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ORIGINAL ARTICLE

Declining vulnerability but rising impacts: the trends of climatic disasters in Nepal

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Abstract
The impacts of climatic disasters have been rising globally. Several studies argue that this upward trend is due to rapid growth in the population and wealth exposed to disasters. Others argue that rising extreme weather events due to anthropogenic climate change are responsible for the increase. Hence, the causes of the increase in disaster impacts remain elusive. Disaster impacts relative to income are higher in low-income countries, but existing studies are mostly from developed countries or at the cross-country level. Here we assess the spatiotemporal trends of climatic disaster impacts and vulnerability and their attribution to climatic and socioeconomic factors at the subnational scale in a low-income country, using Nepal as a case study. Loss of life is the most extreme consequence of disasters. Therefore, we employed human mortality as a measure of disaster impacts, and mortality normalized by exposed population as a measure of human vulnerability. We found that climatic disaster frequency and mortality increased in Nepal from 1992 to 2021. However, vulnerability decreased, most likely due to economic growth and progress in disaster risk reduction and climate change adaptation. Disaster mortality is positively correlated with disaster frequency and negatively correlated with per capita income but is not correlated with the exposed population. Hence, population growth may not have caused the rise in disaster mortality in Nepal. The strong rise in disaster incidence, potentially due to climate change, has overcome the effect of decreasing vulnerability and caused the rise in disaster mortality.

Keywords Climatic disasters · Mortality · Vulnerability · Loss normalization · Attribution · Nepal

Introduction

Loss of life and property due to climatic disasters is increasing globally (Hoeppe 2016; Formetta and Feyen 2019). As a direct result of over 11,000 extreme weather events, more than 475,000 people died worldwide, and economic losses of USD 2.56 trillion (in purchasing power parity) were incurred from 2000 to 2019 (Eckstein et al. 2021). Disaster-induced fatality and economic losses relative to a country's gross domestic product (GDP) are higher in low-income countries (UNDRR 2019; Formetta and Feyen 2019). For example, 90% of disaster deaths during the past two decades have occurred in low- and middle-income countries (UNISDR 2018). An increase in weather and climate extremes has also been observed since about 1950 due to anthropogenic climate change (IPCC 2012, 2021). This is often equated with the growing impact of climatic disasters (Huggel et al. 2013; Bouwer 2019; IPCCB, 2021). However, the detection and attribution of the spatial and temporal trend of climatic disaster impacts remain elusive.

A growing body of research has analyzed the historical trends of climatic disaster impacts and their causes, but the findings are varied and contradictory. One line of argument is that the upward trend in climatic disaster impacts so far is due to the rapid growth in population and wealth exposed to the hazards, and the role of the increase in climatic hazards is not evident (Visser et al. 2014; Bouwer 2019; McAneney

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et al. 2019; Pielke 2021). This argument is valid only if there have not been any disaster preparedness and adaptation efforts so far or if such efforts have been completely unsuccessful in reducing vulnerability (Nicholls 2011). Otherwise, the exposure-normalized impacts in the absence of climate change effects should exhibit a decreasing trend since there has been progress in weather forecasting and disaster preparedness worldwide to reduce vulnerability (Nicholls 2011; Neumayer and Barthel 2011). Several studies have observed a declining trend in exposure-normalized disaster impacts, which is associated with disaster vulnerability (Jongman et al. 2015; Tanoue et al. 2016; Formetta and Feyen 2019). Such vulnerability reduction could be due to economic growth, disaster risk reduction (DRR), and climate change adaptation, which could have masked the effect of an increase in climatic hazards. If the vulnerability is controlled, the effect of climatic hazards is much greater for explaining the increasing trend of disaster impacts (Estrada et al. 2015; Forzieri et al. 2017). Some studies have observed a monotonic decrease in vulnerability with economic growth (Jongman et al. 2015; Wu et al. 2019; Formetta and Feyen 2019), whereas others have claimed an inverted U-shaped trend, indicating an initial increase in vulnerability before it decreases (Kellenberg and Mobarak 2008; Zhou et al. 2014; Tanoue et al. 2016).

The findings on trends in disaster impacts are either from global cross-country studies or from developed countries (Bouwer 2019; Pielke 2021). Global studies are generally based on nationally aggregated data, and the analyses are done at the low spatial resolution, such as by country clusters (low- and high-income countries) or by continents. However, climatic disasters most often are local phenomena, and their impact and vulnerability are highly context specific. Therefore, such cross-country analyses cannot capture the true spatial and temporal dynamics of disaster impacts, vulnerability, and relationship with their drivers in any particular location (Rubin 2014; Wu et al. 2019). Low-income countries are poorly represented in such analyses, and in particular, there is a lack of information at the subnational scale for vulnerable countries (James et al. 2019). Such a knowledge gap significantly hinders the achievement of the goals of the Sendai Framework for Disaster Risk Reduction (SFDRR); Sustainable Development Goals (SDGs) 11 and 13, along with others; and the global adaptation goal of the Paris Agreement.

A country-specific study can explore the association of disaster impacts with their drivers by controlling the governance, institutional, and political variables, which is often not feasible in cross-national studies (Rubin 2014). Such an analysis of observed disaster impacts is important to identify high-impact and vulnerable areas, plan and implement DRR and climate change adaptation measures, monitor the effectiveness of these measures, and study the attribution of impacts to climate change (Koç and Thieken 2018). Therefore, the objectives of our study were to map the high-impact and vulnerable areas of climatic disasters in Nepal; to understand the temporal trends in the occurrence, impact, and vulnerability of climatic disasters; and to provide empirical evidence for the causes of trends in the impact of climatic disasters at the subnational scale in a low-income country.

Nepal is among the top 10 countries worldwide most affected by climatic disasters in the past two decades with 0.82 fatalities per 100,000 inhabitants and 0.39% losses per unit GDP (Eckstein et al. 2021). Extreme precipitation events, such as the numbers of heavy precipitation days and consecutive wet days, are increasing in many parts of the country, especially in the western half (Karki et al. 2017; Chapagain et al. 2021), and warm days and nights are occurring more frequently across the country (DHM 2017). Previous studies have observed increasing trends in the frequency of climatic disasters and mortality from climatic disasters in Nepal (Petley et al. 2007; Aryal 2012; Elalem and Pal 2015; Aksha et al. 2018; Adhikari and Tian 2021; MoFE 2021). However, the underlying causes of growing disaster mortality and its attribution to climatic and socioeconomic change remain unexplored. Previous studies do not provide information on disaster impacts after controlling for exposure or the relationship between vulnerability and economic growth. Most previous spatial analyses were done at the district level, which is no longer a relevant administrative unit in Nepal after the federalization and administrative restructuring in 2015. Similarly, the districts do not provide a sufficiently fine resolution to account for the huge geographic and socioeconomic heterogeneity in Nepal.

We conducted this study in Nepal for the period 1992 to 2021 at the level of the new local administrative units. Our first research question was what are the spatial and temporal trends in the frequency and mortality of climatic disasters in Nepal? We focused on human mortality as a measure of climatic disaster impact. Human mortality is a good measure of non-monetary disaster impact since death is the most extreme consequence of disasters (Rubin 2014). The second question was what are the spatial and temporal trends in human vulnerability to climatic disasters in Nepal? Among various approaches of vulnerability assessment, we followed the most widely used loss normalization approach (Jongman et al. 2015; Tanoue et al. 2016; James et al. 2019; Wu et al. 2019; Formetta and Feyen 2019; Pielke 2021). We normalized disaster mortality by the exposed population as a proxy measure of human vulnerability to climatic disasters. We further explored the relationship of disaster vulnerability with economic growth measured in terms of per capita income. Our final research question was what are the attributions of trends in mortality from climatic disasters to climatic and socioeconomic changes? We applied regression analyses to study the attribution of disaster mortality to disaster frequency, the exposed population, and per capita income as proxy indicators of climatic hazard, exposure, and vulnerability, respectively.

Methods

Study location, units, and period

Nepal is a landlocked country located in South Asia between India and China. It has a total area of 147,516 km^2 and a population of slightly below 30 million (CBS 2022). This mountainous country is divided into five physiographic regions: Tarai, Siwalik, Hills, Middle Mountains, and High Mountains (MoFE 2021). Each region has distinct geographic and climatic characteristics. Within a distance of about 200 km from south to north, the altitude increases from 70 m above sea level (m.a.s.l.) to 8849 m.a.s.l. at Mount Everest, the world's highest peak (DOS 2021). The country is divided into 7 provinces and 753 local administrative units in the new federal system in 2015 (MoFAGA, 2019; Fig. 1). The urban locations consist of six metropolitan cities, 11 sub-metropolitan cities, and 276 municipalities, and the rural locations consist of 460 rural municipalities. These local units are the smallest subnational administrative units in Nepal. Hence, we selected them as the study unit to allow for a very fine resolution of the analysis. The results at the local scale are highly policy relevant and can be easily aggregated into the district, province, and national scale as well as other analytical dimensions such as rural–urban or physiographic regions. We selected the most recent 30 years (1992–2021) as the study period following the World Meteorological Organization (WMO)-recommended minimum time frame in climate research.

Data

DesInventar, EM-DAT, NatCatSERVICE, and Sigma are the major global disaster database (Huggel et al. 2015; Moriyama et al. 2018). Only the first two are open access. EM-DAT managed by the Centre for Research on the Epidemiology of Disasters (CRED) has stricter disaster criteria (10 or more people dead; or 100 or more people affected; or the declaration of a state of emergency: or a call for international assistance) (EM-DAT 2022). On the contrary, DesInventar, hosted by the United Nations Office for Disaster Risk Reduction (UNDRR), records the smaller disasters as well and includes information at the local level (DesInventar 2021). Consequently, the numbers of disasters recorded in EM-DAT are very limited compared to DesInventar (Huggel et al. 2015; Aksha et al. 2018; WMO 2021). Therefore, we selected DesInventar as the most robust and local-level disaster database for Nepal. Disaster data for the period 1971–2013 in Nepal are available in DesInventar. They include information on the type, location, and date of disasters; the numbers of people who died or were injured; and the estimated direct economic losses, along with other information. Since 2011, the Nepal DRR Portal of the Ministry of Home Affairs (MoHA) has also maintained the disaster database for Nepal (MoHA 2021). The two databases are developed in collaboration following a similar recording format. The overlapping years do not show any major inconsistency. Hence, we combined DesInventar and the Nepal DRR portal in this study.

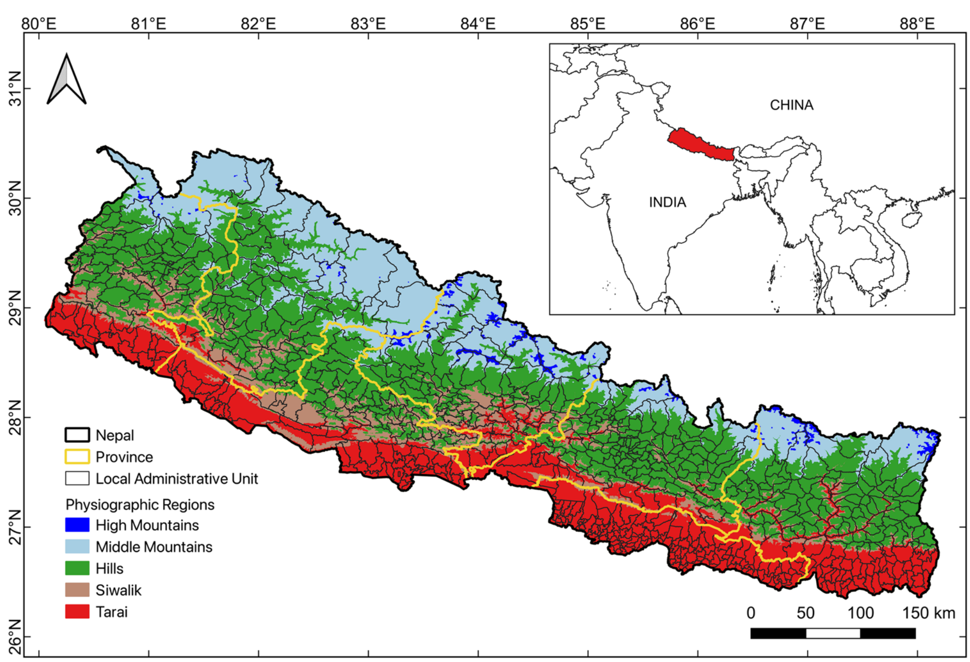

Fig. 1 Map of Nepal showing local administrative units and physiographic regions. Inset: Nepal in the world map

The disaster types listed in the Hydrological, Meteorological, or Climatological family of the DesInventar disaster classification system are the criteria for climatic disasters in this study. We grouped climatic disasters in Nepal into eight types: landslides, floods and heavy rains, thunderstorms, cold waves and frosts, windstorms, snowstorms and avalanches, heat waves, and hailstorms. The exact disaster type as listed in the DesInventar and Nepal DRR Portal and the corresponding disaster type in our grouping is provided in Table S1 in the Electronic Supplementary Materials (ESM). Because of its slow onset, the impacts of drought are poorly documented in Nepal. Similarly, the observed incidences of fires and forest fires were largely linked to human error. Hence, drought, fires, and forest fires, along with other nonclimatic disasters, are excluded from this analysis.

We focused on the mortality aspect of disaster impacts. Therefore, we extracted only the incidences of disaster that caused at least one death. The disaster database was checked for multiple reporting of the same incident, and duplicated events were removed. Each incidence of the disaster was then assigned to the respective new local administrative unit based on the location information available in the database. For incidences with reported locations as old Village Development Committees (VDCs), the new local units were identified based on the list of old VDCs in new local units published in the Gazette by the MoFAGA (2019). The exact location information was missing in around 7% of the total incidences recorded and is distributed throughout the study period. These incomplete incidences were excluded from the analysis.

Population data were accessed from the last four national censuses (1991, 2001, 2011, and 2021) by the Central Bureau of Statistics (CBS), Nepal. For the 1991 and 2001 censuses, the population of old VDCs was aggregated to the new local units using the same local units list as disaster data. Finally, the annual population data by new local units were generated by linear interpolation of the 10-year interval census data. Income data were accessed from the Nepal Living Standard Survey (NLSS) 1995, 2003, and 2010 conducted by the CBS. The nominal per capita income data were available at the NLSS 12 analytical dimensions level covering urban–rural, Tarai–Hills–Mountains, and east–west aspects of Nepal (see Table S2 for the list of the 12 analytical dimensions). The income data were first adjusted for inflation using the World Bank's consumer price index. The inflation-adjusted per capita income was then assigned to the local units that fell under the respective NLSS analytical dimensions. Finally, income data were linearly interpolated and extrapolated for the study period for each local unit.

Disaster impacts and vulnerability

The impact of climatic disaster is determined by the complex interaction of hazard, exposure, and vulnerability, as illustrated in Eq. (1) (IPCC 2012). In this IPCC impact and vulnerability framework, hazard refers to climate-related physical events or trends that may cause loss of life, injury, or other health impacts, as well as damage and loss of property, infrastructure, livelihoods, service provision, and environmental resources. A hazard turns into a disaster and causes impacts when it interacts with exposure (for example, the inventory of people living in the area hit by the hazard) and their vulnerability. Our research deals with the historically observed climatic events that have turned hazards into disasters and caused impacts. Therefore, the observed disaster events represent the hazard, people living in the disaster location represent the exposure, and resulted human mortality represents the impacts component of this framework.

$$Impact = f(Hazard, Exposure, Vulnerability) \tag{1}$$

Vulnerability is the characteristic of the exposed element and is a result of various historical, social, economic, political, cultural, institutional, and environmental conditions (IPCC 2012). The concepts, definitions, and measures of vulnerability have evolved rapidly as knowledge, needs, and contexts vary. In disaster studies, vulnerability is considered the degree of impact in a disaster event (Mechler and Bouwer 2015). Therefore, we normalized the annual disaster mortality (M_{dit}) by the disaster-exposed population (P_{dit}) as a proxy measure of human vulnerability (V_{dit}), as shown in Eq. (2). Even though the adequacy of normalized loss to represent the vulnerability is still not clear (Huggel et al. 2015), this is the most commonly used approach in disaster studies (Jongman et al. 2015; Tanoue et al. 2016; James et al. 2019; Wu et al. 2019; Formetta and Feyen 2019; Pielke 2021). Normalized disaster mortality as a proxy measure of human vulnerability is based on the hypothesis that the normalized impacts are higher in more vulnerable regions than in less vulnerable regions (Jongman et al. 2015; Formetta and Feyen 2019). This measure of vulnerability controls for hazard and exposure elements makes it possible to compare between spatial units and the temporal scale.

$$Human\ Vulnerability\ \left(V_{dit}\right) = \frac{Disaster\ Mortality\ \left(M_{dit}\right)}{Disaster - Exposed\ Population\ \left(P_{dit}\right)} \tag{2}$$

$$\begin{aligned} Where,\ d &= disaster\ type \\ i &= local\ unit \\ t &= year \end{aligned}$$

Even though normalized disaster mortality is a theoretically sound proxy for vulnerability, the exact delineation of the area exposed to the hazard, which determines the boundaries of the population exposed, is challenging (Neumayer and Barthel 2011; Formetta and Feyen 2019). There has been some progress in estimating hazard-specific exposure, such as flood exposure using river and inundation models (Jongman et al. 2015; Tanoue et al. 2016). However, this technique is not feasible for multidisaster analysis because each incidence of disaster is unique (Wu et al. 2019; Formetta and Feyen 2019). Hence, previous global-scale analyses assumed an entire country as an exposed area (Visser et al. 2014) or made the simple assumption that each disaster affects an equal-sized area, such as a 100 × 100 km square (Neumayer and Barthel 2011) or a circle with a radius of 50, 100, 200, or 400 km (Formetta and Feyen 2019), arranged around the reported center of the disaster. Country-specific studies used subnational administrative units such as provinces as exposed areas (Rubin 2014; Zhou et al. 2014; Wu et al. 2019). In our study, local administrative units, with an average area of approximately 195 km^2, are considered the boundaries of the exposed population. Because of the lack of precise information on the hazard-specific exposed area, such assumptions may result in bias in the estimated vulnerability. However, the error is likely to be random, with no systematic under- or overestimation of the true area exposed, and will not have a significant impact on the spatiotemporal trend (Neumayer and Barthel 2011; Formetta and Feyen 2019).

Trend analysis

The presence or absence of temporal trends in disaster frequency, mortality, and vulnerability was examined using the Mann–Kendall test (Mann 1945). This nonparametric test is an appropriate method of assessing the monotonic trend in disaster data because of its lack of any distributional assumptions and its ability to handle missing values and the influence of outliers (Chandler and Scott 2011). The actual slope of the monotonic trend was estimated by the Theil – Sen (TS) slope method (Sen 1968). The TS slope provides a measure of change over a unit time period (Chandler and Scott 2011). Both the Mann–Kendall test and the TS slope are widely used methods in climate and disaster studies (Karki et al. 2017; Wu et al. 2019).

Attribution to climatic and socioeconomic changes

Loss normalization is the commonly used approach in the literature to re-express the impacts in terms of vulnerability through normalization by the exposure and to investigate if there is a residual trend in normalized impacts that could be attributed to climate change (Huggel et al. 2013; Estrada et al. 2015; Bouwer 2019). However, the usefulness of the normalization approach to establish whether there is a remaining trend that could be attributed to climate change is limited, because the underlying assumptions may not hold, such as the relevance of the normalization variables to detrend the impacts due to socioeconomic changes (Estrada et al. 2015). Similarly, its current inability to appropriately account for the change in vulnerability does not allow it to detect the role of climatic hazards in the observed impacts (Huggel et al. 2013). Therefore, we employed a regression-based approach to study the attribution of disaster mortality to indicators of climatic hazards, exposure, and vulnerability.

In our fixed-effect regression model shown in Eq. (3), we used annual multidisaster mortality (M_{it}) in a local unit (i) during the year (t) as the dependent variable, which represents the impacts component of Eq. (1). Disaster frequency (F_{it}), exposed population (P_{it}), and per capita income (I_{it}) as proxy indicators of climatic hazard, exposure, and vulnerability, respectively, were used as the explanatory variables. The location fixed effect (u_i) was introduced in the model to control for other individual differences between the local units and to provide more robust estimates of the parameters. β s are the marginal effects of explanatory variables, and ε is the random error term.

$$ln(M_{it}) = \beta_F ln(F_{it}) + \beta_P ln(P_{it}) + \beta_I ln(I_{it}) + u_i + \varepsilon_{it} \tag{3}$$

The relationship between the dependent and explanatory variables is most likely to be nonlinear. Similarly, the disaster mortality data are highly skewed and non-normally distributed. To capture such nonlinearity and to make the impacts data approximately normal, the variables were log-transformed. In such a log–log model, regression coefficients are interpreted as elasticity, which makes the coefficients more comparable (Wooldridge 2013). Data processing and statistical analysis were performed with the R programming language.

Results

Climatic disaster frequency and mortality trends in Nepal

During the past three decades, almost 5000 deadly climatic disasters were recorded in Nepal, which killed more than 10,000 people across the country. Landslides and floods were the two deadliest disaster types, accounting for 37% and 32% of total disaster mortality, respectively. Thunderstorms were the third major disaster type in terms of total mortality, followed by cold waves and frost, windstorms, snowstorms and avalanches, heat waves, and hailstorms (Table 1). Above 800 people were missing and 5000 were

Table 1 Total climatic disaster mortality by disaster types in Nepal during 1992–2021

S. no	Disaster types	Mortality	Mortality in % of total
1	Landslides	3692	36.66
2	Floods and heavy rains	3201	31.78
3	Thunderstorms	1780	17.67
4	Cold waves and frosts	848	8.42
5	Windstorms	273	2.71
6	Snowstorms and avalanches	223	2.21
7	Heatwaves	35	0.35
8	Hailstorms	20	0.20
	Total	**10,072**	**100**

injured during the disasters. Most of the missing people and several injured people could have died, but this was not updated in the database. Similarly, several incidences of disaster could have gone unreported. Therefore, the recorded numbers are an underestimate of the actual occurrence and mortality of disasters in Nepal.

The number of incidences of disaster recorded and the number of people who died due to these disasters has increased in Nepal since 1992 (Fig. 2). Both multidisaster frequency and mortality showed increasing trends that were significant at the 0.05 level (Table 2). The frequency of climatic disasters increased by about seven incidences per year. Similarly, disaster mortality has increased at the rate of about nine persons per year. Among the individual disaster types, cold waves, and frost had the highest rate of

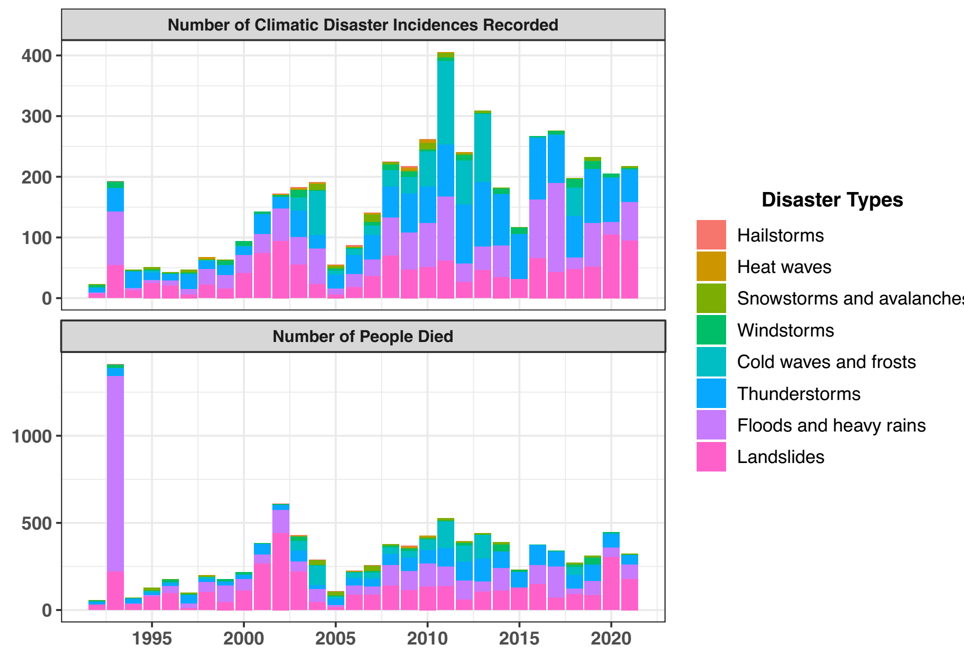

Fig. 2 Annual number of climatic disaster incidences recorded (frequency) and number of people died (mortality) by disaster types in Nepal during 1992–2021

Table 2 Trend (Theil–Sen slope) and its statistical significance (based on Mann–Kendall *p*-value) for disaster mortality, frequency, and vulnerability for multidisaster and individual disaster types for Nepal

Disaster Type	No. of people died/year	No. of incidence recorded/year	Mortality/100 K people exposed/year
Multidisaster (whole Nepal)	8.5 **	7.19 ***	−0.15 ***
Multidisaster (rural areas)	5.111 ***	4.32 ***	−0.44 ***
Multidisaster (urban areas)	3.4 **	3.25 ***	−0.08 **
Cold waves and frost	3.873 **	4.056 **	−0.26 *
Thunderstorms	2.812 ***	2.875 ***	0.01
Floods and heavy rains	2.643 **	2.244 ***	−0.1 **
Landslides	2.417 *	1.56 ***	−0.21 *
Windstorms	0.049	0.133 *	−0.04
Hailstorms	0	0	0.57
Heat waves	0	0	0.03
Snowstorms and avalanches	0	0	1.01

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

increase in mortality, followed by thunderstorms, floods and heavy rains, and landslides. Windstorms, snowstorms and avalanches, heat waves, and hailstorms did not show any significant trends, most likely because of their infrequency or low mortality. 1993 was an extreme year in terms of mortality. Floods due to the torrential rains in July 1993 killed around 1500 people in south-central Nepal (Marahatta and Bhusal 2009; DesInventar 2021). Since both Mann–Kendall test and the TS slope are less sensitive to outliers, the trend results are not significantly different from the trends in the absence of this outlier event.

Disaster mortality showed a clear monthly pattern (Fig. 3). It was highest during the monsoon season (June to September), and July was the deadliest month. However, a shift has been observed in the monthly pattern of mortality. Mortality is decreasing in July but is increasing in the pre-monsoon (March to May) and late monsoon (August to October) months. The July mortality for the 1992–2001 decade was still higher than the latter two decades even if we exclude the 1993 extreme flood event. Mortality in winter (December to February), mainly due to cold waves, has also increased. This shift has spread disaster mortality throughout the year, making all other months more deadly than they used to be.

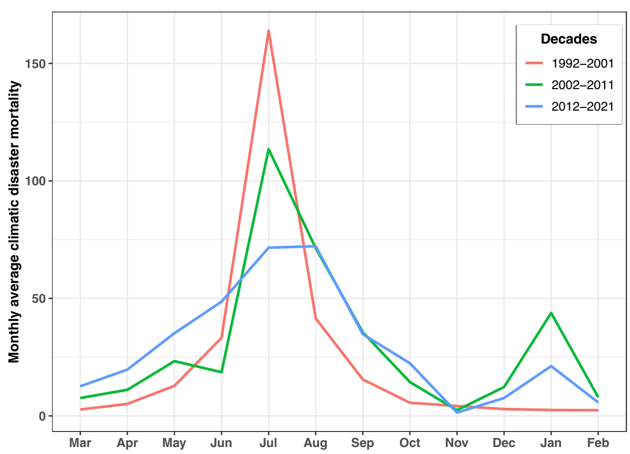

Fig. 3 Monthly pattern of climatic disaster mortality in Nepal by decade

Climatic disaster vulnerability trend in Nepal

In contrast to mortality, multidisaster vulnerability across Nepal showed a significantly decreasing trend at the 0.01 level (Table 2 and Fig. 4a). Multidisaster vulnerability has decreased at the rate of 0.15 deaths per 100 thousand people exposed per year. Vulnerability to cold waves and frost, floods and heavy rains, and landslides decreased significantly. However, vulnerability to other individual disaster types did not show significant trends. Vulnerability in rural Nepal has decreased at a much faster rate (0.44 deaths/100 thousand people exposed/year) than in urban Nepal (0.08 deaths/100 thousand people exposed/year). Even though vulnerability in rural regions is decreasing at a much faster rate and the urban–rural vulnerability gap is narrowing, rural regions are still considerably more vulnerable than urban regions. Multidisaster vulnerability had a nonlinear negative relationship with per capita income (Fig. 4b).

Spatial pattern of climatic disaster mortality and vulnerability in Nepal

Climatic disaster mortality in the past three decades has been recorded all over Nepal, except in a few local units and protected areas (Fig. 5). The locations with high mortality are mainly concentrated in the Mid-Hills and Mountains regions in central and eastern Nepal and in the southern lowlands of eastern Nepal. Landslides, floods and heavy rains, and thunderstorms have caused the highest mortality in these regions. Western Nepal has experienced relatively low mortality. Disaster vulnerability is higher in the Mid-Hills and Mountains regions, mainly in western Nepal. The Mid-Hills and Mountains regions are vulnerable to landslides, and the Tarai and Mid-Hills regions are more vulnerable to floods and heavy rains. The Mountains region is vulnerable to snowstorms and avalanches. Eastern Nepal is highly

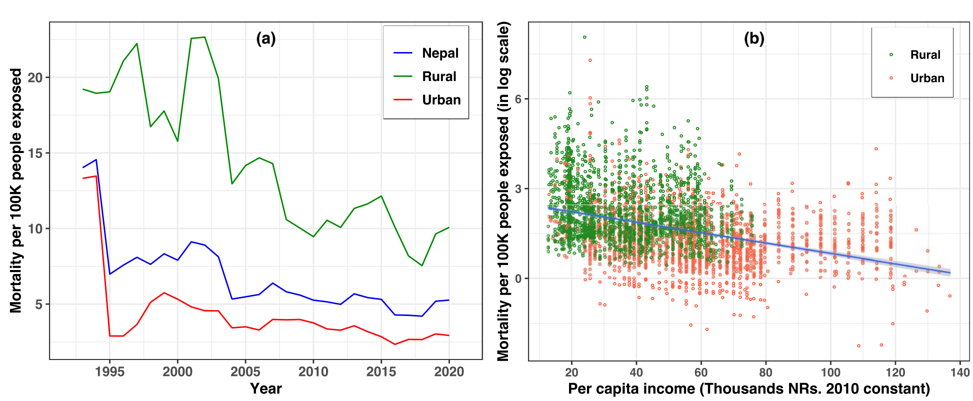

Fig. 4 **a** Multidisaster vulnerability trend (3 years moving average) over time in urban areas, rural areas, and whole Nepal during 1992–2021. **b** Relationship of multidisaster vulnerability (in log scale) to per capita income

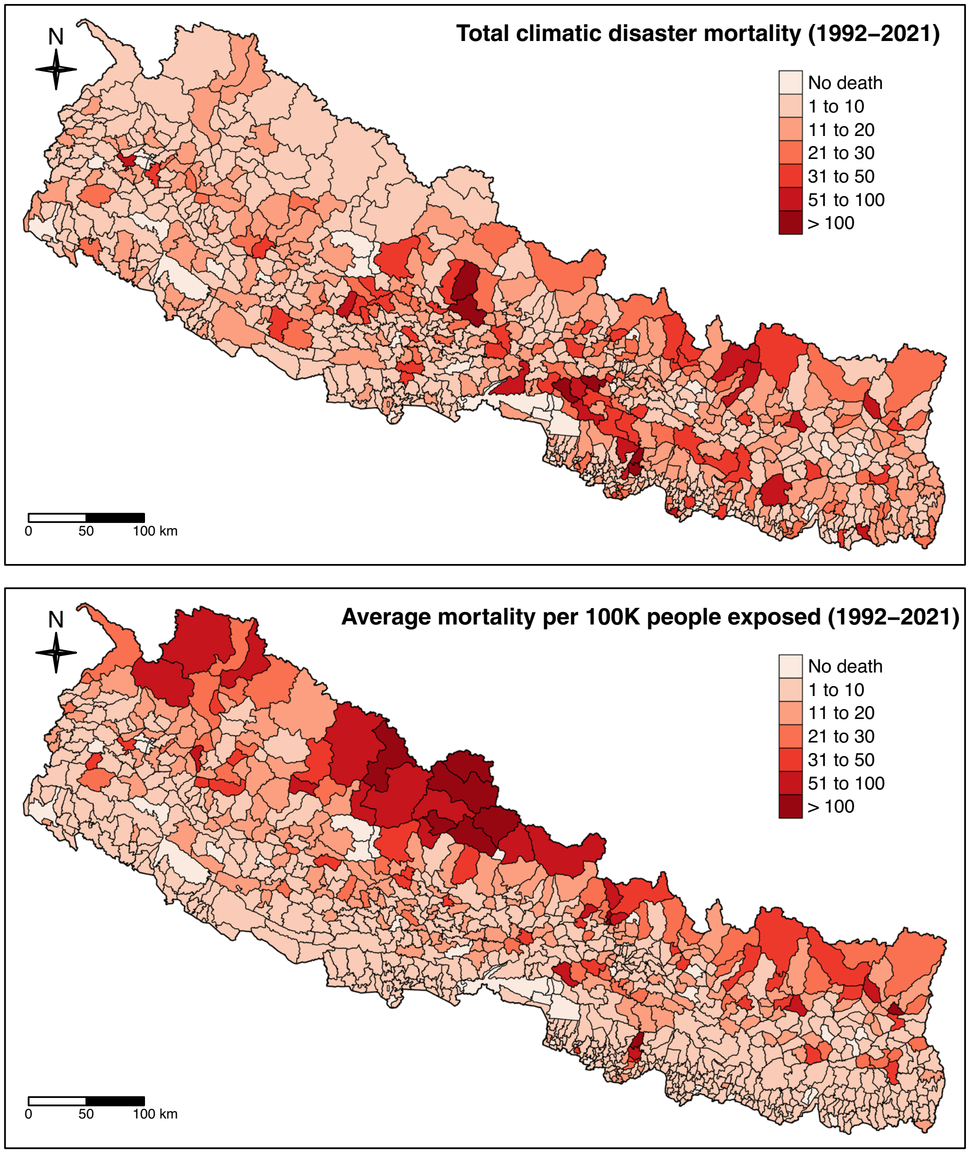

Fig. 5 Spatial distribution of climatic disaster impacts (total mortality) and vulnerability (average annual mortality per 100 K people exposed) in Nepal during 1992–2021. The color code range in the maps is manually assigned, and the range values are shown in the legend

vulnerable to thunderstorms. Spatial patterns of mortality and vulnerability by individual disaster types are presented in ESM.

Attribution of disaster mortality trend

Based on the regression analysis, disaster mortality is significantly positively correlated with disaster frequency and per capita income but is not significantly correlated with the exposed population at the 0.01 level (Table 3). We selected the location fixed-effect model over the ordinary least-squares model (results in Table S1) after the F-test, which rejects the null hypothesis and confirms the existence of a significant fixed effect in our data. Adding the location fixed effect significantly improved the model's goodness-of-fit (R^2) to 0.52, implying that the model could explain 52% of the variability in observed disaster mortality. Moreover, the variance inflation factor analysis ruled out any multicollinearity problem in the model. Furthermore, the location fixed-effect model excellently serves our purpose to control for other location-specific vulnerability parameters and explains the roles of climatic disaster frequency, exposed population, and per capita income in determining disaster mortality.

The results showed that a 1% increase in disaster frequency is expected to increase disaster deaths by 1.16%, while other variables are held constant. On the other hand, if per capita income increases by 1%, disaster deaths are expected to decrease by 0.34%. The change in the exposed population does not have any significant effect on disaster mortality.

Table 3 Results of the regression analysis

	Dependent variable: no. of people died (log)
No. of people exposed to disasters (log)	0.039 (0.095)
No. of disaster incidences recorded (log)	1.156*** (0.028)
Per capita income (log)	$-$0.345*** (0.030)
Observations	3683
R^2	0.521
Adjusted R^2	0.402
Residual std. error	0.575 (df = 2948)
F statistic	4.373*** (df = 734; 2948)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ *Estimate std. error in parentheses*

Discussion

Our study found increasing trends in climatic disaster frequency and mortality in the past three decades in Nepal. However, a potential influence of gradual improvement in the recording of disaster incidence on the observed trends cannot be ruled out. The increase in mortality from climatic disasters is in agreement with the increase in mortality from natural disasters in Nepal during 1971–2011 reported by Aksha et al. (2018). MoFE (2021), however, reported a decline in mortality from climatic disasters in recent years, and Adhikari and Tian (2021) observed no clear trend in mortality from landslides, even though the frequency of landslides is increasing. These differences are mainly due to differences in the study period and the disaster types studied. We found that overall multidisaster vulnerability in Nepal is decreasing, more strongly in the rural regions. This trend is consistent with the observed declining trend in exposure-normalized mortality from climatic disasters in other world regions (Jongman et al. 2015; Bouwer and Jonkman 2018; Wu et al. 2019; Formetta and Feyen 2019). Such vulnerability reduction can be attributed to improvements in socioeconomic conditions and disaster preparedness, mainly due to economic growth and investment in DRR and climate change adaptation. We found a nonlinear decreasing trend in multidisaster vulnerability with economic growth, as also observed by Formetta and Feyen (2019) and Wu et al. (2019). However, we believe that further study of the role of DRR and adaptation in decreasing vulnerability is necessary. In any case, the decreasing vulnerability in Nepal has counterbalanced the effect of the potential increase in climatic hazards on disaster impacts. Hence, we can infer from our results that disaster mortality could have increased much faster than the currently observed rate if there was no progress in vulnerability reduction.

Several studies argue that the upward trend in climatic disaster mortality is due to the rapid growth of the population exposed to the hazards (Visser et al. 2014; Kreibich et al. 2019; McAneney et al. 2019; Pielke 2021). However, we found that the size of the exposed population had no significant effect on disaster mortality. Our results further suggest that the increase in disaster frequency (and probably intensity), potentially due to climate change, has overpowered the effect of decreasing vulnerability, leading to an increase in disaster mortality. The observed increases in the frequency and intensity of extreme weather and climatic events across Nepal in recent decades support this argument (Karki et al. 2017, 2019; Talchabhadel et al. 2018; Pokharel et al. 2019). For example, Pokharel et al. (2019) found that high-intensity (> 300 mm/day) precipitation in the Mid-Hills region started to become more frequent since 2000 and was not common earlier. The observed shift in monthly disaster mortality, particularly the increase in pre-monsoon and post-monsoon mortality, could be due to the change in seasonality in Nepal. A significant increase in pre-monsoon precipitation, which is accompanied by thunderstorms, and delayed monsoon withdrawal have been observed in Nepal (Karki et al. 2017). Nonclimatic factors, such as changes in land use, haphazard construction of roads in steep hills and mountains, and the 2015 earthquake, could have also had a role in increasing landslide occurrence and mortality in Nepal (Petley et al. 2007; Adhikari and Tian 2021). Therefore, a more robust attribution study with a larger number of climatic hazards, exposure, and vulnerability indicators is necessary to confirm the role of climate change.

The Mid-Hills and Mountains regions in central and eastern Nepal have been hit the hardest by climatic disasters in the past three decades. This can be linked with the highest rainfall in eastern and central Nepal due to the dominance of the monsoon and peak annual precipitation between 2000 and 3500 m.a.s.l. due to elevation-dependent precipitation (Talchabhadel et al. 2018). Such high precipitation could have caused the highest occurrence of landslides in the hills with steep slopes and floods and flash floods in the river valleys. When we controlled for the exposed population and only looked at disaster vulnerability, the whole Mid-Hills and Mountains region, especially in western Nepal, was highly vulnerable to climatic disasters. This vulnerability map aligns well with the social vulnerability to natural hazards mapped by Aksha et al. (2019) and other overall climate change vulnerability maps of Nepal (Siddiqui et al. 2012; Mainali and Pricope 2017; MoFE 2021). The higher vulnerability in these regions is mainly due to the underlying poor socioeconomic conditions, steep slopes, limited accessibility, and overall development deficits. The Mid-Hills and Mountains region in western Nepal has the highest multidimensional poverty index in Nepal (NPC 2018).

Conclusions

In this study, we analyzed the spatiotemporal trend of climatic disaster mortality and human vulnerability in Nepal using the observed disaster data for the period 1992–2021. In addition, we explored the attribution of the observed disaster mortality trend to climatic and socioeconomic change. We draw the following key conclusions from our analysis:

- Climatic disaster frequency, as well as mortality, has increased in Nepal in the past three decades. The increase in mortality and shift in monthly mortality patterns have made the entire year more deadly than in the past.
- The Mid-Hills and Mountains region in central and eastern Nepal has the highest disaster mortality. However, disaster vulnerability is higher in western Nepal due to poor socioeconomic conditions.
- Climatic disaster vulnerability has decreased in Nepal, potentially due to the economic growth and progress in DRR and climate change adaptation.
- The size of the exposed population is not significantly related to disaster mortality. Hence, population growth may not be the major cause of the increase in disaster mortality in Nepal.
- Disaster mortality is positively correlated with disaster frequency but negatively correlated with per capita income.
- Despite the strong decrease in vulnerability, disaster mortality has increased in Nepal. This implies that the strong increase in disaster incidences, potentially due to climate change, has overpowered the effect of decreased vulnerability and caused the increase in disaster mortality. However, the potential influence of improvement in disaster recording and nonclimatic factors cannot be ruled out.

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