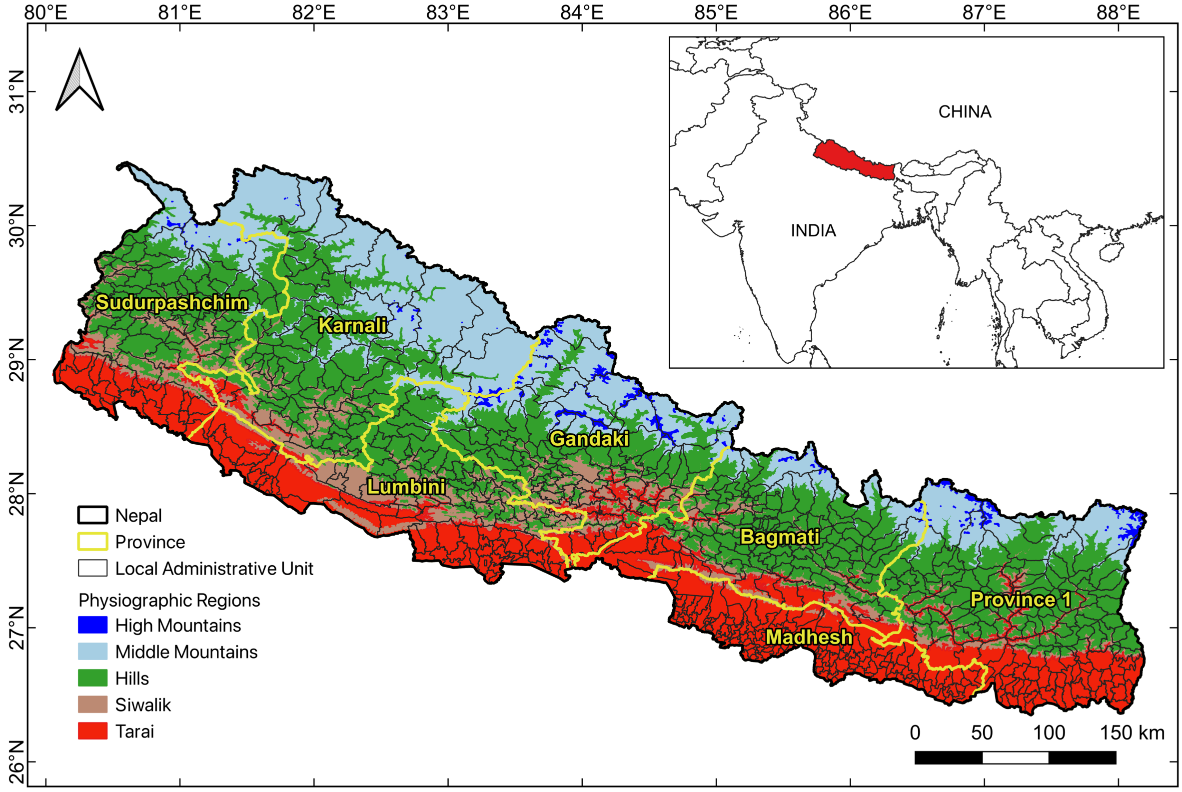


**Figure 1: Map showing Nepal's local administrative units, provinces, and physiographic regions. Inset: Nepal on the world map.**

## 2.2. Data sources and processing

### 2.2.1. Climate-related disaster mortality

The Emergency Events Database (EM-DAT), NatCatSERVICE, Sigma, Geocoded Disasters Dataset (GDIS), and DesInventar are commonly used global disaster databases. Among all, DesInventar is presently the most robust, long-term, local scale, and open-access disaster database for Nepal (Aksha et al., 2018; Chapagain et al., 2022). It is a global disaster information management system of the United Nations Office for Disaster Risk Reduction (UNDRR) to keep inventories of the occurrence and impact of disasters (DesInventar, 2021). Currently, disaster data for 1971-2013 is available in DesInventar for Nepal. In recent years, the Nepal DRR Portal of the Ministry of Home Affairs (MoHA) regularly updates all disaster events in Nepal (MoHA, 2021). Both databases follow a similar recording format and provide information on the type, date, location, and impacts of individual disasters. We used disaster data from DesInventar for the period 1992-2013 and the Nepal DRR portal for the period 2014-2021 to develop 30-year panel data at the local administrative unit level of Nepal for floods and landslides. Further information on the database used, quality control, and geocoding are explained in Chapagain et al. (2022).

### 2.2.2. Climatic hazard indicators

Around 400 surface weather stations of the Department of Hydrology and Meteorology (DHM) across Nepal keep records of daily temperature, precipitation, and other climatic parameters (DHM, 2017). We identified 232 stations across Nepal that provides daily precipitation records for the study period 1992-2021. The observed daily precipitation data from the DHM stations were used to estimate mean precipitation indices and extreme precipitation duration, frequency, and intensity-related indices at an annual scale using Climpact software (ET-SCI, 2016). For this study, we selected six precipitation indices (table 1) from the list of Expert Team on Sector-specific Climate Indices (ET-SCI) that are most relevant to floods and landslides in Nepal (Chapagain et al., 2021; ET-SCI, 2016). Selected precipitation indices estimated by observational stations are used for the spatiotemporal trend analysis in section 3.2.

***Table 1: List of selected*** **precipitation indices (adapted from (ET-SCI 2016)).**

| Index type | ID | Name | Definition | Unit |
|---|---|---|---|---|
| Mean precipitation | PRCPTOT | Total annual precipitation | Sum of daily precipitation ≥ 1.0 mm | mm |
| | SDII | Simple daily intensity index | PRCPTOT divided by the number of wet days | mm/day |
| Extreme precipitation duration | CWD | Consecutive wet days | Maximum annual number of consecutive wet days (when precipitation is ≥1.0 mm) | days |
| Extreme precipitation frequency | R10mm | Number of heavy rain days | Annual number of days when precipitation is ≥10 mm | days |
| Extreme precipitation intensity | R95pTOT | Contribution from very wet days | 100*R95p/PRCPTOT | % |
| | RX1day | Max 1-day precipitation | Maximum annual 1-day precipitation total | mm |

Furthermore, we interpolated station-based daily precipitation data to gridded data for the whole country using a Random Forest based merging procedure (Zambrano-Bigiarini et al., 2020). This procedure combines information from ground-based observations, satellite-based precipitation products, and topographic features to improve the accuracy of spatial interpolation of precipitation data in data-scarce regions (Baez-Villanueva et al., 2020). We used gridded daily precipitation data from the Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al., 2019) as a satellite-based precipitation product covariate. Similarly, the ASTER Global Digital Elevation Model (DEM) V003 (NASA/METI/AIST/Japan Spacesystems and U.S./Japan ASTER Science Team, 2019) was used for topographic features covariates. The one arc-second resolution DEM was aggregated to a coarser 0.025° resolution grid using bilinear interpolation. MSWEP data were disaggregated from 0.1° to 0.025° resolution grids by assigning the same value from the larger original cell. Similar to the station data, the merged gridded daily precipitation data were then used to estimate precipitation indices using Climpact. Finally, average indices values for each local administrative unit were extracted from the gridded data. The precipitation indices by local units were then used for the regression analysis in sections 3.3 and 3.4 as indicators of climatic hazards.

### 2.2.3. Exposure and vulnerability indicators

We accessed population data from the periodic national censuses (1991, 2001, 2011, and 2021) from the Central Bureau of Statistics (CBS), Nepal. The per capita income data was accessed from the national scale periodic Nepal Living Standards Survey (NLSS) conducted by the CBS. The data were then interpolated and extrapolated to develop 30-year panel data at the local administrative unit level of Nepal (see Chapagain et al. (2022) for further explanation). The population density was then estimated from the population and local unit's area.

As an alternate proxy of vulnerability, we used the Social Vulnerability Index (SoVI) to the Natural Hazards data developed by Aksha et al. (2019). Aksha et al. (2019) applied a principal component analysis to estimate the SoVI for Nepal using 39 variables from seven dimensions of vulnerability (Renters and Occupation, Poverty and Poor Infrastructure, Favorable Social Conditions, Migration and Gender, Ethnicity, Medical Services, and Education). The SoVI uses cross-sectional data based on the 2011 national census. Therefore, we also aggregated disaster mortality, climatic hazards, and exposure indicator data for the period 2007 to 2015 for the regression analysis with SoVI data in section 3.4.

## 2.3. Trend analysis

The temporal trends of disaster mortality, frequency, and precipitation indices were estimated using the nonparametric Mann-Kendall test (Mann, 1945) and Theil-Sen slope (Sen, 1968). The Mann-Kendall p-value assesses the presence or absence of a monotonic trend in data, and the Theil-Sen slope estimates the trend slope. Both tests are widely used methods in the disaster trend analysis (Chapagain et al., 2022; Karki et al., 2017; Wu et al., 2019) because of their ability to handle missing data and the influence of outliers as well as the absence of any distributional assumptions (Chandler & Scott, 2011).

## 2.4. Regression model fitting

Climate-related disaster impacts occur due to the complex interaction of hazards, exposure, and vulnerability (IPCC, 2012; Oppenheimer et al., 2014). In this risk framework, since taken forward by the IPCC (IPCC, 2022), climatic hazard usually refers to climate-related physical events or trends or their physical impacts (IPCC, 2014). Climatic hazard becomes a disaster when it interacts with exposure and vulnerability and causes impacts. Exposure, for example, is the people living in places and settings that could be adversely affected; vulnerability is their propensity or predisposition to be adversely affected (IPCC, 2014). In this study, we focused on observed human mortality as a measure of disaster impacts. We developed a regression-based approach to study flood and landslide mortality attribution to climatic hazards, exposure, and vulnerability indicators.

Floods and landslides are precipitation-related disasters, so we used six mean and extreme (duration, frequency, and intensity-based) precipitation indices defined in table 1 as indicators of climatic hazards. Since we are looking at the human aspect of disaster impacts, we used population density as an indicator of exposure. Vulnerability is the characteristic generated by multiple factors such as social, economic, political, cultural, institutional, and environmental conditions (IPCC, 2012). To this effect, we used per capita income as a proxy of vulnerability as in many other disaster studies (Formetta & Feyen, 2019; Jongman et al., 2015; Tanoue et al., 2016; Wu et al., 2019; Zhou et al., 2014). We also used the composite SoVI as a measure of social vulnerability to climate-related disasters. Finally, to control for the effects of all other location-specific unobserved variables on disaster mortality, we added location (local administrative unit) random effects and employed mixed effects regression models (Park, 2011). The regression models were run separately for flood and landslide mortality.

We started fitting the regression models with the ordinary least squares (OLS) mixed effects linear model. However, disaster mortality is right-skewed count data with many small and occasionally large values. Therefore, count data models such as Poisson, negative binomial, and zero-inflated models are better suited for disaster mortality than the linear model (Roback & Legler, 2021). The mortality data also suffered from the overdispersion issue, i.e., variance is greater than the mean and violated the equidispersion assumption for standard Poisson regression (table S1 in supplementary materials - SM). Hence, we tested the negative binomial model to account for overdispersion in the dependent variable (Roback & Legler, 2021). The disaster mortality data also includes many observations where there was zero mortality. To take excess zero into account, we fitted the zero-inflated regression models.

The zero-inflated regression model is a two-part model providing more robust statistical results for the zero-inflated data (Kim et al., 2019; Roback & Legler, 2021). The zero-inflated model part first fits the logistic regression to predict the number of structural and actual zeros. In this case of disaster mortality, the local units in a particular year with a zero probability of disaster fatality are the structural zeros, and the units with a positive probability still did not experience fatality are the actual zeros. The count model part separates the excessive zeros from the structural origin and runs the count data model with a log-linear link function. Results of mixed effects linear, Poisson, negative binomial, zero-inflated Poisson, and zero-inflated negative binomial (ZINB) models are compared to identify the most robust model. These results are presented in table S2 in SM. Descriptive statistics (such as mean, variance, and dispersion), model diagnostics, and goodness-of-fit measures, mainly the Akaike Information Criterion (AIC), Bayesian information criterion (BIC), $R^2$, and Interclass Correlation Coefficient (ICC) were explored in the model selection process. We mostly observed the consistent direction of the association and its significance between dependent and explanatory variables across the models. However, the $R^2$ value is highest (0.47), and AIC and BIC are lowest in the case of the ZINB model. Based on the results, we identified the mixed effects ZINB model as the most appropriate regression model for disaster mortality. The count model part of the regression model with log link is summarized below in equation 1.

$$\log(M_{i,t}) = \alpha + \beta_h H_{i,t} + \beta_e E_{i,t} + \beta_v V_{i,t} + u_i + v_{i,t} \qquad (1)$$

The dependent variable $M_{i,t}$ is the disaster-specific total annual mortality in local administrative unit $i$ in year $t$. The explanatory variable $H_{i,t}$ is the corresponding climatic hazard indicators, i.e., observed mean and extreme precipitation indices defined in table 1. $E_{i,t}$ is the corresponding population density to represent disaster exposure. $V_{i,t}$ is the vulnerability component, and we used PCI and SoVI as vulnerability proxies. The intercept $\alpha$ is the grand mean of location-specific intercepts. $\beta_h$, $\beta_e$, and $\beta_v$ are the marginal effects of hazards, exposure, and vulnerability indicators. $u_i$ is the random effect variable to accommodate local administrative unit-specific heterogeneity. $v_{i,t}$ is the standard random error term.

# 3. Results

## 3.1. Spatiotemporal trends of climate-related disaster mortality in Nepal

More than 10,000 people lost their lives due to climate-related disasters in Nepal in the past three decades. Landslides and floods killed 3,692 and 3,201 people respectively, which together account for 70% of the total climate-related disaster mortality. Landslide mortality was highest in mid-hills and mountains in eastern (Province 1) and central Nepal (Bagmati and Gandaki). Flood mortality was highest in central Nepal (Madhesh, Bagmati, and Gandaki) (fig. 2). Western Nepal (Lumbini, Karnali, and Sudurpashchim) has experienced relatively lesser disaster mortality in the past.

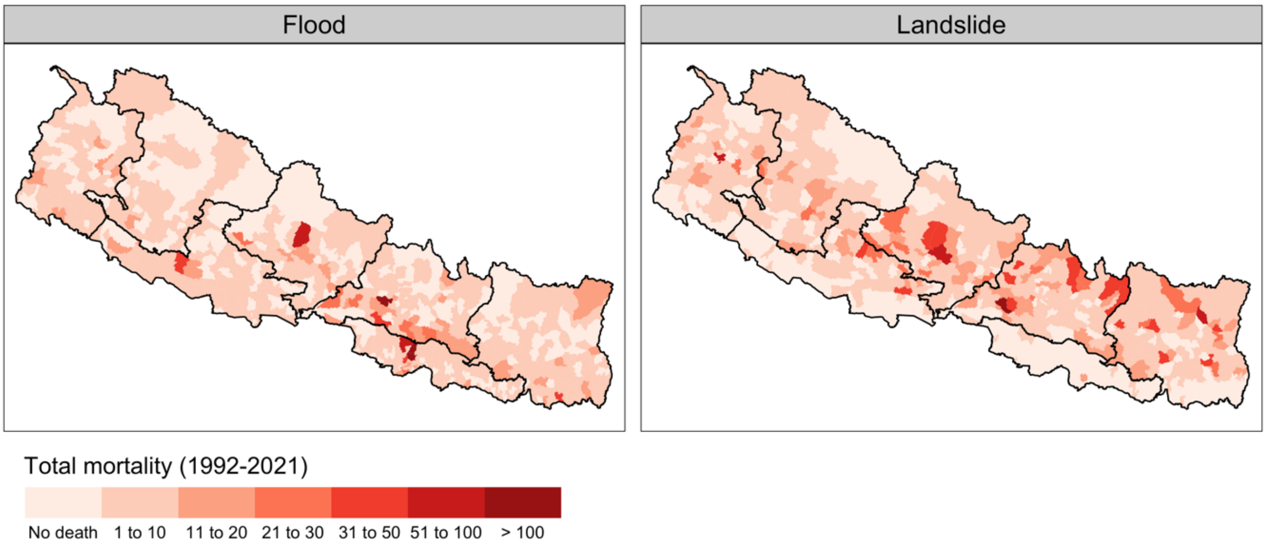


***Figure 2: Spatial trends of landslide and flood mortality in Nepal during 1992 - 2021.***

Temporal trends show that disaster mortality is mainly increasing in western Nepal, which was historically less impacted regions. Both the frequency and mortality of the flood and landslide showed statistically significant increasing trends at p = 0.05 level during the past three decades in Lumbini, Karnali, and Sudurpashchim provinces. The trends are mostly not significant but positive in Gandaki, Bagmati, Madhesh, and Province 1 in central and eastern Nepal (table 2). Flood frequency in Province 1 and landslide frequency in Bagmati and Gandaki showed statistically significant increasing trends.

***Table 2: Trends of flood and landslide mortality (number of fatalities/year) and frequency (number of incidences recorded/year) in Nepal by provinces. Trends slope based on Theil-Sen slope and significance based on Mann-Kendall p-value.***

| Province | Flood | | Landslide | |
|---|---|---|---|---|
| | **Mortality** | **Frequency** | **Mortality** | **Frequency** |
| 1. Province 1 | 0.211 | 0.4 *** | 0 | 0.059 |
| 2. Madhesh | 0.167 | 0.1 | 0 | 0 |
| 3. Bagmati | 0 | 0.118 | 0.222 | 0.3 ** |
| 4. Gandaki | 0.182 | 0.1 * | 0.375 | 0.273 ** |
| 5. Lumbini | 0.524 *** | 0.4 *** | 0.4 ** | 0.25 *** |
| 6. Karnali | 0.167 ** | 0.105 *** | 0.579 *** | 0.286 *** |
| 7. Sudurpashchim | 0.24 ** | 0.2 ** | 0.318 ** | 0.25 *** |

*Significance codes: *p < 0.1; **p < 0.05; ***p < 0.01*

## 3.2. Spatiotemporal trends of mean and extreme precipitation indices in Nepal

Mean and extreme precipitation indices showed mixed trends across the country, with mostly rising trends in western Nepal but decreasing in central Nepal in the past 30 years (fig. 3). Rising trends in total annual precipitation (PRCPTOT) have been observed in 75% of the stations in Karnali (significant in 13%), and 57% in Sudurpashchim province (significant in 5%). Consecutive wet days (CWD), a duration-based extreme precipitation index, showed rising trends in 50% of the stations in Karnali (significant in 6%) and 42% in Sudurpashchim (significant in 11%). The annual number of heavy rain days (R10mm), an extreme precipitation frequency index, showed increasing trends in 53% of stations in Sudurpashchim (significant in 5%). Maximum 1-day precipitation (RX1day), an indicator of extreme precipitation intensity, showed increasing trends in 68% of the stations in Sudurpashchim (significant in 11%) and 58% in Lumbini (significant in 15%). Contribution from very wet days (R95pTOT), another intensity-based index, also showed an increasing trend in 58% of the stations in both Sudurpashchim and Lumbini (significant in 5% and 4% respectively).

In central Nepal, precipitation indices mostly showed decreasing trends. PRCPTOT and simple daily intensity index (SDII) have decreased in 83% of the stations in Bagmati (significant in 21% and 24%). Similarly, CWD showed decreasing trends in 60% (significant in 24%) and R10mm in 86% of stations (significant in 29%). RX1day and R95pTOT showed decreasing trends in 76% (significant in 10%) and 69% of the stations respectively (significant in 14%). A similar pattern has been observed in Gandaki province. R10mm and R95pTOT showed decreasing trends in 53% and 58% of stations in Gandaki (significant in 18% and 13%).

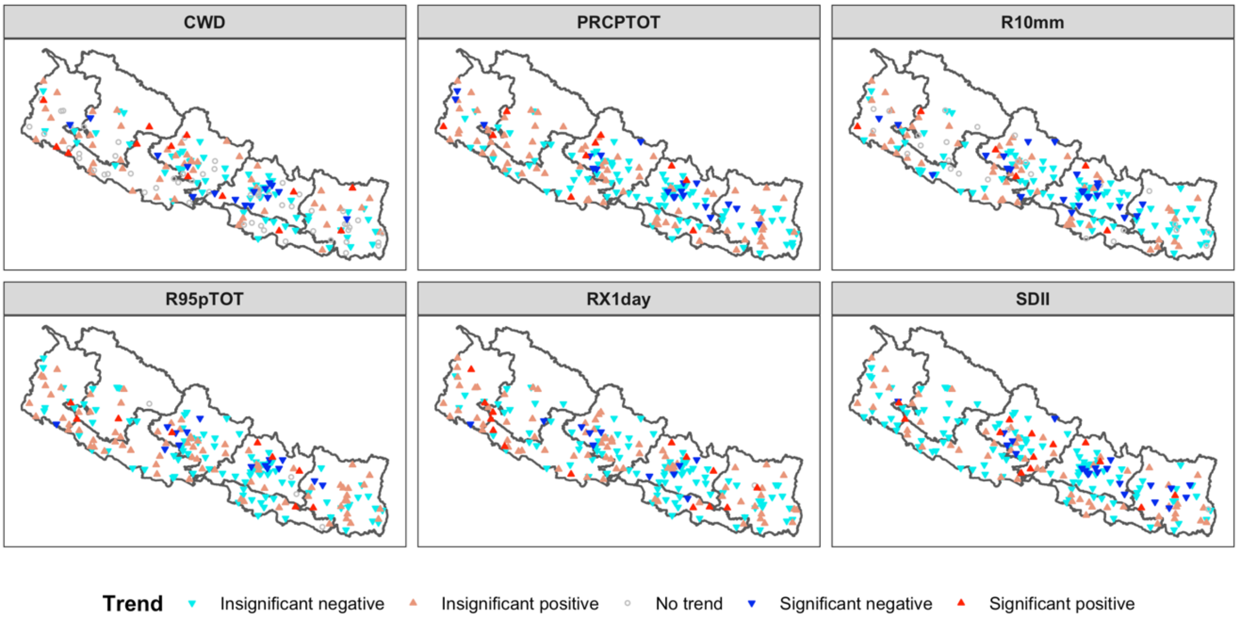


***Figure 3: Temporal trends of mean and extreme precipitation indices during 1992-2021 by observational stations across Nepal.***

## 3.3. Attribution of disaster mortality to climatic hazards

All the mean and extreme precipitation indices studied showed a significant positive association with landslide mortality and most of the indices showed a significant positive association with flood mortality (fig. 4). Results of selected regression models are presented in table 3 and all regression models are presented in table S3 and S4 in SM. Regression results show that one unit (one standard deviation from the mean) increase in PRCPTOT increases landslide mortality by 41% and flood mortality by 16 % (ceteris paribus). The rise in extreme precipitation intensity showed the most potent effect on flood mortality. A one unit increase in RX1day and R95pTOT increase flood mortality by 33% and 31% respectively. The effects of extreme precipitation frequency and duration are highest in landslide mortality. Landslide mortality increased by 45% and 34% with a one unit increase in R10mm and CWD respectively.

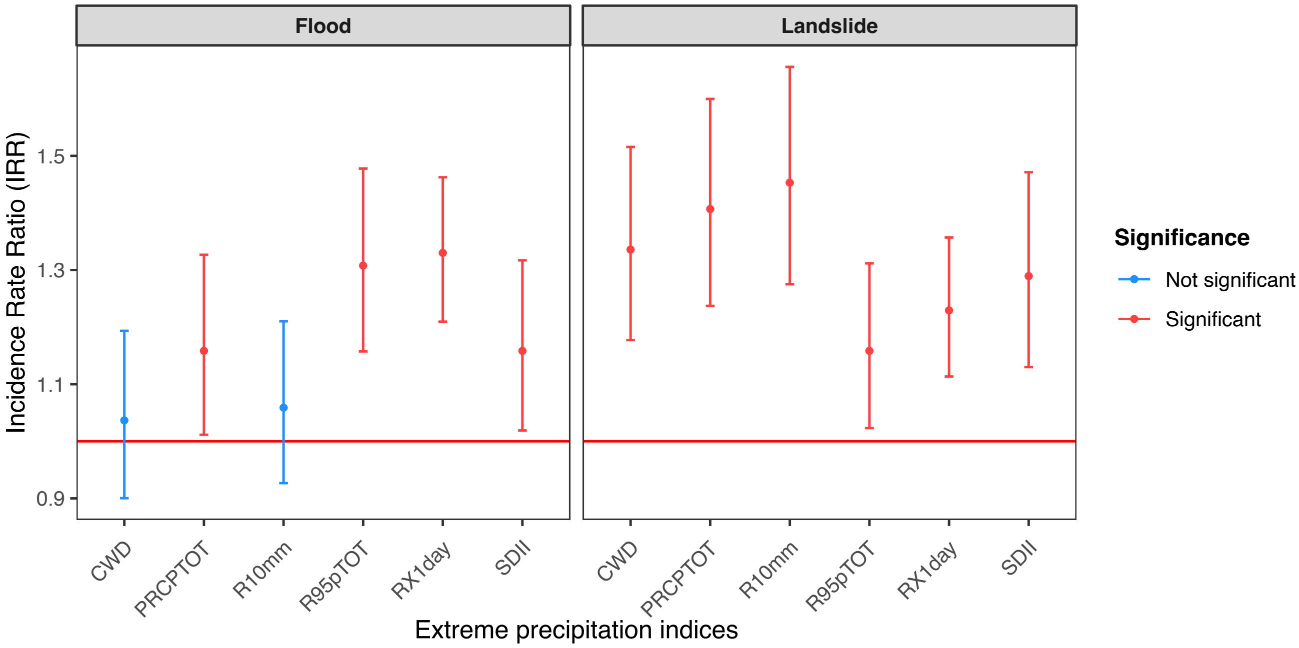


***Figure 4: Effects of mean and extreme precipitation indices (in standardized Z-score) on flood and landslide mortality shown as Incidence Rate Ratios - IRR (points), and its 95% confidence interval (lines). IRRs are estimated from the mixed effects ZINB models and equal to the exp ($\beta_h$) in equation 1. Statistical significance at the 0.05 level (see SM table S3 and S4 for the complete regression results).***

The differences in effect size and significance of extreme precipitation indices with flood and landslide mortality could also be due to the nature of disaster types. Landslides are largely local phenomena, so the local unit's boundary appears sufficient to capture the precipitation events associated with the landslides. However, floods are not only determined by the local precipitation events but also by upstream precipitation. Our regression model does not capture the precipitation events that could have been observed in the local units upstream but caused flooding in the local units downstream.

***Table 3: Results of mixed effects ZINB models. Disaster mortality as a dependent variable and indicators of exposure, vulnerability, and hazard (in standardized Z-score) as explanatory variables.***

| | Flood mortality | | | Landslide mortality | | |
|---|---|---|---|---|---|---|
| *Predictors* | *IRR* | *CI* | *p* | *IRR* | *CI* | *p* |
| **Count Model** | | | | | | |
| Intercept | 0.42 | 0.33 – 0.54 | **<0.001** | 0.61 | 0.39 – 0.96 | **0.033** |
| Pop. density | 1.03 | 0.91 – 1.17 | 0.637 | 0.96 | 0.87 – 1.06 | 0.432 |
| Per capita income | 0.55 | 0.48 – 0.63 | **<0.001** | 0.70 | 0.62 – 0.78 | **<0.001** |
| RX1day | 1.33 | 1.21 – 1.46 | **<0.001** | | | |
| R10mm | | | | 1.45 | 1.28 – 1.66 | **<0.001** |
| **Zero-Inflated Model** | | | | | | |
| Intercept | 1.96 | 1.38 – 2.79 | **<0.001** | 1.56 | 0.69 – 3.50 | 0.283 |
| Pop. density | 1.21 | 1.04 – 1.40 | **0.014** | 0.99 | 0.83 – 1.17 | 0.878 |
| Per capita income | 0.29 | 0.23 – 0.36 | **<0.001** | 0.45 | 0.32 – 0.64 | **<0.001** |
| RX1day | 0.66 | 0.58 – 0.74 | **<0.001** | | | |
| R10mm | | | | 0.77 | 0.67 – 0.89 | **<0.001** |
| Observations | 15420 | | | 13020 | | |
| Marginal $R^2$ | 0.303 | | | 0.466 | | |
| Conditional $R^2$ | 1.00 | | | 1.00 | | |

## 3.4. Attribution of disaster mortality to vulnerability and exposure

Per capita income as a proxy indicator of vulnerability showed a significant negative association with disaster mortality. A one-unit increase in per capita income decreases landslide mortality by 30% and flood mortality by 45% (table 3). The social vulnerability index showed a positive association with disaster mortality but was significant only with landslide mortality (table 4). A one-unit increase in SoVI increases landslide mortality by 22%. The population density as a proxy of exposure does not show any significant association with disaster mortality.

***Table 4: Results of negative binomial models. Disaster mortality as a dependent variable and indicators of exposure, vulnerability, and hazard (in standardized Z-score) as explanatory variables.***

| | Flood mortality | | | Landslide mortality | | |
|---|---|---|---|---|---|---|
| *Predictors* | *IRR* | *CI* | *p* | *IRR* | *CI* | *p* |
| Intercept | 2.98 | 2.67 – 3.33 | **<0.001** | 3.80 | 3.40 – 4.25 | **<0.001** |
| Pop. density | 0.80 | 0.67 – 0.92 | **0.008** | 0.95 | 0.82 – 1.09 | 0.443 |
| Social Vulnerability Index | 1.08 | 0.97 – 1.21 | 0.154 | 1.22 | 1.08 – 1.38 | **0.001** |
| RX1day | 1.13 | 1.01 – 1.26 | **0.036** | | | |
| R10mm | | | | 1.38 | 1.24 – 1.54 | **<0.001** |
| Observations | 271 | | | 252 | | |
| $R^2$ Nagelkerke | 0. 079 | | | 0.212 | | |

# 4. Discussion

Landslides and floods have been the two deadliest disasters in Nepal, accounting for 70% of the total climate-related disaster mortality during 1992 - 2021. Historically, flood and landslide mortality have been highest in central and eastern Nepal and lowest in western Nepal. This spatial pattern of disaster mortality aligns exactly with Nepal's mean and extreme precipitation pattern. Eastern and central Nepal have received higher precipitation due to the dominance of the Indian summer monsoon (Karki et al., 2017; Talchabhadel et al., 2018). The highest mean annual precipitation (> 3,500 mm) has been mostly located in around 83° – 85° longitudinal zones in central Nepal between 2,000 to 3,500 m elevation (Talchabhadel et al., 2018). Similarly, the southern foothills of central Nepal have received the highest extreme precipitation, and pocket areas in the middle mountain received relatively higher extreme precipitation (Karki et al., 2017; Talchabhadel et al., 2018). Western Nepal has received less precipitation than the country on average, and the disaster mortality has also been the lowest in this region.

When we look at the temporal trends of disaster mortality and frequency, it is significantly increasing in western Nepal but does not show significant trends in central and eastern Nepal. Almost similar temporal trends are observed in mean and extreme precipitation indices. Most of the stations in western Nepal have shown a rise in mean and extreme precipitation, although the trends are statistically significant in a relatively small proportion of the stations. Rising precipitation extremes in western Nepal are also confirmed by previous studies (Bohlinger & Sorteberg, 2018; Karki et al., 2017; Pokharel et al., 2019; Talchabhadel et al., 2018). There is high confidence that such a rise in precipitation extremes at the global and regional scales is a direct consequence of increased radiative forcing and the increase in the water-holding capacity of the atmosphere due to global warming (Seneviratne et al., 2021). For example, 1°C of warming results in a 7% increase in atmospheric water vapor content, leading to a robust increase in precipitation extremes such as RX1day (Seneviratne et al., 2021). The change in precipitation patterns and the rise in extreme precipitation in the Himalayas are attributed to the warming Indian Ocean, alteration of Arctic Oscillation, and intensification of an upper tropospheric mid-latitude shortwave due to the rise in greenhouse gases and aerosols (Karki et al., 2017; Wang et al., 2013).

Nepal's flood and landslide mortality showed a mostly significant positive association with the mean precipitation and extreme precipitation duration, frequency, and intensity. The rise in extreme precipitation intensity, such as maximum one-day precipitation (RX1day) and contribution from very wet days (R95pTOT), is mainly associated with flood mortality in Nepal. Most of the deadliest flooding events in recent years in Nepal, such as the Melamchi flood of 2021, the Terai flood of 2017, and the western Nepal flood of 2014, were triggered by unusually high-intensity precipitation events (Bhandari et al., 2018; ISET, 2015; Maharjan et al., 2021). Such high-intensity precipitation events cause a sudden rise in peak flow triggering floods, particularly flash floods, along the river valleys providing no time for people to escape and causing higher mortality. Landslide mortality in Nepal is strongly associated with extreme precipitation frequency indices such as the annual number of heavy rain days (R10mm) and duration indices such as consecutive wet days (CWD). The accumulated rain over the previous 3, 7, and 10-day is directly associated with the landslide occurrence in the hills and mountains in Nepal (Dahal & Hasegawa, 2008; Muñoz-Torrero Manchado et al., 2021). Because the continuous precipitation events saturate the soil water triggering slope failure (Kirschbaum et al., 2015). Moreover, the highest incidences of landslides in western Nepal have been recorded when the wet monsoon has been preceded by a warm and dry monsoon (Muñoz-Torrero Manchado et al., 2021).

As a proxy of vulnerability, per capita income showed a significant negative association with flood and landslide mortality. This may suggest that income increases are associated with reduced disaster vulnerability, thus ultimately reducing disaster mortality. Because higher income increase the demand for higher safety and also enable people to spend more on physical and non-physical risk reduction measures such as better housing, early warning systems, and disaster response (Formetta & Feyen, 2019; Jongman et al., 2015; Wu et al., 2019). A significant positive association of landslide mortality with the social vulnerability index indicates that regions with high social vulnerability experience higher landslide mortality. We do not find a significant role of population density on landslide and flood mortality in Nepal. In the context of Nepal, this refutes the conclusion that the observed increase in disaster impacts is mainly due to exposure increments (Bouwer 2011; Visser et al. 2014; McAneney et al. 2019; Pielke 2021). We argue that the mortality in highly populated regions is not higher because urban areas in Nepal are relatively less vulnerable to climate-related disasters than rural areas (Chapagain et al., 2022).

With additional global warming, extreme precipitation events will inevitably become more frequent and intense worldwide. For each 1°C of global warming, the extreme daily precipitation events are projected to intensify by around 7% on a global scale (IPCC, 2021). In Nepal, extreme precipitation events are projected to rise with the strongest rise in high emission scenarios (Chapagain et al., 2021; MoFE, 2019; Rajbhandari et al., 2017). For example, the number of extremely wet days is projected to increase by 28% in 2016-2045 and by 60% in 2036-2065 in the high emission (RCP8.5) scenario compared to the 1981-2010 period (MoFE, 2019). Such a rise in precipitation extremes in Nepal and worldwide is most likely to increase disaster mortality if the vulnerability of the exposed population is not reduced.

This study is based on the most robust and high-resolution empirical data currently available for a country like Nepal. Nevertheless, climate change attribution science is complex and inherits several uncertainties. Further improvements in geocoding of the disaster locations, improved delineation of the disaster-specific exposure boundary, and inclusion of more indicators of explanatory variables, particularly the vulnerability indicators, could further improve the accuracy of our findings. Moreover, similar studies for other climate-related disaster types and in other countries, regions, and on a global scale could provide more empirical evidence of the role of climate change on disaster impacts from different parts of the world.

# 5. Conclusions

There have been increasing trends of climate-related disasters and their socio-economic impacts worldwide. Particularly, the poor people in the Global South are mainly impacted by such disasters. The extreme weather and climate events have also increased due to anthropogenic climate change and are projected to increase further in future GHG emission scenarios. Nevertheless, extremely limited studies have looked at the role of climate change on rising disaster impacts in low-income countries. Here, we studied the spatiotemporal trends of flood and landslide mortality and its attribution to climatic and socio-economic changes at the sub-national scale in the low-income country's context, taking Nepal as a case study.

We found that the flood and landslide mortality in the past three decades was highest in central and eastern Nepal and lowest in western Nepal. This pattern of disaster mortality matched closely with the observed spatial pattern of mean and extreme precipitation in Nepal. The temporal trends of extreme precipitation events mainly showed increasing trends in western Nepal but mostly decreasing trends in central Nepal. Correspondingly, the landslide and flood frequency and mortality have also increased in western Nepal, but no significant trends were observed in central and eastern Nepal. Such spatiotemporal patterns showed a direct association between precipitation extremes and landslide and flood mortality.

Regression results confirmed that the extreme precipitation events, mainly the extreme precipitation intensity (RX1day and R95pTOT), have increased flood mortality, and extreme precipitation frequency and duration (R10mm and CWD) have increased landslide mortality. A one unit increase in RX1day and R95pTOT increase flood mortality by 33% and 31% respectively. A one unit increase in R10mm and CWD increase Landslide mortality by 45% and 34% respectively. Lower vulnerability, represented by higher income and lower social vulnerability, has decreased flood and landslide mortality. A one-unit increase in per capita income decreases landslide mortality by 30% and flood mortality by 45%. However, population exposure did not show a significant effect on mortality. Hence, the observed rise in flood and landslide mortality, mainly in western Nepal, is attributable primarily to the rise in precipitation extremes in these regions due to climate change. Moreover, the projected rise in precipitation extremes is most likely to increase climate-related disaster mortality in the future if no actions are taken to reduce the vulnerability strongly.

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# Supplementary materials

*Table S1: Descriptive statistics of dependent variable*

| Parameter | Landslide mortality | Flood mortality |
|---|---|---|
| Observations (n) | 13020 | 15420 |
| Mean | 0.28 | 0.21 |
| Variance | 3.97 | 16.9 |
| Dispersion<br>(Dispersion test results for Poisson model) | 12.23<br>(p-value = 0.0016) | 70.34<br>(p-value = 0.0821) |

*Table S2: Comparison of OLS and count data regression models. Explanatory variables in standardized Z-score.*

| | **Dependent variable: number of fatalities due to landslides** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Linear** | | | **Poisson** | | | **Negative Binomial** | | | **Zero-Inflated Poisson** | | | **Zero-Inflated Negative Binomial** | | |
| *Predictors* | *Estimates* | *std. Error* | *p* | *IRR* | *std. Error* | *p* | *IRR* | *std. Error* | *p* | *IRR* | *std. Error* | *p* | *IRR* | *std. Error* | *p* |
| Intercept | 0.28 | 0.02 | **<0.001** | 0.16 | 0.01 | **<0.001** | 0.20 | 0.01 | **<0.001** | 1.90 | 0.11 | **<0.001** | 0.61 | 0.14 | **0.033** |
| Pop. density | -0.01 | 0.02 | 0.586 | 0.95 | 0.04 | 0.206 | 0.95 | 0.05 | 0.294 | 1.02 | 0.06 | 0.770 | 0.96 | 0.05 | 0.432 |
| Per capita income | -0.00 | 0.02 | 0.994 | 1.06 | 0.02 | **0.005** | 1.06 | 0.06 | 0.235 | 0.75 | 0.02 | **<0.001** | 0.70 | 0.04 | **<0.001** |
| R10mm | 0.14 | 0.02 | **<0.001** | 1.72 | 0.05 | **<0.001** | 1.69 | 0.09 | **<0.001** | 1.29 | 0.04 | **<0.001** | 1.45 | 0.10 | **<0.001** |
| **Zero-Inflated Model** | | | | | | | | | | | | | | | |
| Intercept | | | | | | | | | | 9.09 | 0.42 | **<0.001** | 1.56 | 0.64 | 0.283 |
| Pop. density | | | | | | | | | | 1.03 | 0.05 | 0.507 | 0.99 | 0.09 | 0.878 |
| Per capita income | | | | | | | | | | 0.71 | 0.03 | **<0.001** | 0.45 | 0.08 | **<0.001** |
| R10mm | | | | | | | | | | 0.76 | 0.03 | **<0.001** | 0.77 | 0.06 | **<0.001** |
| **Random Effects** | | | | | | | | | | | | | | | |
| $\sigma^2$ | 3.94 | | | 1.91 | | | 3.26 | | | 0.01 | | | 0.00 | | |
| $\tau_{00}$ | 0.01 Local units | | | 0.81 Local units | | | 0.23 Local units | | | 0.72 Local units | | | 0.32 Local units | | |
| ICC | 0.00 | | | 0.30 | | | 0.07 | | | 0.99 | | | 1.00 | | |
| N | 434 Local units | | | 434 Local units | | | 434 Local units | | | 434 Local units | | | 434 Local units | | |
| Observations | 13020 | | | 13020 | | | 13020 | | | 13020 | | | 13020 | | |
| Marginal $R^2$ | 0.005 | | | 0.099 | | | 0.075 | | | 0.164 | | | 0.466 | | |
| Conditional $R^2$ | 0.008 | | | 0.366 | | | 0.135 | | | 0.990 | | | 1.000 | | |
| AIC | 54870.8 | | | 22536.7 | | | 11376.1 | | | 12750.5 | | | 11277.2 | | |
| BIC | 54915.6 | | | 22574.1 | | | 11421.0 | | | 12795.4 | | | 11326.1 | | |
| log-Likelihood | -27429. 4 | | | -11263.4 | | | -5682.1 | | | -6364.3 | | | -5626.6 | | |

***Table S3: Results of mixed effects zero-inflated negative binomial models. Flood mortality as dependent variable and indicators of exposure, vulnerability, and hazard (in standardized Z-score) as explanatory variables.***

| | **Dependent variable: number of fatalities due to floods** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | | **(2)** | | **(3)** | | **(4)** | | **(5)** | | **(6)** | |
| *Predictors* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* |
| **Count Model** | | | | | | | | | | | | |
| Intercept | 0.35 | **<0.001** | 0.37 | **<0.001** | 0.36 | **<0.001** | 0.40 | **<0.001** | 0.42 | **<0.001** | 0.41 | **<0.001** |
| Pop. density | 1.00 | 0.987 | 1.04 | 0.569 | 1.00 | 0.975 | 1.04 | 0.531 | 1.03 | 0.637 | 1.04 | 0.547 |
| Per capita income | 0.60 | **<0.001** | 0.58 | **<0.001** | 0.60 | **<0.001** | 0.57 | **<0.001** | 0.55 | **<0.001** | 0.57 | **<0.001** |
| CWD | 1.04 | 0.617 | | | | | | | | | | |
| PRCPTOT | | | 1.16 | **0.034** | | | | | | | | |
| R10mm | | | | | 1.06 | 0.399 | | | | | | |
| R95pTOT | | | | | | | 1.31 | **<0.001** | | | | |
| RX1day | | | | | | | | | 1.33 | **<0.001** | | |
| SDII | | | | | | | | | | | 1.16 | **0.025** |
| **Zero-Inflated Model** | | | | | | | | | | | | |
| Intercept | 0.99 | 0.981 | 1.21 | 0.397 | 1.03 | 0.890 | 1.64 | **0.014** | 1.96 | **<0.001** | 1.55 | **0.029** |
| Pop. density | 0.67 | 0.142 | 1.12 | 0.425 | 0.77 | 0.315 | 1.20 | **0.026** | 1.21 | **0.014** | 1.19 | **0.042** |
| Per capita income | 0.22 | **<0.001** | 0.22 | **<0.001** | 0.21 | **<0.001** | 0.26 | **<0.001** | 0.29 | **<0.001** | 0.26 | **<0.001** |
| CWD | 0.85 | 0.102 | | | | | | | | | | |
| PRCPTOT | | | 0.69 | **<0.001** | | | | | | | | |
| R10mm | | | | | 0.79 | **0.009** | | | | | | |
| R95pTOT | | | | | | | 0.68 | **<0.001** | | | | |
| RX1day | | | | | | | | | 0.66 | **<0.00** | | |
| SDII | | | | | | | | | | | 0.74 | **<0.001** |
| **Random Effects** | | | | | | | | | | | | |
| $\sigma^2$ | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 | |
| $\tau_{00}$ | 0.77 Local units | | 0.83 Local units | | 0.78 Local units | | 0.85 Local units | | 0.90 Local units | | 0.86 Local units | |
| ICC | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | |
| N | 514 Local units | | 514 Local units | | 514 Local units | | 514 Local units | | 514 Local units | | 514 Local units | |
| Observations | 15420 | | 15420 | | 15420 | | 15420 | | 15420 | | 15420 | |
| Marginal $R^2$ | 0.254 | | 0.264 | | 0.257 | | 0.304 | | 0.303 | | 0.267 | |
| Conditional $R^2$ | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | |
| AIC | 10695.5 | | 10626.4 | | 10680.7 | | 10536.4 | | 10471.8 | | 10631.6 | |
| BIC | 10746.5 | | 10677.3 | | 10731.6 | | 10587.3 | | 10522.7 | | 10682.5 | |

***Table S4: Results of mixed effects zero-inflated negative binomial models. Landslide mortality as dependent variable and indicators of exposure, vulnerability, and hazard (in standardized Z-score) as explanatory variables.***

| | **Dependent variable: number of fatalities due to landslides** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | | **(2)** | | **(3)** | | **(4)** | | **(5)** | | **(6)** | |
| *Predictors* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* | *IRR* | *p* |
| **Count Model** | | | | | | | | | | | | |
| Intercept | 0.50 | **0.001** | 0.60 | **0.035** | 0.61 | **0.033** | 0.69 | 0.103 | 0.79 | 0.195 | 0.64 | 0.069 |
| Pop. density | 0.98 | 0.703 | 0.97 | 0.490 | 0.96 | 0.432 | 0.95 | 0.381 | 0.95 | 0.399 | 0.95 | 0.313 |
| Per capita income | 0.75 | **<0.001** | 0.69 | **<0.001** | 0.70 | **<0.001** | 0.70 | **<0.001** | 0.69 | **<0.001** | 0.69 | **<0.001** |
| CWD | 1.34 | **<0.001** | | | | | | | | | | |
| PRCPTOT | | | 1.41 | **<0.001** | | | | | | | | |
| R10mm | | | | | 1.45 | **<0.001** | | | | | | |
| R95pTOT | | | | | | | 1.16 | **0.020** | | | | |
| RX1day | | | | | | | | | 1.23 | **<0.001** | | |
| SDII | | | | | | | | | | | 1.29 | **<0.001** |
| **Zero-Inflated Model** | | | | | | | | | | | | |
| Intercept | 0.97 | 0.942 | 1.56 | 0.307 | 1.56 | 0.283 | 1.96 | 0.066 | 2.61 | **<0.001** | 1.67 | 0.224 |
| Pop. density | 0.89 | 0.437 | 1.01 | 0.868 | 0.99 | 0.878 | 1.02 | 0.862 | 1.04 | 0.616 | 1.02 | 0.760 |
| Per capita income | 0.36 | **<0.001** | 0.45 | **<0.001** | 0.45 | **<0.001** | 0.50 | **<0.001** | 0.55 | **<0.001** | 0.47 | **<0.001** |
| CWD | 0.74 | **0.001** | | | | | | | | | | |
| PRCPTOT | | | 0.71 | **<0.001** | | | | | | | | |
| R10mm | | | | | 0.77 | **<0.001** | | | | | | |
| R95pTOT | | | | | | | 0.72 | **<0.001** | | | | |
| RX1day | | | | | | | | | 0.72 | **<0.001** | | |
| SDII | | | | | | | | | | | 0.81 | **0.003** |
| **Random Effects** | | | | | | | | | | | | |
| $\sigma^2$ | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 | |
| $\tau_{00}$ | 0.28 Local units | | 0.33 Local units | | 0.32 Local units | | 0.42 Local units | | 0.50 Local units | | 0.39 Local units | |
| ICC | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | |
| N | 434 Local units | | 434 Local units | | 434 Local units | | 434 Local units | | 434 Local units | | 434 Local units | |
| Observations | 13020 | | 13020 | | 13020 | | 13020 | | 13020 | | 13020 | |
| Marginal $R^2$ | 0.41 | | 0.44 | | 0.47 | | 0.26 | | 0.25 | | 0.34 | |
| Conditional $R^2$ | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | | 1.00 | |
| AIC | 11310.4 | | 11258.9 | | 11277.2 | | 11318.8 | | 11280.9 | | 11334.9 | |
| BIC | 11359.3 | | 11307.7 | | 11326.1 | | 11367.7 | | 11329.7 | | 11383.8 | |