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

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ABSTRACT

Climate-related disaster impacts, such as loss of human life as its most severe consequence, have been rising globally. Some studies attribute this increase to population growth, while others point to climate change as the primary cause. However, empirical evidence linking climate change to disaster impacts remains limited, particularly in the Global South. This study addresses the impact attribution question in Nepal, a low-income and highly disaster-prone country. We applied a robust regression-based method that accounts for the role of hazard, exposure and vulnerability in flood and landslide mortality, using subnational scale empirical data from 1992 to 2021.

Historically, flood and landslide mortality has been highest in central and eastern Nepal due to the stronger influence of the Indian monsoon. However, disaster impacts have surged in recent years in western Nepal, driven largely by an increase in extreme precipitation events. For example, a one standardized unit increase in maximum one-day precipitation increases flood mortality by 33%, and heavy rain days increases landslide mortality by 45%. In contrast, a one standardized unit increase in per capita income reduces landslide and flood mortality by 30% and 45%, respectively. While reductions in vulnerability have helped lower disaster mortality, population exposure has not played a significant role. Therefore, the rise in flood and landslide mortality, particularly in western Nepal, is primarily attributable to the increase in precipitation extremes linked to climate change. With climate change expected to further intensify such extremes, disaster mortality is likely to increase unless significant efforts are made to reduce vulnerability.

1. Introduction

On average, weather and climate-related disasters caused 27,031 deaths and USD 126.2 billion in economic losses annually worldwide between 2001 and 2020 (CRED, 2021). Climate-related disaster occurrences, as well as loss of life and property, are on the

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rise globally (Formetta and Feyen, 2019; Hoeppe, 2016; UNDRR, 2022). These observed impacts have been increasingly attributed to anthropogenic climate change (Bouwer, 2019; Huggel et al., 2013; IPCC, 2022). The latest report of the Intergovernmental Panel on Climate Change (IPCC) has confirmed 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.

During 1998–2017, 91 % of global disaster mortality has occurred in low- and middle-income countries (UNISDR, 2018). The economic losses due to disasters in these countries represent 0.8–1 % of their gross domestic product (GDP) compared to 0.1–0.3 % in high- and upper-middle-income countries (UNDRR, 2022). Moreover, almost 90 % of the around 1.5 billion people exposed to flood risk and a large proportion of the 3.6 billion people highly vulnerable to climate change live in low- and middle-income countries (IPCC, 2022; Rentschler and Salhab, 2020). Therefore, a better understanding of disaster impact trends and the role of climate-related hazards, exposure, and vulnerability in developing countries is essential for effective planning and implementation of climate change adaptation and disaster risk reduction (DRR) measures. Otherwise, achieving the goals of the Sendai Framework for Disaster Risk Reduction, the adaptation goal associated with the Paris Agreement, and the Sustainable Development Goals will be extremely difficult. Poor and vulnerable countries have been calling for burden-sharing mechanisms, including compensation for unavoidable loss and damage due to climate change (Mechler and Deubelli, 2021). The United Nations Climate Change Conference (COP27) in Egypt agreed to establish a new loss and damage fund for vulnerable countries impacted by climate-related disasters (UNFCCC, 2022). However, the attribution has been the crux of the loss and damage debate in the global climate negotiations (Bouwer, 2019; James et al., 2019).

Several past studies argue that the main cause of the rise in disaster impacts has been the rapid growth in population and assets exposed to disaster events and that the role of climate change is not evident (Bouwer, 2011; McAneney et al., 2019; Pielke, 2021; Visser et al., 2014). These studies, focusing on socioeconomic 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. Vulnerability, however, is often not or incompletely accounted for in this literature, which given the dynamic nature of vulnerability, potentially results in the false attribution of disaster impact trends (Botzen et al., 2021; Mechler and Bouwer, 2015). A regression-based approach has been used to appropriately account for the change in exposure and vulnerability (Estrada et al., 2015). One of such studies found an upward trend in the economic losses from hurricanes in the United States that cannot be explained by the exposure variable. The effect of climate-related 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 summary, the empirical evidence linking rising climate extremes to disaster impacts remains limited, particularly in the context of the Global South. Most of the existing climate-related disaster impact attribution studies are from the United States, Europe, or other developed countries (Bouwer, 2019; Pielke, 2021). Information from low-income countries is extremely limited, with a particular knowledge gap at the subnational scale (James et al., 2019). Given the urgent need for climate action, it is essential to deepen our understanding of the complex interactions between hazards, exposure, and vulnerability as drivers of climate-related disaster impacts. Thus, our main research question seeks to investigate whether climate change has led to an increase in disaster impacts in Nepal, a low-income and highly disaster-prone country. To address this question, we employed a robust regression-based method that considers the roles of hazard, exposure and vulnerability in disaster impacts, rather than relying on the commonly used loss normalization approach. The objective of this study is to provide an empirical example of attributing climate-related disaster mortality to key indicators of climate-related hazards, exposure, and vulnerability at the subnational scale in Nepal. This research aims to fill a critical knowledge gap and inform more effective climate adaptation and DRR strategies in vulnerable regions.

Nepal was among the top ten countries worldwide most affected by climate-related disasters in the past two decades (Eckstein et al., 2021). Over 10,000 people have lost their lives to climate-related disasters in the past 30 years, with landslides and floods together accounting for almost 70 % of the total climate-related disaster mortality in Nepal (Chapagain et al., 2022). The INFORM Risk Index 2022 also categorized it as a high-disaster risk country, and a significant increase in disaster risk and vulnerability by 2050 is projected for Nepal, due to climatic, demographic, and socioeconomic changes (Inter-Agency Standing Committee and the European Commission, 2022). Therefore, Nepal is identified as a relevant case study for studying climate-related disaster risk in the context of climate change.

We focus on the loss of human life as a measure of disaster impact, as this 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 attribution studies. We first studied the spatio-temporal trends of the past 30 years (1992–2021) in flood and landslide mortality in Nepal using local administrative units as unit of analysis. Second, we studied the spatio-temporal trends of six mean and extreme precipitation indices in a climate change context. Third, we employed a disaster-specific mixed-effects zero-inflated negative Binomial (ZINB) regression model to study the attribution of disaster mortality to climate-related hazards, exposure, and vulnerability. We used mean and extreme precipitation indices as indicators of climate-related hazards, population density as an indicator of exposure, and per capita income (PCI) and the social vulnerability index (SoVI) as indicators of vulnerability. Finally, we synthesized the observed spatio-temporal trends of disaster mortality with climate-related 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 landlocked, mountainous country in South Asia located between 26° 22′ to 30° 27′ N and 80° 04′ to 88° 12′ E (Fig. 1). It 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 a lowest point of 60 m.a.s.l. and a tropical climate (Karki et al., 2015). Within the country's 193 km width from south to north, the altitude increases up to 8,849 m.a.s.l. at Mount Everest with a permanently snow-covered polar climate in the High Mountains (DOS, 2021). Such a dramatic variation in altitude within such a 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. Therefore, the analysis and results presented in this study are at local administrative unit levels, unless specified otherwise. 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).

2.2. Data source and processing

In this study, we used data on identified variables from multiple sources. An overview of the data sources, spatial resolution, temporal resolution and coverage of the raw data is provided in Table S1 in the electronic supplementary materials (ESM). The raw data and processing steps for each variable are summarized below.

2.2.1. Climate-related disaster mortality

The Emergency Events Database (EM-DAT), NatCatSERVICE, Sigma, Geocoded Disasters Dataset (GDIS), and DesInventar are some of the commonly used global disaster databases. Of all of them, 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

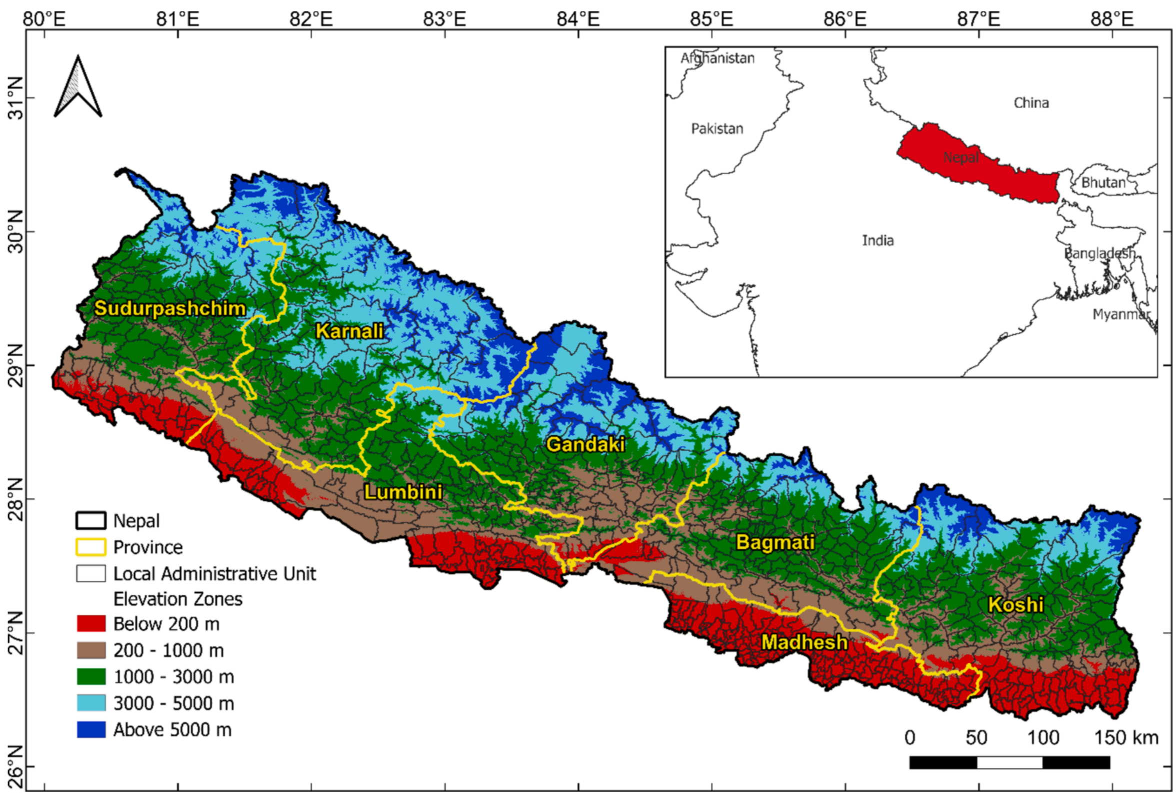

Fig. 1. Map showing Nepal's local administrative units, provinces, and elevation zones. Inset: Nepal on the world map.

Table 1
List of selected precipitation indices (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	Fraction of total wet-day precipitation that comes from very wet days	%
	RX1day	Max 1-day precipitation	Maximum annual 1-day precipitation total	mm

system of the United Nations Office for Disaster Risk Reduction (UNDRR) and used to keep inventories of the occurrence and impact of disasters (DesInventar, 2021). Currently, disaster data for 1971–2013 are available in DesInventar for Nepal. In recent years, the Nepal DRR Portal of the Ministry of Home Affairs (MoHA) has regularly updated all disaster events in the country (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 1992–2013 and the Nepal DRR portal for 2014–2021 to develop 30-year panel data at the local administrative unit level for floods and landslides.

2.2.2. Climate-related 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 provided 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 were used for the spatio-temporal trend analysis in section 3.2.

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 feature 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 (see Table 1) using Climpact. Finally, annual average indices values for each local administrative unit were extracted from the gridded data. The past 30 years annual precipitation indices by local units were then used for the regression analysis in sections 2.3 and 2.4 as indicators of climate-related hazards.

2.2.3. Exposure and vulnerability indicators

We accessed population data from the periodic national censuses (1991, 2001, 2011, and 2021) from the Nepal's Central Bureau of Statistics (CBS). The per capita income data were 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 (Aksha et al., 2019). This study 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, climate-related hazards, and exposure indicator data for the period 2007–2015 for the regression analysis with SoVI data in section 2.4, in Table 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 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 and 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, climate-related hazard usually refers to climatic physical events or trends or to their physical impacts (IPCC, 2014). A climate-related hazard becomes a disaster when it interacts with exposure and vulnerability and causes impacts. Exposure, for example, relates to the people living in places and settings that could be adversely affected; vulnerability is their propensity or predisposition to be adversely affected (IPCC, 2014). We focused on observed human mortality as a measure of disaster impacts and developed a regression-based approach to study flood and landslide mortality attribution to climate-related hazards, exposure, and vulnerability indicators.

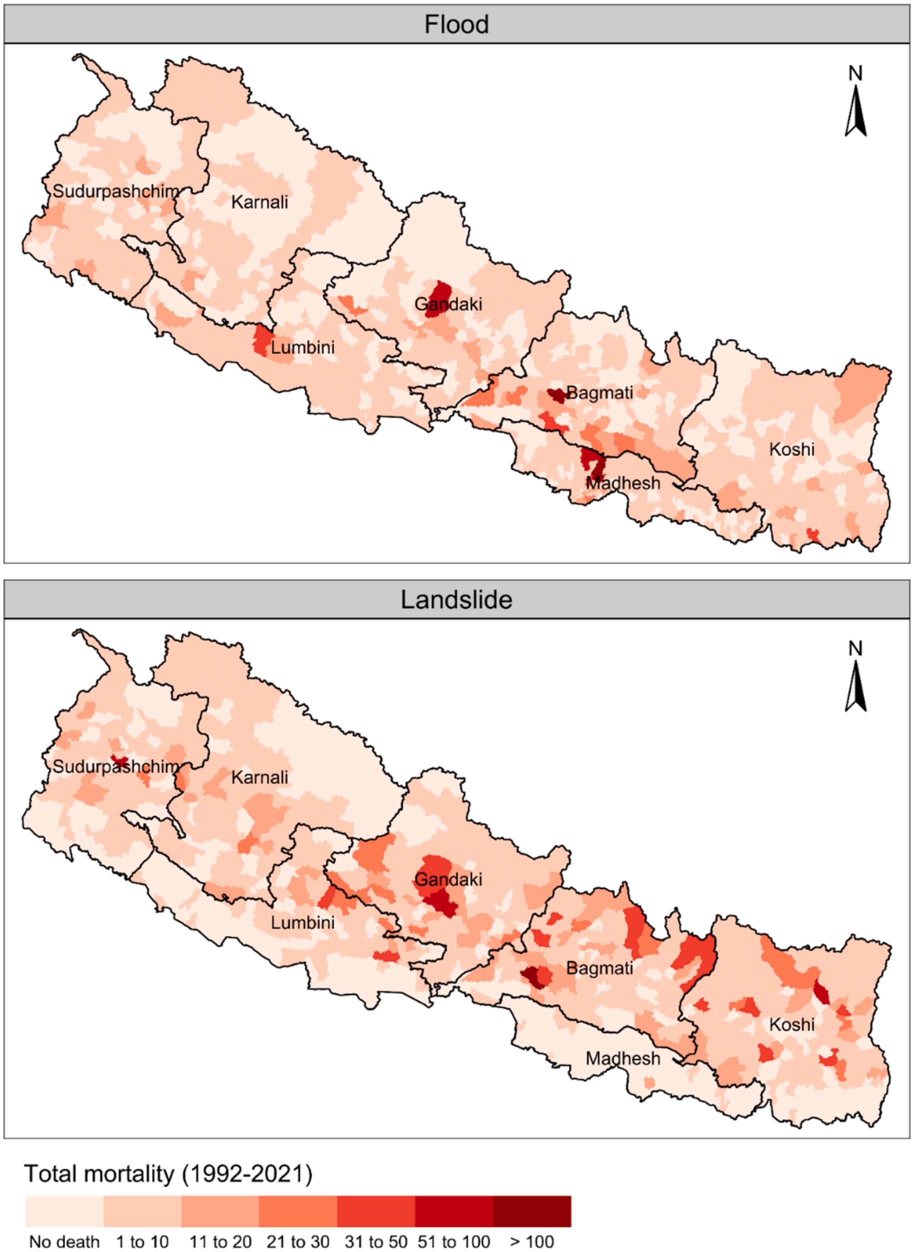

Fig. 2. Spatial pattern of landslide and flood mortality in Nepal during 1992–2021.

As floods and landslides are precipitation-related disasters, we used six mean and extreme precipitation indices (duration, frequency, and intensity-based) defined in Table 1 as indicators of climate-related hazards. As we are looking at the human aspect of disaster impacts, we used population density as an indicator of exposure. Vulnerability is a characteristic generated by multiple factors such as social, economic, political, cultural, institutional, and environmental conditions (IPCC, 2012). To this effect, as in many other disaster studies (Formetta and Feyen, 2019; Jongman et al., 2015; Tanoue et al., 2016; Wu et al., 2019; Zhou et al., 2014), we used per capita income as a proxy of vulnerability. Nevertheless, per capita income is primarily an economic indicator and may not fully capture the multidimensional nature of disaster vulnerability. To address other aspects of vulnerability, 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 out by fitting the regression models with the ordinary least squares (OLS) mixed-effects linear model. However, disaster mortality, which is right-skewed count data, has 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 a linear model (Roback and Legler, 2021). The mortality data also suffered from the overdispersion issue, that is, variance is greater than the mean, and violated the equidispersion assumption for standard Poisson regression (Table S2 in ESM). Hence, we tested the negative Binomial model to account for overdispersion in the dependent variable (Roback and 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 model adds an additional parameter to the classical counting models (Poisson or the negative Binomial) to accommodate the fact that often the probability of zero counts is higher than predicted by these counting models data (Kim et al., 2019; Roback and Legler, 2021). In the case of disaster mortality, a zero count may be structural (in this year no disaster was observed) or actual (if there was a disaster, but no fatalities). In this two-part model, the zero-inflated model part first fits the logistic regression to predict the number of structural and 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. Therefore, the zero-inflated model give a better fit than the non-inflated models. The 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 model results are presented in Table S3 in ESM. 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 mainly 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 these 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 Eq. (1).

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

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 climate-related hazard indicator, that is, the 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 α is the grand mean of location-specific intercepts. β_h, β_e, and β_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 have lost their lives due to climate-related disasters in Nepal in the past three decades. Landslides and

Table 2

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

Province	Flood		Landslide	
	Mortality	Frequency	Mortality	Frequency
1. Koshi	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* floods killed 3,692 and 3,201 people, respectively, which together account for 70 % of the total climate-related disaster mortality in the country. Landslide mortality was highest in mid-hills and mountains in eastern (Koshi) 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 less disaster mortality in the past.

The number of disaster events at the local administrative unit level is too small for conducting a reliable temporal trend analysis. Therefore, we present the temporal trend at the provincial scale instead. It shows that disaster mortality is by and large increasing in western Nepal, which has been a historically less impacted region. Both the frequency and mortality of the floods and landslides showed significantly increasing trends (at $p = 0.05$ level) during the past three decades in Lumbini, Karnali, and Sudurpashchim provinces. Most of the trends for Gandaki, Bagmati, Madhesh, and Koshi provinces in central and eastern Nepal were positive but not significant (Table 2). Flood frequency in Koshi and landslide frequency in Bagmati and Gandaki province showed statistically significant increasing trends.

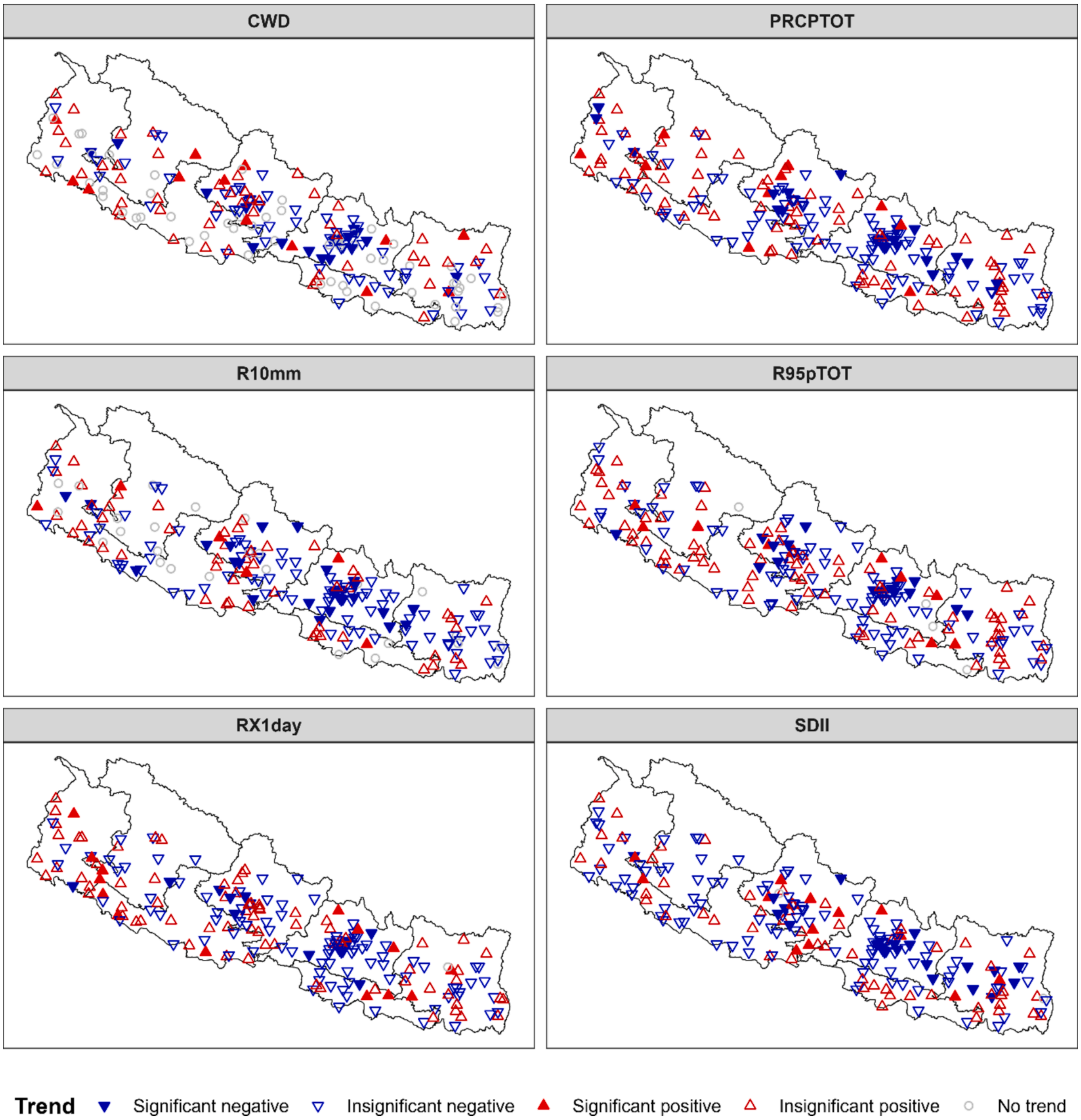

Fig. 3. Temporal trends of mean and extreme precipitation indices during 1992–2021 by observational stations across Nepal. Significance at $p = 0.05$ level. Each point on the map also indicates the location of a meteorological station.

3.2. Spatio-temporal trends of mean and extreme precipitation indices in Nepal

Mean and extreme precipitation indices showed mixed trends across the country in the past 30 years, with mainly rising trends in western but decreasing trends in central Nepal (Fig. 3). Rising trends in total annual precipitation (PRCPTOT) were observed in 75 % of the stations in Karnali (significant in 13 % of the stations), 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 % of the stations) 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 % of the stations). Maximum 1-day precipitation (RX1day), an indicator of extreme precipitation intensity, showed increasing trends in 68 % of the stations in Sudurpashchim (significant in 11 % of the stations), 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 % of the stations, respectively).

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

3.3. Attribution of disaster mortality to climate-related hazards

All the mean and extreme precipitation indices studied showed a significant positive association with landslide mortality, and most of the indices showed also a significant positive association with flood mortality (Fig. 4). The results of selected regression models are presented in Table 3 and all regression models are presented in Tables S4 and S5 in the ESM. Regression results revealed that a one-unit increase (one standard deviation from the mean) in PRCPTOT increases landslide mortality by 41 % and flood mortality by 16 % (*ceteris paribus*). The rise in extreme precipitation intensity proved to have 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 %, respectively, with a one-unit increase in R10mm and CWD.

The differences in effect size and significance of extreme precipitation indices with flood and landslide mortality could also be due to the nature of the disaster types. As landslides are largely local phenomena, the local unit's boundary appears sufficient to capture the precipitation events associated with the landslides. However, floods are not only determined by 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 that then caused flooding in the local units downstream.

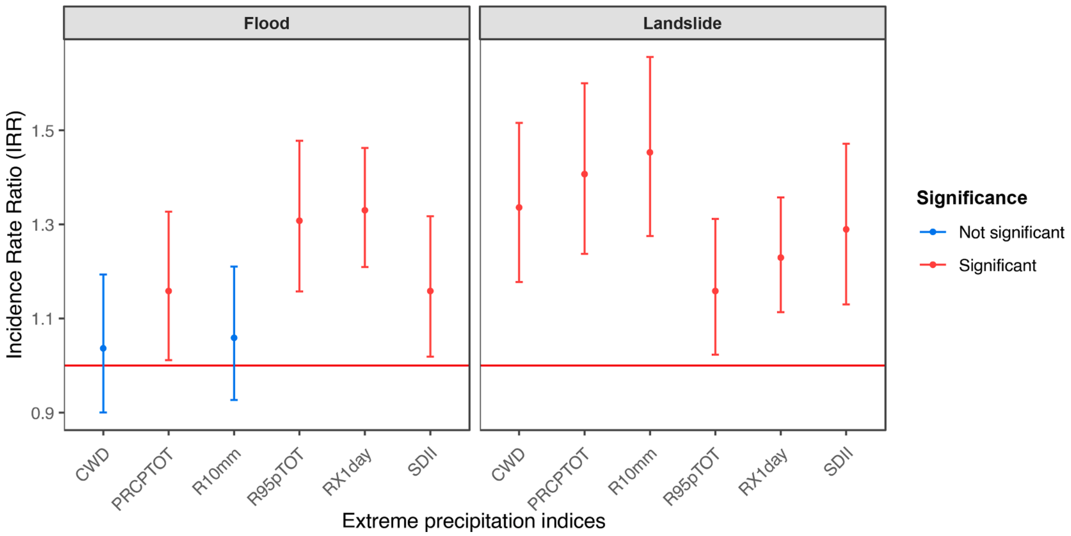

Fig. 4. Effects of mean and extreme precipitation indices (in standardized Z-score) on flood and landslide mortality shown as Incidence Rate Ratios–IRR (points), and its 95% confidence interval – CI (lines). IRRs are estimated from the mixed effects ZINB models and equal to the exp (β_h) in Eq. (1). Statistical significance at the 0.05 level (see ESM Tables S4 and S5 for the complete regression results).

Table 3
Results of mixed effects ZINB models (count model part). 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**	**95 % CI**	**p**	**IRR**	**95 % CI**	**p**
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**
Observations	15,420			13,020		
Marginal R^2	0.303			0.466		

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.

4. Discussion

Landslides and floods have been the two deadliest forms of disaster in Nepal during 1992–2021, accounting for 70 % of the total climate-related disaster mortality. Historically, flood and landslide mortality have been highest in central and eastern, 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 located mainly in and around the 83°–85° longitudinal zones in central Nepal at between 2,000–3,500 m above sea level (m.a.s.l.) 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 have received relatively higher extreme precipitation (Karki et al., 2017; Talchabhadel et al., 2018). This high precipitation pattern explains the concentration of flood and landslide mortality in the mid-hills and mountains of eastern and central Nepal. In contrast, western Nepal has experienced less precipitation than the country on average, and its historical disaster mortality has also been the lowest in this country.

As for the temporal trends of disaster mortality and frequency, these are increasing significantly in western Nepal but do not show significant trends in the central and eastern part of the country. Almost similar temporal trends are observed in the 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 significant only in a relatively small proportion of the stations. Rising precipitation extremes in western Nepal have also been reported in previous studies (Bohlinger and 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 increased 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 the Arctic Oscillation, and intensification of an upper tropospheric mid-latitude shortwave due to the rise in GHGs and aerosols (Karki et al., 2017; Wang et al., 2013).

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**	**95 % CI**	**p**	**IRR**	**95 % 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		

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. A one-unit increase in RX1day and R95pTOT increases flood mortality by 33 % and 31 %, respectively. Most of the deadliest flooding events in recent years in Nepal, such as the Melamchi flood of 2021, the Tarai flood of 2017, and the western Nepal flood of 2014 and 2021, 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 and allowing no time for people to escape, thus causing higher mortality.

Landslide mortality in Nepal is strongly associated with extreme precipitation frequency indices, such as the annual number of heavy rain days (R10 mm), and duration indices, such as consecutive wet days (CWD). A one-unit increase in R10mm and CWD increases landslide mortality by 45 % and 34 %, respectively. The accumulated rain over the previous 3-, 7-, and 10-day periods is directly associated with landslide occurrence in the hills and mountains in Nepal (Dahal and Hasegawa, 2008; Muñoz-Torrero Manchado et al., 2021), as 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. A one-unit increase in per capita income decreases landslide mortality by 30 % and flood mortality by 45 %. This may suggest that increases in income are associated with reduced disaster vulnerability, thus ultimately reducing disaster mortality. This is because people with higher income also have a higher desire for more safety measures. A higher income also enables people to spend more on physical and non-physical risk reduction measures such as better housing, early warning systems, and disaster response (Formetta and 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; McAneney et al., 2019; Pielke, 2021; Visser et al., 2014). 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 ones (Chapagain et al., 2022).

With additional global warming, extreme precipitation events will inevitably become more frequent and intense worldwide (Seneviratne et al., 2021). In Nepal, extreme precipitation events are projected to rise, with the strongest rise being 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 scenario (RCP8.5) compared to the 1981–2010 period (MoFE, 2019). Such a rise in precipitation extremes in Nepal and worldwide is highly likely to increase disaster mortality if no actions are taken to strongly reduce the vulnerability.

While this study employs robust methodology and the latest available data, certain limitations should be acknowledged. The accuracy of the findings relies on the completeness and accuracy of disaster mortality data from DesInventar and the Nepal DRR Portal. Underreporting or inconsistencies within these databases could influence the results. Future research could enhance these findings by refining the geocoding of disaster locations and improving the delineation of disaster-specific exposure boundaries. Additionally, the meteorological station network's density, particularly in remote and mountainous areas, presented a data gap. Although this was addressed using satellite-based precipitation data and robust spatial interpolation, a denser network of observational stations would further strengthen the results. Furthermore, while per capita income serves as a common proxy for vulnerability, it might not fully capture its multi-faceted nature. The inclusion of the SoVI aimed to address this, but its availability for only a single time step (2011) limited its use in the regression model for the entire study period. Incorporating additional vulnerability indicators could enhance the accuracy of causal attribution. Finally, it's important to recognize that disaster impacts extend beyond human mortality. Future research could apply this approach to investigate trends and attribution of other crucial impacts, such as direct and indirect economic losses, disaster morbidity and health costs, and displacement.

5. Conclusions

Attribution studies on the impacts of climate change are scarce, particularly in the Global South, as most researchers think that lack of comprehensive data sets are a major constraint in carrying out analysis. However, given the urgent need for climate action, results and analysis are much needed and cannot be delayed by waiting for further data acquisition. We demonstrated an example of using the most robust and high-resolution empirical data currently available for a low-income and highly vulnerable country Nepal. Additionally, we applied a robust regression-based method that considers the role of hazard, exposure and vulnerability in disaster impacts.

Landslides and floods are the two deadliest climate-related disasters in Nepal, claiming 3,692 and 3,201 lives, respectively, between 1992 and 2021. Historically, flood and landslide mortality has been highest in central and eastern Nepal, where the Indian monsoon exerts a greater influence. However, in recent years, disaster impacts have been rising significantly, and most rapidly, in the historically less affected western Nepal. This trend is largely linked to the increasing trend of extreme precipitation events in the western Nepal. For example, a one standardized unit increase in maximum one-day precipitation increases flood mortality by 33 %, and heavy rain days increases landslide mortality by 45 %. In contrast, a one standardized unit increase in per capita income reduces landslide and flood mortality by 30 % and 45 %, respectively.

While reductions in vulnerability have played a role in lowering disaster mortality, population exposure has not shown a significant impact. Therefore, the observed rise in flood and landslide mortality, particularly in western Nepal, is primarily attributable to the increase in precipitation extremes due to climate change. Our findings challenge the dominant narrative that population growth is the main driver of rising disaster impacts, at least in the context of Nepal. With climate change projected to further intensify extreme precipitation, disaster mortality is likely to increase unless vulnerability is drastically reduced. Hence, investing in climate change adaptation, DRR, and averting, minimizing and addressing loss and damage is essential to breaking the cycle of rising disaster impacts in low-income and vulnerable countries such as Nepal.

CRediT authorship contribution statement

Dipesh Chapagain: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Luna Bharati:** Conceptualization, Supervision, Resources. **Reinhard Mechler:** Conceptualization, Resources, Supervision. **Samir K.C.:** Conceptualization, Supervision. **Georg Pflug:** Supervision. **Christian Borgemeister:** Conceptualization, Resources, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2024.100669.

Data availability

Data will be made available on request.

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