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Dipesh Chapagain

Summary

The socioeconomic impacts of climatic disasters are increasing globally. Some studies have argued that this increasing trend results from the growing population and assets exposed to hazardous events. Other studies have reported that it is caused by the increased frequency, intensity, and duration of extreme weather and climate events owing to climate change. Therefore, the reasons behind the increasing impact of disasters remain elusive. Limited information is available on future scenarios of extreme climate indices and their implications in various sectors, including disasters. Although disaster impacts relative to the country's economy are felt more acutely in low-income countries, existing studies focus primarily on developed countries or at the cross-country level. Therefore, this dissertation addresses the issue of detecting and attributing trends of climatic disaster impacts in the context of low-income countries using Nepal as a case study. Furthermore, this dissertation investigates future climate extremes scenarios and their potential impacts on climate-sensitive sectors in the Karnali river basin in western Nepal.

First, this study assessed the spatiotemporal trends of the frequency, impacts, and vulnerability of multiple climate disasters using the observed 30-year (1992–2021) disaster data at the scale of the 753 subnational units of Nepal. Loss of human life is the most extreme consequence of disasters. Therefore, this study employed human mortality as a measure of disaster impacts and mortality normalized by the exposed population as a measure of vulnerability. Second, the attribution of flood and landslide mortality to indicators of climatic hazards, exposure, and vulnerability was assessed. Floods and landslides were selected for the attribution study because they account for 70% of all climatic disaster mortality in Nepal. This study employed a disaster-specific mixed-effects zero-inflated negative binomial regression model to study the causality of the observed mortality. As explanatory variables, this study used mean and extreme precipitation indices, population density, and per capita income and a social vulnerability index as indicators of hazards, exposure, and vulnerability. Finally, this study provided future projections of 26 mean and extreme climate indices in western Nepal for the near (2021–2045), mid (2046–2070), and far (2071–2095) future for low- and high-emission scenarios (RCP4.5 and RCP8.5, respectively) using bias-corrected ensembles of 19 regional climate models from the COordinated Regional Downscaling EXperiment for South Asia. In addition, a qualitative analysis based on expert interviews and a literature review of the potential implications of the projected climate extremes on the climate-sensitive sectors are performed. Western Nepal was selected to study the future scenario where the strongest rise in precipitation extremes, disaster frequency, and mortality was observed in the past decades.

Results show that ~5,000 fatal climatic disasters were recorded from 1992–2021 in Nepal, killing >10,000 people. The frequency of disasters has increased by about seven incidences per year, and mortality has increased by nearly nine persons per year. However, vulnerability has decreased, most likely owing to economic growth and progress in disaster risk reduction and adaptation. The spatiotemporal trends of disaster mortality closely follow the trend of precipitation extremes. An increase in one standardized unit in maximum one-day precipitation has increased flood mortality by 33%, and heavy rain days have increased landslide mortality by 45%. A one-unit increase in per capita income has decreased landslide and flood mortality by 30% and 45%, respectively. Population exposure does not show significant effects. Hence, this study concludes that the observed rise in climatic disaster mortality, mainly in western Nepal, is primarily attributable to the increased precipitation extremes caused by climate change. Temperature and precipitation patterns in western Nepal are projected to deviate significantly from the historical reference in the near future with an increase in extreme events. Low-intensity precipitation events will decline, but the magnitude, frequency, and duration of extreme precipitation events will increase. This projected rise in precipitation extremes will most likely increase climate-related disaster mortality if actions are not taken to strongly reduce the vulnerability. Similarly, the compounding effects of the increase in extreme temperature and precipitation events will have largely negative implications for the six climate-sensitive sectors in the Karnali region, namely water resources and energy, climate induced disasters, agriculture and food security, forest and biodiversity, tourism, natural and cultural heritage, and public health.

Zusammenfassung

Die sozioökonomischen Auswirkungen von Klimakatastrophen nehmen weltweit zu. Einigen Studien zufolge ist dieser zunehmende Trend auf die wachsende Bevölkerung und die Vermögenswerte zurückzuführen, die gefährlichen Ereignissen ausgesetzt sind. Andere Studien berichten, dass dies auf die zunehmende Häufigkeit, Intensität und Dauer extremer Wetter- und Klimaereignisse infolge des Klimawandels zurückzuführen ist. Die Gründe für die Zunahme der Auswirkungen von Katastrophen sind daher nach wie vor nicht klar. Es liegen nur begrenzte Informationen über künftige Szenarien extremer Klimaindizes und deren Auswirkungen auf verschiedene Sektoren, einschließlich Katastrophen, vor. Obwohl die Auswirkungen von Katastrophen im Verhältnis zur Wirtschaft eines Landes in Ländern mit niedrigem Einkommen stärker zu spüren sind, konzentrieren sich die vorhandenen Studien in erster Linie auf Industrieländer oder auf die länderübergreifende Ebene. Daher befasst sich diese Dissertation mit der Erkennung und Zuordnung von Trends bei den Auswirkungen von Klimakatastrophen im Kontext von Ländern mit niedrigem Einkommen. Nepal dient dabei als Fallstudie. Darüber hinaus werden in dieser Dissertation künftige Szenarien für Klimaextreme und ihre möglichen Auswirkungen auf klimasensible Sektoren im Einzugsgebiet des Karnali im Westen Nepals untersucht.

Zunächst wurden in der Studie die raumzeitlichen Tendenzen der Häufigkeit, Auswirkungen und Vulnerabilität für verschiedene Klimakatastrophen anhand der beobachteten 30-jährigen (1992-2021) Katastrophendaten der 753 subnationalen Einheiten Nepals untersucht. Der Verlust von Menschenleben ist die extremste Folge von Katastrophen, weshalb in dieser Studie die menschliche Sterblichkeit als Maß für die Katastrophenauswirkungen verwendet wurde. Die auf die exponierte Bevölkerung normierte Sterblichkeit wurde wiederum als Maß für die Anfälligkeit verwendet. Zweitens wurden Sterblichkeitsraten bei Überschwemmungen und Erdrutschen als Indikatoren für klimatische Gefahren und Vulnerabilität herangezogen. Überschwemmungen und Erdrutsche wurden für die Zuordnungsstudie ausgewählt, da sie für 70 % der gesamten klimabedingten Todesfälle in Nepal verantwortlich sind. In der Studie wurde ein katastrophenspezifisches Regressionsmodell mit gemischten Effekten und negativem Binomialmodell mit Null-Inflation verwendet, um die Kausalität der beobachteten Sterblichkeit zu untersuchen. Als erklärende Variablen wurden in dieser Studie Indizes für mittlere und extreme Niederschläge, Bevölkerungsdichte und Pro-Kopf-Einkommen sowie ein Index der sozialen Verwundbarkeit als Indikatoren für Gefahren, Exposition und

Verwundbarkeit verwendet. Schließlich lieferte diese Studie Zukunftsprojektionen von 26 mittleren und extremen Klimaindizes in Westnepal für die nahe (2021-2045), mittlere (2046-2070) und ferne (2071-2095) Zukunft. Die Projektionen behandeln dabei Szenarien mit niedrigen und hohen Emissionen (RCP4.5 bzw. RCP8.5) unter Verwendung von verzerrungskorrigierten Ensembles von 19 regionalen Klimamodellen aus dem COordinated Regional Downscaling EXperiment for South Asia. Darüber hinaus wird eine qualitative Analyse auf der Grundlage von Experteninterviews und einer Literaturrecherche zu den möglichen Auswirkungen der prognostizierten Klimaextreme auf die klimasensiblen Sektoren durchgeführt. Für die Untersuchung des Zukunftsszenarios wurde Westnepal ausgewählt, wo in den vergangenen Jahrzehnten der stärkste Anstieg von Niederschlagsextremen, Katastrophenhäufigkeit und Sterblichkeit zu beobachten war.

Die Ergebnisse zeigen, dass zwischen 1992 und 2021 wurden in Nepal insgesamt ~5.000 tödliche Klimakatastrophen registriert, bei denen mehr als 10.000 Menschen ums Leben kamen. Die Häufigkeit der Katastrophen hat um etwa sieben Ereignisse pro Jahr zugenommen, und die Sterblichkeit ist um fast neun Personen pro Jahr gestiegen. Jedoch hat die Anfälligkeit gegenüber Klimakatastrophen abgenommen, was höchstwahrscheinlich auf das Wirtschaftswachstum und die Fortschritte bei der Verringerung des Katastrophenrisikos und der Anpassung an den Klimawandel zurückzuführen ist. Diese Entwicklung der Katastrophensterblichkeit folgt eng dem Trend der Niederschlagsextreme. Ein Anstieg des maximalen Tagesniederschlags um eine standardisierte Einheit hat die Sterblichkeit bei Überschwemmungen um 33 % erhöht, und die Sterblichkeit bei Erdrutschen ist um 45 % gestiegen. Ein Anstieg des Pro-Kopf-Einkommens um eine Einheit hat die Erdrutsch- und Hochwassersterblichkeit um 30 % bzw. 45 % verringert. Die Exposition der Bevölkerung zeigt keine signifikanten Auswirkungen. Daher kommt diese Studie zu dem Schluss, dass der beobachtete Anstieg der Sterblichkeit bei Klimakatastrophen, vor allem im Westen Nepals, in erster Linie auf die durch den Klimawandel verursachten vermehrten Niederschlagsextreme zurückzuführen ist. Es wird prognostiziert, dass die Temperatur- und Niederschlagsmuster im Westen Nepals in naher Zukunft erheblich von den historischen Referenzwerten abweichen werden, was zu einer Zunahme von Extremereignissen führen wird. Niederschlagsereignisse mit geringer Intensität werden abnehmen, aber Ausmaß, Häufigkeit und Dauer von extremen Niederschlagsereignissen werden zunehmen. Dieser prognostizierte Anstieg der Niederschlagsextreme wird höchstwahrscheinlich zu einem Anstieg der klimabedingten Katastrophensterblichkeit führen, wenn keine Maßnahmen ergriffen werden, um die Resilienz gegen Katastrophen zu stärken. Auch die sich verstärkenden Auswirkungen der Zunahme Temperatur- und Niederschlagsextreme werden für die sechs klimasensiblen Sektoren in der Karnali-Region weitgehend negative Folgen haben, nämlich Wasserressourcen und Energie, Klimakatastrophen, Landwirtschaft und Ernährungssicherheit, Wald und Biodiversität, Tourismus, Natur- und Kulturerbe, und Gesundheit.

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List of Acronyms

AIC	Akaike Information Criterion
AR6	Sixth Assessment Report
BIC	Bayesian Information Criterion
BIGS-DR	Bonn International Graduate School for Development Research
CBS	Central Bureau of Statistics
CDD	Consecutive Dry Days
CI	Confidence Interval
CMA	Conferences of the Parties serving as the meeting of the Parties to the Paris Agreement
COP	Conference of the Parties
CORDEX	COordinated Regional Downscaling EXperiment for South Asia
CSDI	Cold Spell Duration Indicator
CWD	Consecutive Wet Days
DEM	Digital Elevation Model
DHM	Department of Hydrology and Meteorology
DRR	Disaster Risk Reduction
EDW	Elevation Dependent Warming
EM-DAT	Emergency Events Database
ET-SCI	Expert Team on Sector-specific Climate Indices
ETCCDI	Expert Team on Climate Change Detection and Indices
GCM	Global Climate Model

GDDgrow10	Growing Degree Days
GDIS	Geocoded Disasters Dataset
GDP	Gross Domestic Product
GHG	Greenhouse Gas
ICC	Interclass Correlation Coefficient
IPCC	Intergovernmental Panel on Climate Change
IRR	Incidence Rate Ratio
LDCs	Least Developed Countries
m.a.s.l.	Meters Above Sea Level
MK	Mann–Kendall
MoFAGA	Ministry of Federal Affairs and General Administration
MoFE	Ministry of Forest and Environment
MoHA	Ministry of Home Affairs
MSWEP	Multi-Source Weighted-Ensemble Precipitation
NAP	National Adaptation Plan
NLSS	Nepal Living Standard Survey
OLS	Ordinary Least Squares
PCI	Per Capita Income
PRCPTOT	Total Precipitation
R10mm	Number of heavy rain days
R30mm	Number of very heavy rain days

R95pTOT	Contribution from very wet days
R99pTOT	Contribution from extremely wet days
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RX1day	Max 1-day precipitation
RX5day	Max 5-day precipitation
SDGs	Sustainable Development Goals
SDII	Simple Daily Intensity Index
SFDRR	Sendai Framework for Disaster Risk Reduction
SIDs	Small Island Developing States
SoVI	Social Vulnerability Index
SU	Summer Days
TN10P	Amount of cold nights
TN90P	Amount of warm nights
TNm	Annual mean daily minimum temperature
TNn	Annual coldest daily minimum temperature
TNx	Annual warmest daily minimum temperature
TR	Tropical Nights
TS	Theil−Sen
TX10P	Amount of cool days
TX90P	Amount of hot days

TXm	Annual mean daily maximum temperature
TXn	Annual coldest daily maximum temperature
TXx	Annual warmest daily maximum temperature
UNDRR	United Nations Office for Disaster Risk Reduction
UNFCCC	United Nations Framework Convention on Climate Change
USD	United States Dollar
VDC	Village Development Committee
WDAYS	Number of Wet Days
WMO	World Meteorological Organization
WSDI	Warm Spell Duration Indicator
ZEF	Center for Development Research
ZINB	Zero-Inflated Negative Binomial

Chapter One: Introduction

1.1. Problem statement and motivation

Global warming and climate change due to human-induced greenhouse gas (GHG) emissions have adversely impacted people and the environment worldwide (IPCC 2022a). This recently published Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) concluded with high confidence that anthropogenic climate change has caused widespread impacts on various sectors such as ecosystems and biodiversity, water, agriculture, health, settlements, and infrastructures. The frequency and intensity of climate and weather extremes, such as hot extremes, heavy precipitation events and drought, have increased resulting the rise in climate-related disasters and its impacts (IPCC 2022a). Furthermore, global warming will intensify the weather and climate extremes in the future. Extreme precipitation events will increase nonlinearly with global warming, and the frequency of rare events, such as 10- and 50-year events, are likely to double and triple compared with the past at 4°C of global warming (Seneviratne et al. 2021). Hence, a better understanding of the behavior of the extreme climate indices is important to understand its impacts in various climate sensitive sectors and plan for adaptation (ETCCDI 2009).

During 1970–2019, weather- and climate-related disasters caused 2.06 million deaths and economic losses of 3.6 trillion USD worldwide (WMO 2021). In the last two decades (2001–2020), at least 27,031 people died, and economic losses of 126.2 billion USD were incurred as a direct result of 331 climatic disaster events annually (CRED 2021). Moreover, the incidence and impact of climatic disasters are rising globally. On average, ~90–100 medium- and large-scale disasters were recorded annually during 1970–2000. However, this increased to 350–500 events per year during 2001–2020 (UNDRR 2022). Consequently, inflation-adjusted global economic losses owing to multiple climatic disasters increased by 2.6 billion USD/year during 1980–2016 (Formetta and Feyen 2019). Furthermore, climatic disaster-related human mortality also increased in the long term, with large spatial and interannual variability (Formetta and Feyen 2019; UNDRR 2022).

The disaster-induced fatality and economic losses relative to the country's gross domestic product (GDP) are unevenly distributed worldwide; they are higher in developing countries. Further, ~91% of the global disaster mortality during 1998–2017 occurred in low- and middle-income countries, and only 9% in high-income countries (UNISDR 2018). Similarly, on average, disaster-induced economic losses in low- and lower-middle-income countries are 0.8%–1% of GDP compared with only 0.1%–0.3% in high- and upper-middle-income countries (UNDRR 2022). According to the INFORM Risk Index, the countries at the highest future risk of climatic disasters are also low- and middle-income countries, mainly in Africa and South Asia (Inter-Agency Standing Committee and the European Commission 2022). Most of the 3.6 billion people living in conditions highly vulnerable to climate change are in developing countries (IPCC 2022a). Similarly, ~90% of the ~1.5 billion people worldwide exposed to flood risk live in low- and middle-income countries (Rentschler and Salhab 2020). The high impacts and risks in developing countries mainly result from the increased vulnerability caused by socioeconomic factors such as poverty, development deficit, marginalization, inequality, and governance challenges (IPCC 2022a).

Small island developing states (SIDSs) and least developed countries (LDCs) have advocated a burden-sharing mechanism for climate change–induced loss and damage since the establishment of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 (Mechler et al. 2019). However, attributing impacts and risks to anthropogenic climate change has been a major challenge in this loss and damage debate (Bouwer 2019; James et al. 2019). Attribution in this climate change impacts and loss and damage context is the process of studying the relative contribution of multiple causal factors, such as the anthropogenic climate change or socioeconomic factors, to a change or event, such as the rise in disaster impacts (IPCC 2022b). For the first time since the beginning of the UNFCCC negotiation process, the UNFCCC 27th Conference of the Parties (COP 27) and 4th Conferences of the Parties serving as the meeting of the Parties to the Paris Agreement (CMA 4) held in Sharm el-Sheikh in Egypt in November 2022 decided to establish funding mechanisms for responding to loss and damage due to climate change (UNFCCC 2022). Nevertheless, empirical evidence of the climate change–induced rise in extreme climate events that increased disaster impacts remains limited (IPCC 2014a, 2022a).

Previous studies have analyzed the historical trends of climatic disaster impacts and their causes. However, the results are diverse and contradictory. Some studies have reported that the increasing trend of climatic disaster impacts so far results from the rapid growth in population and assets exposed to hazardous events, and the role of anthropogenic climate change is not evident (Bouwer 2011, 2019; Visser et al. 2014; Mohleji and Pielke 2014; McAneney et al. 2019; Pielke 2021). These studies have used the standard loss normalization approach to normalize the disaster impacts by exposure and investigate any remaining trends of the exposure-normalized losses that can be attributed to climate change. However, vulnerability is not often, or incompletely, accounted for in these studies, resulting in the false attribution of disaster impacts given the dynamic nature of vulnerability (Mechler and Bouwer 2015; Botzen et al. 2021). In contrast, several studies have observed a decreasing trend of exposure-normalized disaster impacts, also used as a proxy for disaster vulnerability (Kellenberg and Mobarak 2008; Jongman et al. 2015; Tanoue et al. 2016; Wu et al. 2019; Formetta and Feyen 2019). Disaster vulnerability reduction could have resulted from climate change adaptation, disaster risk reduction (DRR), and overall economic growth, which could have covered the climate change effects. The climate change effect is much greater in explaining the increasing trend of disaster impacts if vulnerability is controlled for (Estrada et al. 2015; Forzieri et al. 2017).

Disaster trends and attribution findings are derived from global cross-country studies or high-income countries (Bouwer 2019; Pielke 2021). Cross-country studies are mainly based on nationally aggregated data. Analyses are performed at a low spatial resolution, such as by country clusters (low- and high-income countries) or by continents. However, climatic disasters are often local phenomena, and their impact and vulnerability are particular to locations. Therefore, such global cross-country analyses cannot capture the spatiotemporal dynamics of disaster impacts, vulnerabilities, and relationships with their drivers for any particular location (Rubin 2014; Wu et al. 2019). The few available studies in low-income countries (Aryal 2012; Rubin 2014; Mechler and Bouwer 2015; Aksha et al. 2018) are very limited in the scope of analysis or have several methodological limitations. This knowledge gap significantly hinders the achievement of the goals and targets of the 2030 Agenda for Sustainable Development and their stated Sustainable Development Goals (SDGs), the Sendai Framework for Disaster Risk Reduction (SFDRR), and the global adaptation goal of the 2015 Paris Agreement. Burden-sharing, such as compensation for unavoidable loss and damage due to climate change, has been a critical agenda of LDCs and SIDSs in the UNFCCC negotiations (Deubelli and Mechler 2021). However, attribution has been the crux of this loss and damage debate (Bouwer 2019; James et al. 2019). Therefore, much evidence from attribution science is necessary to avert, minimize, and address residual loss and damage caused by climatic disasters (James et al. 2019; Mechler et al. 2020).

A country-specific study can investigate the relationship between disaster impacts and their drivers considering the governmental, political, institutional, and other unobserved variables, often not feasible in cross-country studies (Rubin 2014). Studying the observed disaster impacts is significant in identifying high-impact and vulnerable areas, planning and implementing DRR and adaptation measures, monitoring and evaluating the effectiveness of these measures, and investigating the attribution of impacts to climate and socioeconomic change (Koç and Thieken 2018). Therefore, this study examined the spatiotemporal trends of climatic disaster impacts and vulnerability and its attribution to climatic and socioeconomic variables in Nepal, a low-income country.

Based on the Global Climate Risk Index 2021, Nepal is among the top ten countries worldwide suffering from extreme weather events in recent decades (Eckstein et al. 2021). In the past 30 years (1992–2021), climate-related disasters caused >10,000 deaths in the country (Chapagain et al. 2022). Additionally, economic losses amounted to 380 million Nepalese rupees (2010 price) (i.e., USD~3.8 million/year) over the past decade, which is a 55% increase over the previous decade (DesInventar 2021; MoHA 2021). Nepal has been classified as a high-disaster risk country by the INFORM Risk Index 2022. Hence, Nepal can be a case study of a low-income and highly disaster-prone country.

A significant increase in disaster risk and vulnerability is projected by 2050 owing to climate change and demographic and socioeconomic changes (Inter-Agency Standing Committee and the European Commission 2022). In addition to the climate-related disasters, the change in climate extremes in the future is most likely to have impacts on other sectors. Water resources and energy; climate-induced disasters; agriculture and food security; forests and biodiversity; tourism and natural and cultural heritage; public health; and urban settlements and infrastructure are the six key climate sensitive sectors in Nepal (MoPE 2017). However, only limited studies so far have studied the future scenarios of climate extremes and their consequences in these climate sensitive sectors. Therefore, this study further investigated future extreme weather and climate scenarios and their potential consequences in climate-sensitive sectors in the Karnali river basin in western Nepal. Due to the very high geographic and climatic heterogeneity within small spatial distance in Nepal, the future climate projections and impact assessments is required at a finer spatial scale (Dhaubanjar et al. 2020; Chapagain et al. 2021). Karnali is the poorest and one of the most climate vulnerable regions in the country (Siddiqui et al. 2012; NPC 2018; Panthi et al. 2018; Matheswaran et al. 2019). Moreover, this study found that western Nepal has experienced the fastest increase in climate extremes and disaster impacts in the past compared to the other regions (see chapter three for the findings).

Therefore, this study focused on Karnali river basin in western Nepal to study the future climate extremes scenarios and its implications in the climate sensitive sectors.

The research objectives and dissertation structure are presented in Sections 1.3 and 1.4.

1.2. State of the art

The frequency and intensity of weather and climate extremes have increased since around the 1950s because of anthropogenic greenhouse gas (GHG) emissions (Seneviratne et al. 2021), which are increasingly likened to the increasing incidence and impact of climatic disasters (Huggel et al. 2013; IPCC 2014a, 2022a; James et al. 2019). However, several studies have concluded that anthropogenic climate change has not had a significant role in increasing the impact of climatic disasters (Bouwer 2011, 2019; Neumayer and Barthel 2011; Visser et al. 2014; Mohleji and Pielke 2014; McAneney et al. 2019; Pielke 2021). These authors have argued that the increase in disaster exposure due to population and economic growth is the most important driver of the increasing disaster impacts because the impact trend after normalization for exposure is constant. Nevertheless, this argument is valid only if there are no DRR and adaptation efforts or if such efforts are completely unsuccessful in reducing vulnerability (Nicholls 2011). Otherwise, the exposure-normalized impacts on the absence of climate change effects should exhibit a downward trend because of the global advancement in weather forecasting, disaster preparedness, adaptation, and development efforts (Nicholls 2011; Neumayer and Barthel 2011; IPCC 2022a).

Loss normalization is the most used approach in the literature to i) re-express impacts in terms of vulnerability through normalization by exposure, and ii) investigate whether there is a residual trend of normalized impacts that could be attributed to climate change (Huggel et al. 2013; Estrada et al. 2015; Bouwer 2019). Several studies have normalized disaster mortality and economic losses by the exposed population and the exposed GDP, respectively, as a measure of human and economic vulnerabilities. Such normalized human and economic losses have shown a decreasing trend in different world regions (Kellenberg and Mobarak 2008; Zhou et al. 2014; Wu et al. 2019; Formetta and Feyen 2019). Exposure-normalized impacts caused by a single hazard, such as floods (Jongman et al. 2015; Tanoue et al. 2016) and storms (Bouwer and Jonkman 2018), have also declined in all world regions. The normalized impacts or vulnerabilities in low-income countries have decreased considerably faster, fostering the convergence of the vulnerability gap between the rich and the poor. Declining vulnerabilities, particularly in low-income countries, are linked to improved socioeconomic conditions, mainly due to economic growth, DRR, and adaptation. This shows that the effect of the potential increase in climatic hazards on disaster impacts because of climate change is counterbalanced by a decrease in vulnerability.

Some studies have observed a clear nonlinear (power function) decreasing trend of disaster vulnerability with economic growth (Jongman et al. 2015; Wu et al. 2019; Formetta and Feyen 2019). Others have argued that vulnerability follows an inverted U-shape trend, indicating an initial increase in vulnerability before declining. Because, the implementation and effects of DRR and adaptation progress more slowly than increases in exposure (Kellenberg and Mobarak 2008; Huang 2014; Zhou et al. 2014). The monotonic downward trend supports the role of economic growth in reducing disaster vulnerability. At the same time, an inverted U-shaped relationship questions the prominent belief that the best way for developing countries to avoid disaster impacts is by developing and growing faster (Kellenberg and Mobarak 2008). Vulnerabilities may increase with economic growth because low-income countries, such as Nepal, may not have reached the turning point. Although the role of DRR and adaptation in reducing vulnerabilities and impacts are acknowledged, such an association has not been studied empirically. Bahinipati et al. (2016) attempted to introduce adaptation variables into normalization models. They concluded that adaptation significantly reduced economic losses resulting from climatic extremes in Odisha, India.

The effectiveness of the loss normalization approach in determining whether there is a residual trend that can be attributed to changing climatic hazards is limited because the underlying assumptions, such as the relevance of the normalization variables to detrend the impacts of socioeconomic changes, may not hold (Estrada et al. 2015). Likewise, its inability to adequately explain the change in vulnerability does not allow for detecting the role of climatic hazards in the observed impacts (Huggel et al. 2013; Mechler and Bouwer 2015; Botzen et al. 2021). When the vulnerability is controlled, Forzieri et al. (2017) concluded, based on the historical loss trend, that climate change is the dominant driver accounting for >90% of the projected rise in the risk to humans (number of deaths) in Europe, with only a minor (~10%) contribution of population growth and distribution. Therefore, Estrada et al. (2015) proposed a regression-based approach with socioeconomic and climatic variables to explain the variability of US tropical cyclone losses. They reported that the upward loss trend is consistent with changes in its climatic drivers. Nevertheless, such an approach is not yet conclusive, and there is a need for further confirmation through consecutive studies (Bouwer 2019). Moreover, DRR and adaptation variables are still not included in their regression model because of data unavailability.

The literature and findings discussed above are mostly from developed countries or global cross-country studies. Low-income countries are poorly represented in such analyses, and in particular, there is a lack of information at the subnational scale (James et al. 2019). Furthermore, whether the observed results at a global scale or in one country apply to other countries or regions is unclear (Neumayer and Barthel 2011). Among the few studies available in a low-income country context, Rubin (2014) attempted to study disaster vulnerability at the provincial scale in Vietnam. However, analysis is limited to the provincial distribution pattern of disaster mortality (decadal average instead of annual trend) and per capita economic losses over a very short study period (2000–2009). Mechler and Bouwer (2015), in a flood-specific study in Bangladesh, observed a decreasing trend of economic losses relative to the GDP in the flooded area and fatalities relative to the area flooded. In Nepal, Aryal (2012) observed an increasing trend of the reported disaster incidence and casualty per disaster incidence (the author defined it as vulnerability). This study was based on disaster data extracted from the review of newspaper articles. They did not provide any information on disaster impacts (life or asset) and impacts after controlling for exposure. Aksha et al. (2018) observed an increasing trend of total deaths due to natural disasters in Nepal, with a higher crude death rate in the mid- and high-mountain regions. However, research in Nepal is limited to disaster mortality and includes death caused by non-climatic hazards, such as earthquakes. Furthermore, the crude death rate does not control the exposed population to provide vulnerability measures.

In Nepal, several studies have investigated previous extreme climate indices and found a rise in heavy precipitation events and hot extremes (Khatiwada et al. 2016; Karki et al. 2017, 2019; Bohlinger and Sorteberg 2018; Talchabhadel et al. 2018; Pokharel et al. 2019; Sharma et al. 2020; Poudel et al. 2020). However, only a few studies have examined the scenarios of future climate extremes, and even fewer have explored the implications for different climate-sensitive sectors (Rajbhandari et al. 2017; MoFE 2019; Pokharel et al. 2019; Dahal et al. 2020; Singh et al. 2021). These previous studies mostly looked at the mean climate indices and limited number of old and generic indices based on Expert Team on Climate Change Detection and Indices (ETCCDI). The Expert Team on Sector-specific Climate Indices (ET-SCI) introduced in 2011 recommend a more comprehensive mean and extreme climate indices for the sector-specific impact assessments (ET-SCI 2016). The limited number of future climate projection studies in Nepal are mostly based on a small number of global climate models (GCMs). However, regional climate models (RCMs) are better suitable for a region specific assessments as they are richer in spatial and temporal detail to better simulate the local phenomena and extremes (Flato et al. 2013; Dhaubanjar et al. 2020).

1.3. Research objectives

The overall objective of this research is to increase our understanding of climate change impacts through the detection of spatiotemporal trends of climatic disaster impacts and relevant climatic and socioeconomic indices in a low-income country Nepal. This study also provides new insights on the attribution of disaster impacts to climatic and socioeconomic changes through an empirical example from a low-income country, Nepal.

The specific objectives of this research are as follows:

i. To understand the spatiotemporal trends of the occurrence, impacts, and vulnerability of multiple climatic disasters in Nepal.

ii. To assess the attribution of flood and landslide mortality to climatic hazards, exposure, and vulnerability in Nepal.

iii. To evaluate future scenarios of extreme climate indices and their sectoral implications in the Karnali Basin of western Nepal.

1.4. Research design and dissertation structure

This cumulative doctoral dissertation is divided into five main chapters and appendices. Chapter one introduces the main research problem and motivation, state of the art in the research topic, and the research objectives. Chapters two, three, and four are the interconnected analytical chapters dealing with the first, second, and third research objectives listed in Section 1.3. The research design of the three analytical chapters of this dissertation is schematically illustrated in Fig. 1.1. Chapter five is the concluding chapter. Supplementary information from these chapters are presented as appendices.

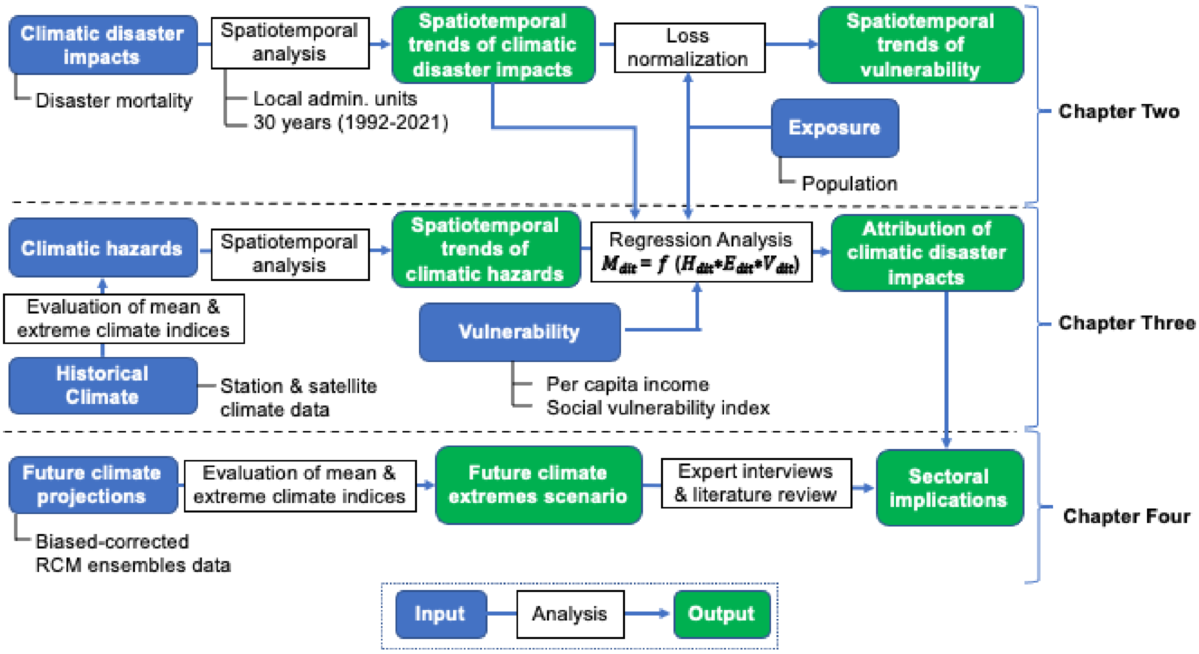

Figure 1.1: Research design of the three analytical chapters of the Ph.D. dissertation.

Chapter two starts by investigating the spatiotemporal trends of the past 30 years (1992–2021) multiple climatic disaster frequency, impacts, and vulnerability in Nepal. It focuses on disaster mortality as a measure of disaster impact because the loss of human life is the most extreme impact of a disaster. Mortality data are better recorded than other impacts, making them an appropriate proxy for disaster impacts. The 753 local administrative units of Nepal, the smallest subnational units, are used as the study unit to allow analysis at a very high resolution. This study follows the most used loss normalization approach for vulnerability assessment in which disaster mortality was normalized by the exposed population as a proxy measure of human vulnerability to climatic disasters. The use of this normalization approach to study multiple disaster vulnerabilities at the smallest sub-national unit scale in a low-income country is unique to this study. This study further explores the relationship between disaster vulnerability and economic growth measured in terms of per capita income (PCI). The findings of chapter two have been published in Regional Environmental Change journal as Chapagain et al. (2022).

Chapter three investigates the attribution of disaster mortality to climatic hazards, exposure, and vulnerability using a regression-based approach. Among the eight types of climatic disasters studied in chapter two, floods and landslides were selected for this attribution study because they are the deadliest climatic disasters in Nepal, accounting for 70% of the total climatic disaster mortality. Six mean and extreme precipitation indices were climatic hazard indicators, the population density was an exposure indicator, and the PCI and social vulnerability index (SoVI) were vulnerability indicators. Finally, regression models were employed to study the causality of flood and landslide mortality. This regression-based approach overcomes the limitations of the commonly used loss normalization approach in studying the attribution of disaster impacts. The findings of chapter three have been submitted for publication in Climate Risk Management and are currently under review.

Chapter four presents projections for mean and extreme climate indices in western Nepal for the near (2021–2045), mid (2046–2070), and far future (2071–2095) for low- and high-emission scenarios (RCP4.5 and RCP8.5, respectively) using bias-corrected ensembles of 19 regional climate models from the COordinated Regional Downscaling EXperiment (CORDEX) for South Asia. Furthermore, the potential implications of the projected climate extremes in six key climate-sensitive sectors in the region were analyzed based on expert interviews and a literature review. The most substantial rise in extreme precipitation events, climatic disaster frequency, and mortality in the historical period was observed in western Nepal compared with other regions. Hence, the Karnali River Basin of western Nepal was selected for the future scenario study. The findings of this chapter have been published in Climatic Change as Chapagain et al. (2021).

Finally, the key results and conclusions from the three analytical chapters are synthesized in chapter five. Furthermore, the study findings are discussed in the global, national, and local policy context. This chapter also addresses future research perspectives.

Chapter Two: Spatio-Temporal Trends of Climatic Disaster Impacts and Vulnerability in Nepal

This chapter has been published as

Chapagain, D., Bharati, L., & Borgemeister, C. (2022). Declining vulnerability but rising impacts: the trends of climatic disasters in Nepal. *Regional Environmental Change*, *22*(2), 55. https://doi.org/10.1007/s10113-022-01903-5

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 spatio-temporal 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

2.1. 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; IPCC 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 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.

2.2. Methodology

2.2.1. 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 meters 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 (see Fig. 2.1) (MoFAGA 2019). 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.

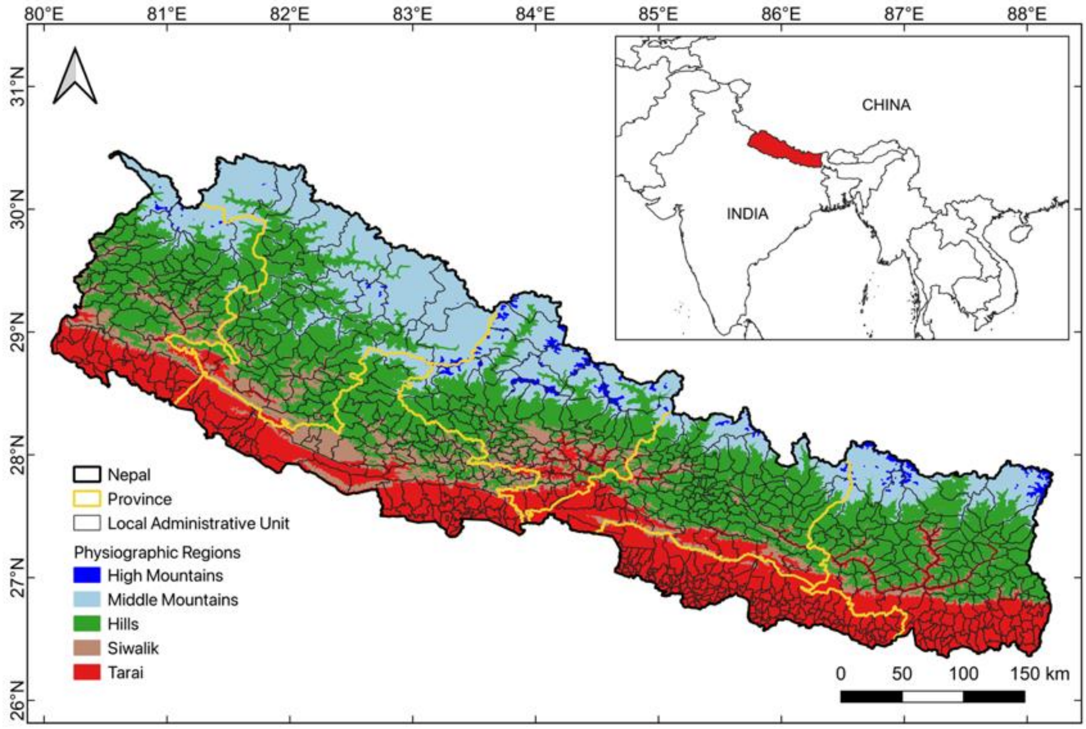

Figure 2.1: Map of Nepal showing local administrative units and physiographic regions. Inset: Nepal in the world map.

2.2.2. 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.

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 A2.1 in the appendices. 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 A2.2 in the appendices 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.

2.2.3. 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 represent the impacts component of this framework.

$$Impact = f\,(Hazard, Exposure, Vulnerability) \qquad (1)$$

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 ($\mathrm{M_{dit}}$) by the disaster-exposed population ($\mathrm{P_{dit}}$) as a proxy measure of human vulnerability ($\mathrm{V_{dit}}$), 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.

$$Human\ Vulnerability\ (V_{dit}) = \frac{Disaster\ Mortality\ (M_{dit})}{Disaster\text{−}Exposed\ Population\ (P_{dit})} \qquad (2)$$

Where, d = disaster type

i = local unit

t = year

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 spatio-temporal trend (Neumayer and Barthel 2011; Formetta and Feyen 2019).

2.2.4. 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).

2.2.5. 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. βs are the marginal effects of explanatory variables, and ε is the random error term.

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

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.

2.3. Results

2.3.1. Climatic disaster frequency and mortality trends in Nepal

During the past three decades, almost 5,000 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 2.1). Above 800 people were missing and 5,000 were 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.

Table 2.1: 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.	Heat waves	35	0.35
8.	Hailstorms	20	0.20
	TOTAL	**10072**	**100**

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. 2.2). Both multidisaster frequency and mortality showed increasing trends that were significant at the 0.05 level (Table 2.2). 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 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.

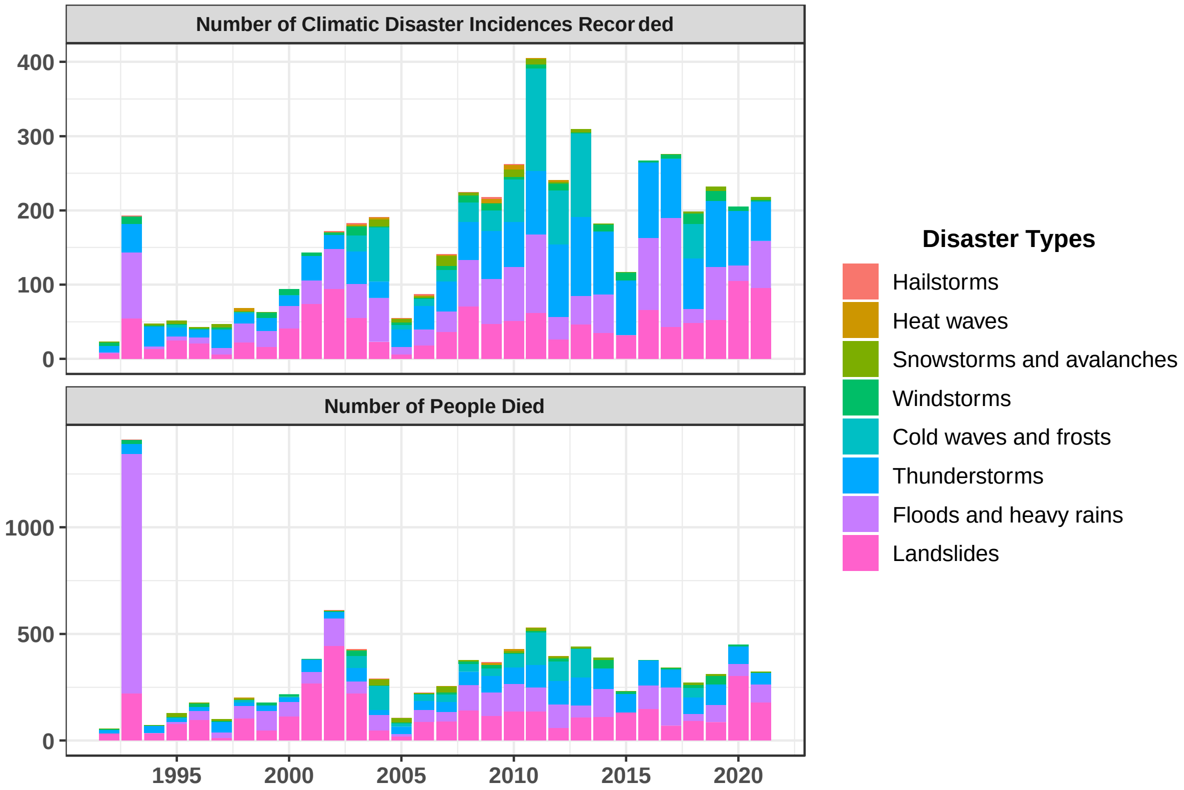

Figure 2.2: Annual number of climatic disaster incidences recorded (frequency) and number of people died (mortality) by disaster types in Nepal during 1992–2021.

Disaster mortality showed a clear monthly pattern (Fig. 2.3). 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.

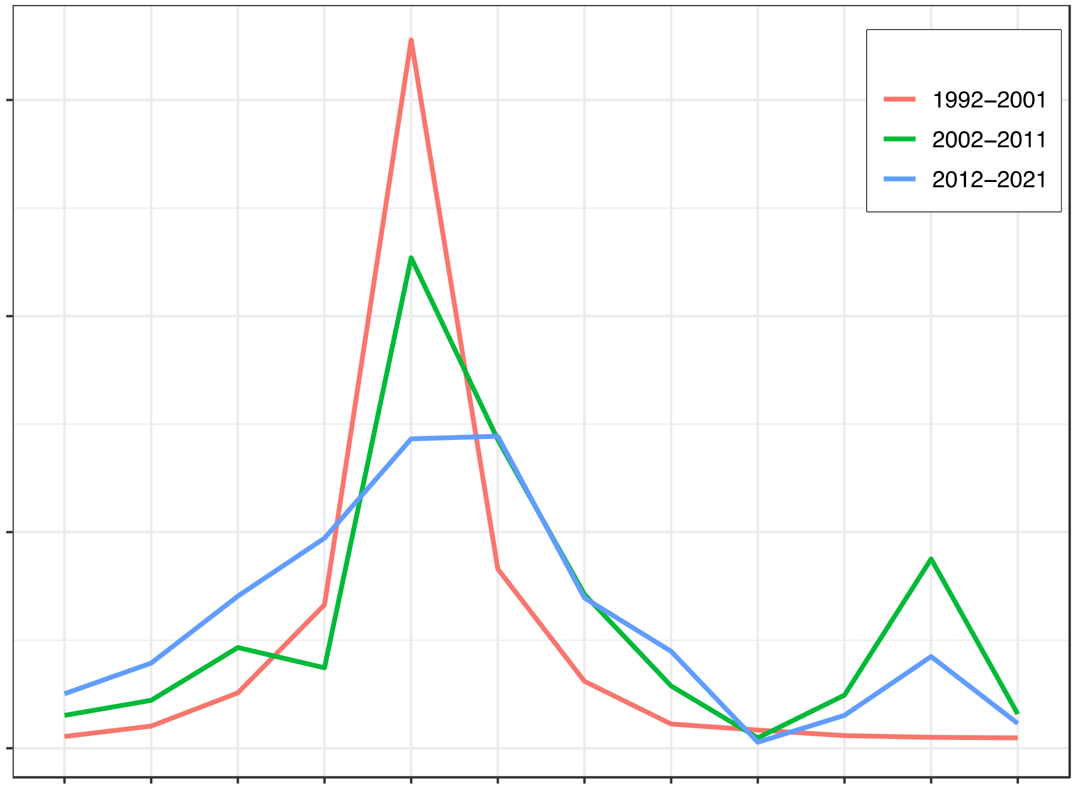

Figure 2.3: Monthly pattern of climatic disaster mortality in Nepal by decade.

2.3.2. 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 2.2 and Fig. 2.4a). 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. 2.4b).

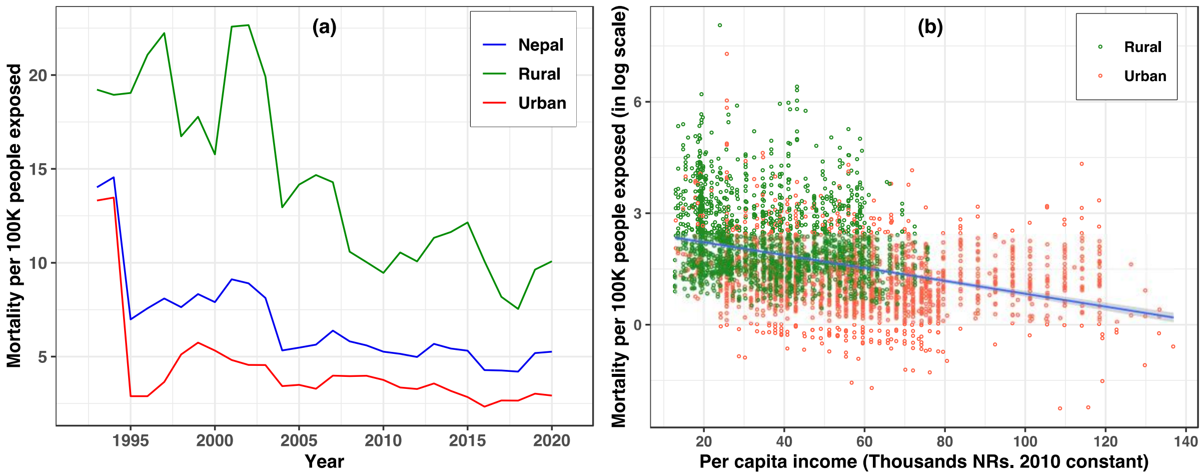

Figure 2.4: Multidisaster vulnerability trend (3 years moving average) over time in urban areas, rural areas, and whole Nepal during 1992–2021. b Relationship of multidisaster vulnerability (in log scale) to per capita income.

Table 2.2: 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/100K 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.*

2.3.3. 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. 2.5). 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 vulnerable to thunderstorms. Spatial patterns of mortality and vulnerability by individual disaster types are presented in appendices.

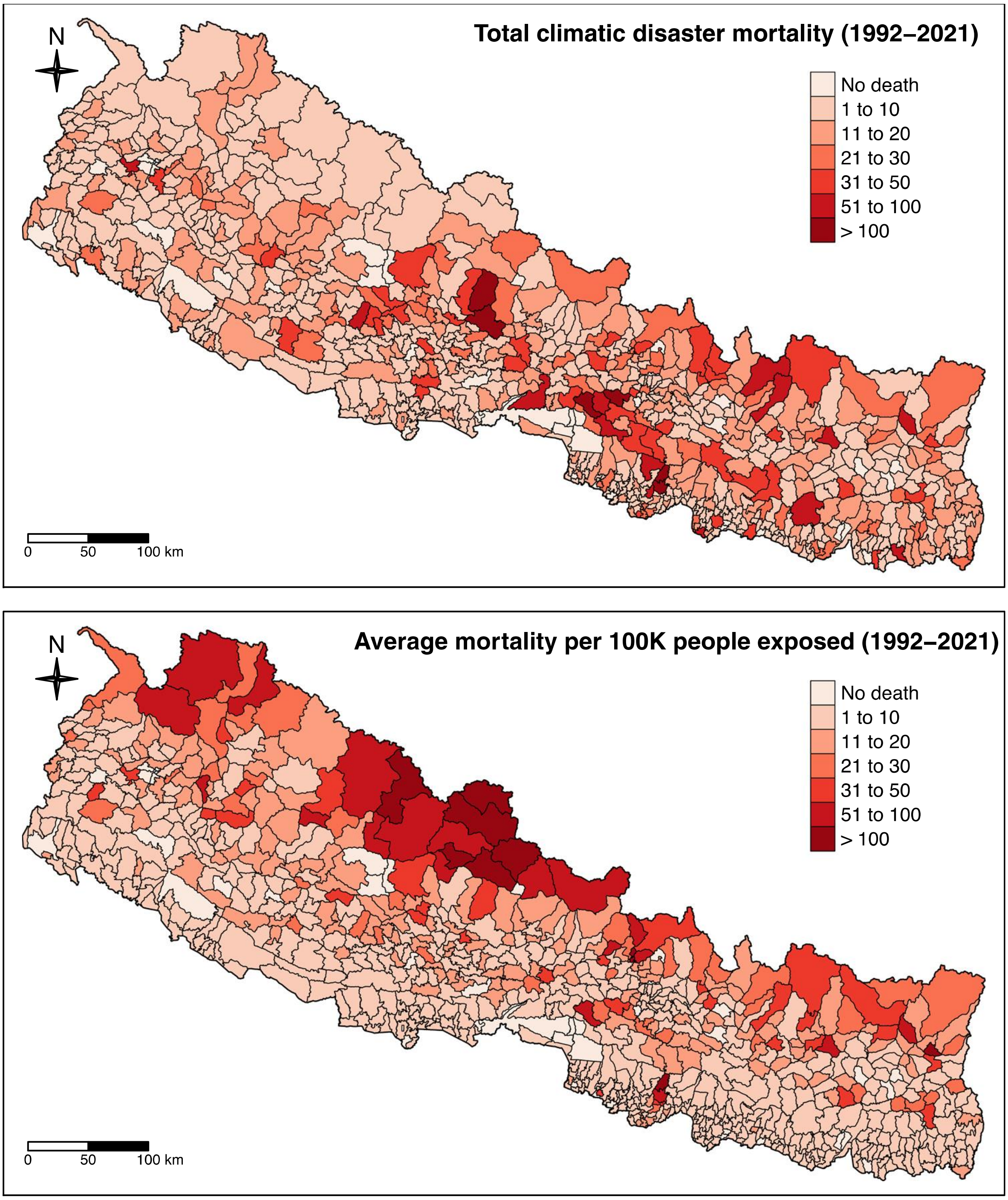

Figure 2.5: Spatial distribution of climatic disaster impacts (total mortality) and vulnerability (average annual mortality per 100K people exposed) in Nepal during 1992–2021. The color code range in the maps is manually assigned, and the range values are shown in the legend.

2.3.4. 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 2.3). We selected the location fixed-effect model over the ordinary least-squares model (results in Table A2.3 in the appendices) 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.

Table 2.3: 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*

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.

2.4. 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 2,000 and 3,500 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).

2.5. Conclusions

In this study, we analyzed the spatio-temporal 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.

Chapter Three: Attribution of Climatic Disaster Impacts to Climatic and Socioeconomic Changes

This chapter has been submitted for publication as

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Abstract

Climatic disaster impacts, such as loss of human life as its most severe consequence, have been rising globally. Several studies argue that population growth is responsible for the rise, and the role of climate change is not evident. While disaster mortality is highest in low-income countries, existing studies focus mostly on developed countries. Here we address this impact attribution question in the context of the Global South using disaster-specific mixed-effects regression models. We show that the rise in landslide and flood mortality in a low-income country such as Nepal between 1992-2021 is primarily attributable to increased precipitation extremes. An increase in one standardized unit in maximum one-day precipitation increases flood mortality by 33%, and heavy rain days increase landslide mortality by 45%. Similarly, a one-unit increase in per capita income decreases landslide and flood mortality by 30% and 45%, respectively. Population density does not show significant effects.

Keywords: climatic disaster, disaster impacts, precipitation extremes, attribution, regression model, Nepal

3.1. Introduction

On average, weather and climate-related disasters caused 27,031 deaths and USD 126.2 billion in economic losses annually worldwide between 2001–2020 (CRED 2021). Climatic disaster occurrences, as well as loss of life and property, are on the rise globally (Hoeppe 2016; Formetta and Feyen 2019; UNDRR 2022). These observed impacts have been increasingly attributed to anthropogenic climate change (Huggel et al. 2013; Bouwer 2019; IPCC 2022c). 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. Nevertheless, empirical evidence of the rise in climate extremes leading to an increase in disaster impacts is still limited and focuses primarily on the Global North.

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; Visser et al. 2014; McAneney et al. 2019; Pielke 2021). 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 (Mechler and Bouwer 2015; Botzen et al. 2021). 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 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).

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 (Rentschler and Salhab 2020; IPCC 2022c). Therefore, a better understanding of disaster impact trends and the role of climatic 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 recent United Nations Climate Change Conference (COP 27) in Egypt agreed to establish a new loss and damage fund for vulnerable countries impacted by climatic 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).

Most of the existing climatic disaster impact attribution studies are from the United States, Europe, or other developed countries (Bouwer 2019; Pielke 2021). Therefore, to address these scientific and policy-relevant issues in the Global South context, we present an empirical example of the attribution of climatic disaster mortality to indicators of climatic hazards, exposure, and vulnerability in a low-income country. Nepal was among the top ten countries worldwide most affected by climatic disasters in the past two decades (Eckstein et al. 2021). Over 10,000 people have lost their lives to climatic disasters in the past 30 years, with landslides and floods together accounting for almost 70% of the total climatic 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). Nepal is thus a useful case study of climatic disaster risk in low-income and highly disaster-vulnerable countries.

In our study, 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. 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 climatic hazards, exposure, and vulnerability. We used mean and extreme precipitation indices as indicators of climatic 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 climatic hazards, exposure, and vulnerability indicators, together with their statistical association, to draw a conclusion on the attribution of disaster mortality.

3.2. Methodology

3.2.1. 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. 3.1). It has a total area of 147,516 km2 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. 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).

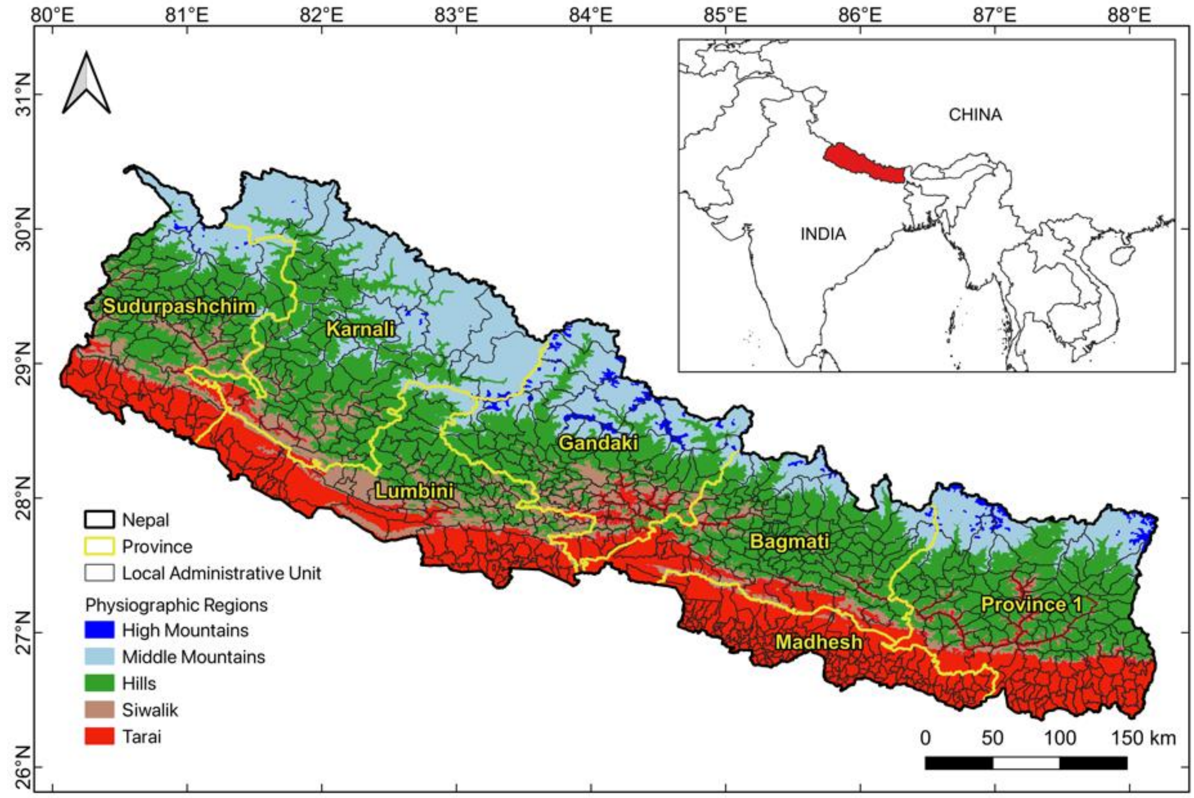

Figure 3.1: Map showing Nepal's local administrative units, provinces, and physiographic regions. Inset: Nepal on the world map.

3.2.2. Data source and processing

3.2.2.1. Climatic 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 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.

3.2.2.2. 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 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 3.1) from the list of Expert Team on Sector-specific Climate Indices (ET-SCI) that are most relevant to floods and landslides in Nepal (ET-SCI 2016; Chapagain et al. 2021). Selected precipitation indices estimated by observational stations were used for the spatio-temporal trend analysis in section 3.3.2.

Table 3.1: 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

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 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 3.3.3 and 3.3.4 as indicators of climatic hazards.

3.2.2.3. 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, climatic hazards, and exposure indicator data for the period 2007-2015 for the regression analysis with SoVI data in section 3.3.4.

3.2.3. 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 (Karki et al. 2017; Wu et al. 2019; Chapagain et al. 2022) 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).

3.2.4. Regression model fitting

Climatic disaster impacts occur due to the complex interaction of hazards, exposure, and vulnerability (IPCC 2012; Oppenheimer et al. 2014). In this risk framework, climatic hazard usually refers to climatic physical events or trends or to their physical impacts (IPCC 2014b). A climatic 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 2014b). 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 climatic hazards, exposure, and vulnerability indicators.

As floods and landslides are precipitation-related disasters, we used six mean and extreme precipitation indices (duration, frequency, and intensity-based) defined in Table 3.1 as indicators of climatic 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 (Zhou et al. 2014; Jongman et al. 2015; Tanoue et al. 2016; Wu et al. 2019; Formetta and Feyen 2019), we used per capita income as a proxy of vulnerability. We also used the composite SoVI as a measure of social vulnerability to climatic 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 A3.1 in appendices. 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 A3.2 in appendices. 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 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 indicator, that is, the observed mean and extreme precipitation indices defined in Table 3.1. $E_{i,t}$ 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.

3.3. Results

3.3.1. Spatiotemporal trends of climatic disaster mortality in Nepal

More than 10,000 people have lost their lives due to climatic 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 climatic disaster mortality in the country. 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. 3.2). Western Nepal (Lumbini, Karnali, and Sudurpashchim) has experienced relatively less disaster mortality in the past.

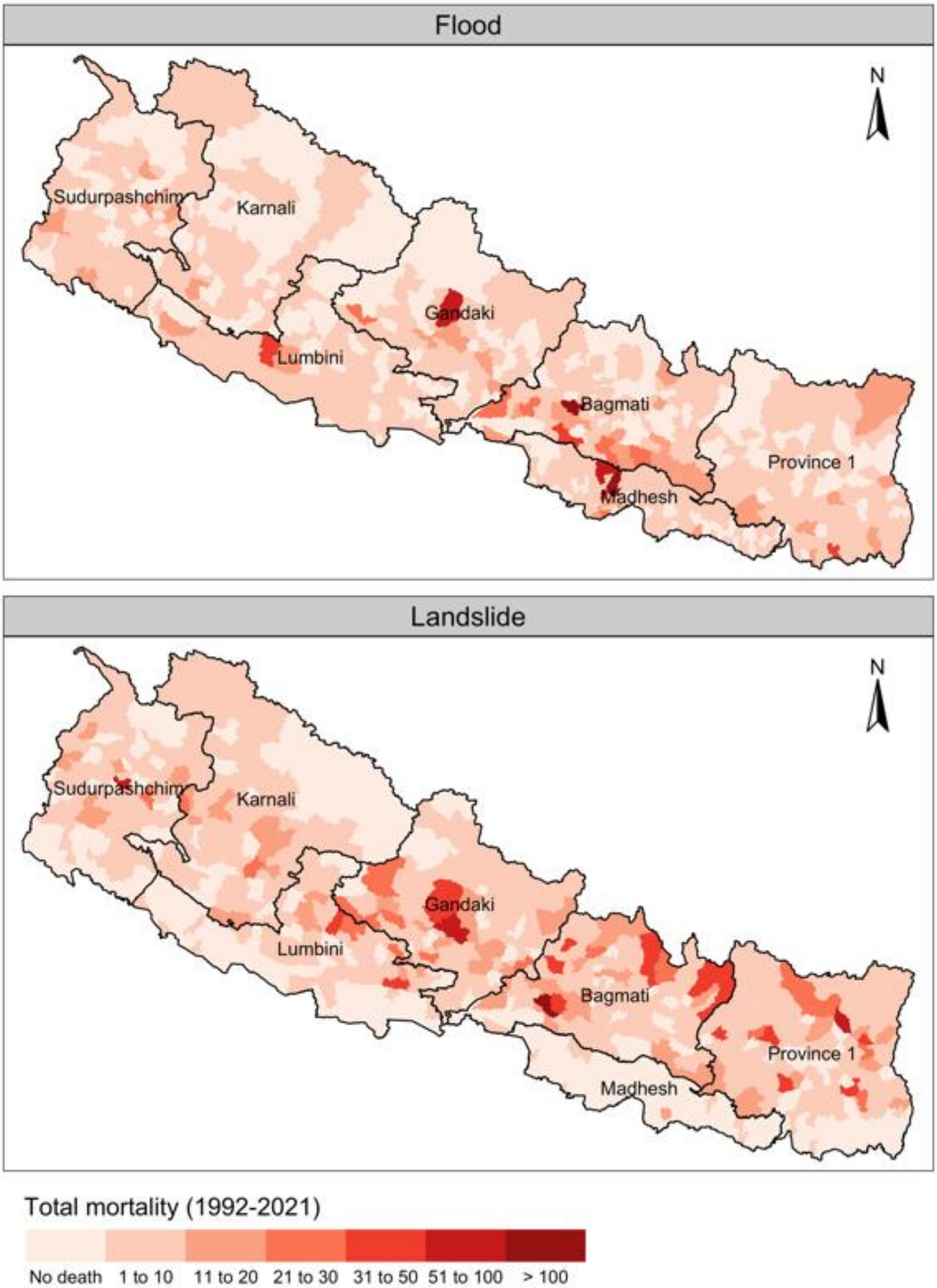

Figure 3.2: Spatial trends of landslide and flood mortality in Nepal during 1992–2021.

Temporal trends show 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 Province 1 in central and eastern Nepal were positive but not significant (Table 3.2). Flood frequency in Province 1 and landslide frequency in Bagmati and Gandaki showed statistically significant increasing trends.

Table 3.2: 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. 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*

3.3.2. 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. 3.3). 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).

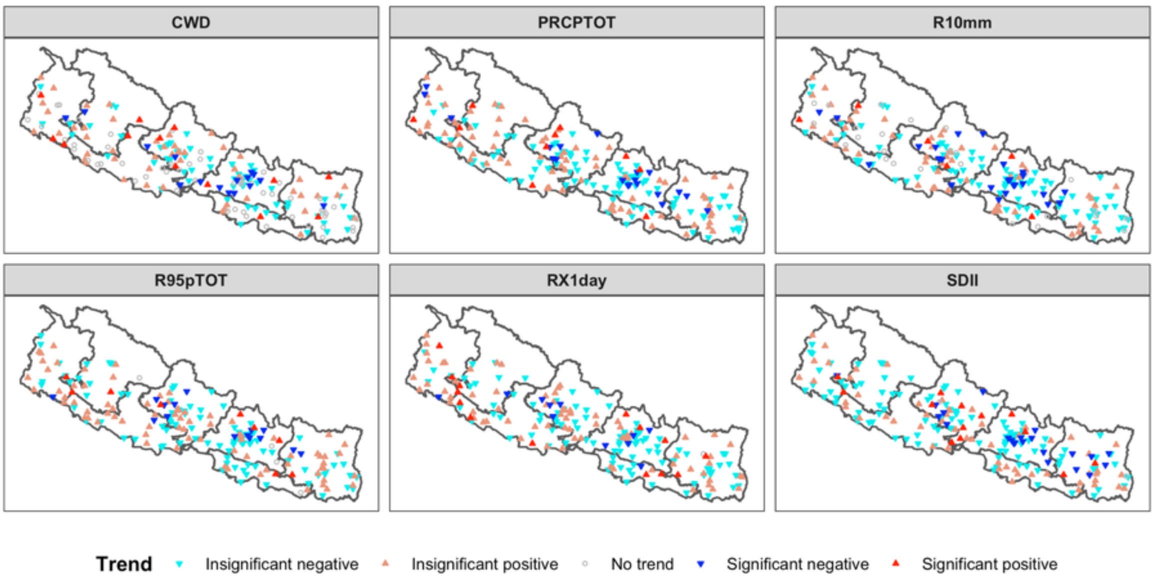

Figure 3.3: Temporal trends of mean and extreme precipitation indices during 1992–2021 by observational stations across Nepal. Significance at p = 0.05 level.

3.3.3. 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 also a significant positive association with flood mortality (Fig. 3.4). The results of selected regression models are presented in Table 3.3 and all regression models are presented in Tables A3.3 and A3.4 in the appendices. 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.

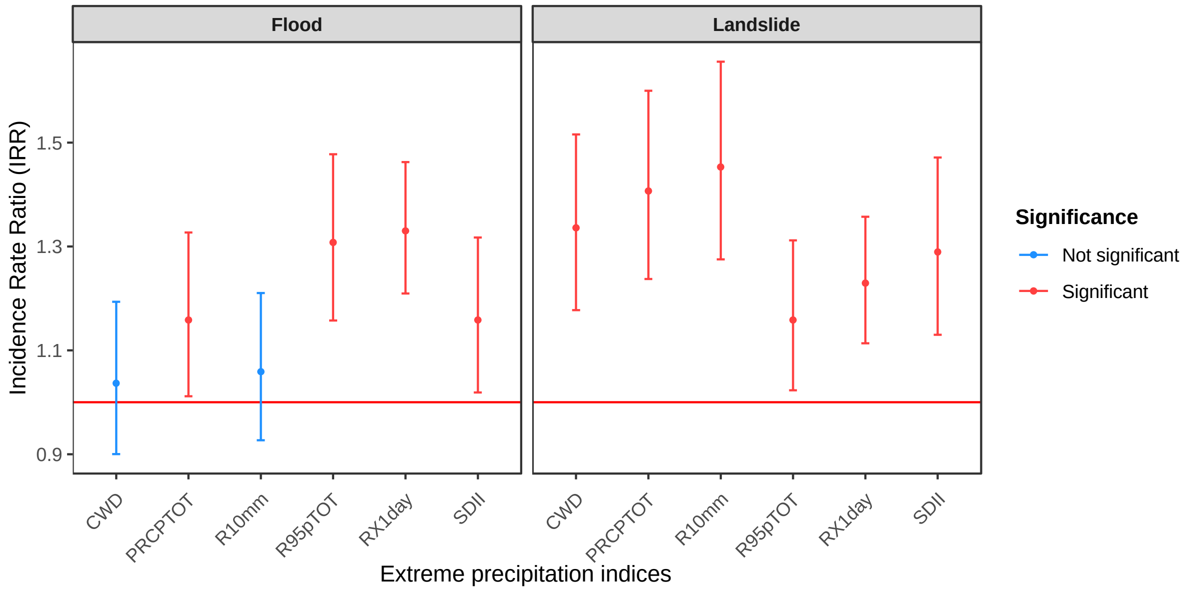

Figure 3.4: Effects of mean and extreme precipitation indices (in standardized Z-score) on flood and landslide mortality shown as Incidence Rate Ratios–IRR (points), and its 95% confidence interval - CI (lines). IRRs are estimated from the mixed effects ZINB models and equal to the exp (β_h) in equation 1. Statistical significance at the 0.05 level (see appendices Tables A3.3 and A3.4 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 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.

Table 3.3: 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	15420			13020		
Marginal R^2	0.303			0.466		

3.3.4. 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 3.3). The social vulnerability index showed a positive association with disaster mortality but was significant only with landslide mortality (Table 3.4). 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 3.4: 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		

3.4. Discussion and Conclusion

Landslides and floods have been the two deadliest forms of disaster in Nepal during 1992–2021, accounting for 70% of the total climatic 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 meters 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). Western Nepal has experienced less precipitation than the country on average, and its 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 (Karki et al. 2017; Bohlinger and Sorteberg 2018; Talchabhadel et al. 2018; Pokharel et al. 2019). 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 (Wang et al. 2013; Karki et al. 2017).

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 Terai flood of 2017, and the western Nepal flood of 2014 and 2021, were triggered by unusually high-intensity precipitation events (ISET 2015; Bhandari et al. 2018; 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 (Jongman et al. 2015; Wu et al. 2019; Formetta and Feyen 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 climatic disasters than rural ones (Chapagain et al. 2022). Hence, the observed rise in flood and landslide mortality, mainly in western Nepal, is attributable primarily to the rise in precipitation extremes in those regions due to climate change.

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 (Rajbhandari et al. 2017; MoFE 2019; Chapagain et al. 2021). 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.

Overall, climate change impacts attribution studies from the Global South are scarce, as most researchers think that lack of comprehensive data sets are a major constraint in carrying out analysis. However, due to the urgency for climate action, especially in low-income and highly vulnerable countries, results and analysis are much needed and cannot wait for further data acquisition. We demonstrated an example of using the most robust and high-resolution empirical data currently available for countries in the Global South. The findings are highly relevant in the global policy context to plan and implement adaptation and DRR measures. Moreover, it also highlights the need for urgent and stronger mitigation action and establishing mechanism to address loss and damage. This study can be replicated in other countries, regions, and at the global scale to further explore the role of climate change on disaster impacts in different parts of the world. Moreover, the statistical models developed here can be applied to predict future risks of climate-related disaster mortality in different climate and socioeconomic scenarios. Nevertheless, 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.

Chapter Four: Future Scenarios of Climate Extremes and their Implications in Key Climate Sensitive Sectors in Western Nepal

This chapter has been published as

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Abstract

Existing climate projections and impact assessments in Nepal only consider a limited number of generic climate indices such as means. Few studies have explored climate extremes and their sectoral implications. This study evaluates future scenarios of extreme climate indices from the list of the Expert Team on Sector-specific Climate Indices (ET-SCI) and their sectoral implications in the Karnali Basin in western Nepal. First, future projections of 26 climate indices relevant to six climate-sensitive sectors in Karnali are made for the near (2021–2045), mid (2046–2070), and far (2071–2095) future for low- and high-emission scenarios (RCP4.5 and RCP8.5, respectively) using bias-corrected ensembles of 19 regional climate models from the COordinated Regional Downscaling EXperiment for South Asia (CORDEX-SA). Second, a qualitative analysis based on expert interviews and a literature review on the impact of the projected climate extremes on the climate-sensitive sectors is undertaken. Both the temperature and precipitation patterns are projected to deviate significantly from the historical reference already from the near future with increased occurrences of extreme events. Winter in the highlands is expected to become warmer and dryer. The hot and wet tropical summer in the lowlands will become hotter with longer warm spells and fewer cold days. Low-intensity precipitation events will decline, but the magnitude and frequency of extreme precipitation events will increase. The compounding effects of the increase in extreme temperature and precipitation events will have largely negative implications for the six climate-sensitive sectors considered here.

Keywords: Climate extremes; ET-SCI, Climate change impacts, ClimPACT2, Karnali, Nepal

4.1. Introduction

Extreme weather and climate events linked with anthropogenic climate change have become more frequent and intense around the world since the 1950s (IPCC 2013, 2021). Furthermore, the changes in extremes will be larger with projected global warming (IPCC 2021). Nepal is one of the most impacted countries by extreme weather events and is at high risk due to its high vulnerability and low readiness (ND-GAIN 2018; Eckstein et al. 2021). Climatic disaster incidences have been increasing in recent decades, which is also the leading cause of natural disaster mortality in Nepal (Aksha et al. 2018). Warmer temperatures have intensified the risk of vector-borne diseases and epidemics (Thakur et al. 2012; Dhimal et al. 2015). Agricultural productivity losses due to changing climate cause severe food insecurity and have a detrimental impact on the country's overall economy (Chalise et al. 2017; Bocchiola et al. 2019). Therefore, a better understanding of the behavior of extreme values is necessary, particularly to understand its sectoral implications and plan for adaptation (ETCCDI 2009).

The characterization of climate extremes and their evolution over time can be made using standardized extreme indices (ETCCDI 2009). In 1999, the Expert Team on Climate Change Detection and Indices (ETCCDI) formulated a set of indices to detect and characterize the nature of climate extremes in terms of frequency, amplitude, and persistence. Subsequently, the Expert Team on Sector-specific Climate Indices (ET-SCI) was introduced in 2011 to expand the generic ETCCDI indices to more comprehensive and sector-specific climate indices (ET-SCI 2016). The team noted however that the sectorial practices and climate characteristics vary across the region and recommend the customization of the ET-SCI indices to fit the study location.

Past studies have analyzed historical extreme climate indices trends and observed a rise in heavy precipitation events and hot extremes across Nepal (Khatiwada et al. 2016; Karki et al. 2017, 2019; Bohlinger and Sorteberg 2018; Talchabhadel et al. 2018; Pokharel et al. 2019; Sharma et al. 2020; Poudel et al. 2020). For example, Karki *et al.,* (2019) observed a rising trend for warm days (13 days/decade) and nights (4 days/decade), but the cold days and nights are decreasing (6 days/decade). The high-intensity (> 300 mm/day) precipitation started becoming more frequent since 2000, which was not common earlier (Pokharel et al. 2019). DHM (2017) observed an increasing trend in the number of rainy days, especially in the northern region. Nevertheless, only a few studies have addressed the future climate extremes, and even fewer have explored their implications for various sectors (Rajbhandari et al. 2017; MoFE 2019; Pokharel et al. 2019; Dahal et al. 2020; Singh et al. 2021). Moreover, these studies are mostly based on means and a small subset of the old and generic ETCCDI indices.

The location-specific climate responses due to the heterogeneous geographic and climatic conditions within small spatial extents in Nepal demand future climate projections and impact assessments on a finer scale (Rajbhandari et al. 2017; Dhaubanjar et al. 2020). The faster increase in extreme precipitation in western Nepal compared to other parts of the country highlights the necessity of future climate assessments in this region (Bohlinger and Sorteberg 2018; Talchabhadel et al. 2018; Pokharel et al. 2019). However, basin-scale climate assessments are mostly concentrated in eastern Nepal (Bharati et al. 2014, 2019; Devkota and Gyawali 2015; Nepal 2016) as opposed to western Nepal (Dahal et al. 2020; Pandey et al. 2020).

Regional climate models (RCMs) are designed for a specific region and are richer in spatial and temporal detail to better simulate topography-influenced phenomena and extremes (Flato et al. 2013). Therefore, RCMs are more suitable than global climate models (GCMs) for climate projections in countries with diverse and steep terrain, such as Nepal (Dhaubanjar et al. 2020). Multi-modal ensembles are recommended for climate impact assessments (Knutti et al. 2010). However, most climate projections and impact assessments in Nepal have used a limited number of GCMs. The development of RCMs specifically for South Asia remains a relatively new initiative by the COordinated Regional Downscaling EXperiment for South Asia (CORDEX-SA) (Sanjay et al. 2017) to generate dynamically downscaled projections for the region. Dhaubanjar et al. (2020) presented one of the first and the most comprehensive studies that utilized all available 19 RCMs in CORDEX-SA to generate application-specific multi-model ensemble climate projections for the Karnali Basin. However, the scope of Dhaubanjar et al. (2020) was limited to ensemble generation.

Leveraging the bias-corrected and application-specific RCM ensemble projections generated by Dhaubanjar et al. (2020), this study presents the first assessment of the ET-SCI indices to understanding changes in future climate extremes and their sectoral implications in Karnali. We first identify sector-relevant climate indices for Karnali. Second, we project future scenarios of these climate indices. A total of 26 climate indices were selected based on an index evaluation, expert consultation, and literature review. Their trends were projected for three future timeframes, i.e., near (2021–2045), mid (2046–2070), and far (2071–2095) future, for two emission scenarios (RCP4.5 and RCP8.5). Unlike a pure climate projection study, we finally analyzed the potential implications of the projected index trends in six key climate-sensitive sectors in the region based on expert interviews and literature review.

4.2. Methodology

4.2.1. Study area

Covering an area of 49,889 km^2 with an elevation ranging from 142 to 8143 m along a south-north transect in western Nepal, the Karnali River Basin (Fig. 4.1), also referred to as Karnali in this paper, is at the headwaters of the Ganges Basin (Pandey et al. 2020). Area-wise, Karnali is the biggest river basin in Nepal, yet it is the least developed and most food-insecure region in the country (UN-WFP 2014). This region has the highest poverty rate in Nepal, with every second person being multidimensionally poor (NPC 2018). The highlands in Karnali are relatively water-poor regions in Nepal (Panthi et al. 2018). The indigenous communities rely on natural springs as their primary source of water for drinking and irrigation and are highly vulnerable to changes in precipitation (Matheswaran et al. 2019). The southern lowlands are prone to disasters, such as floods and droughts, and the northern highlands experience landslides and flash floods.

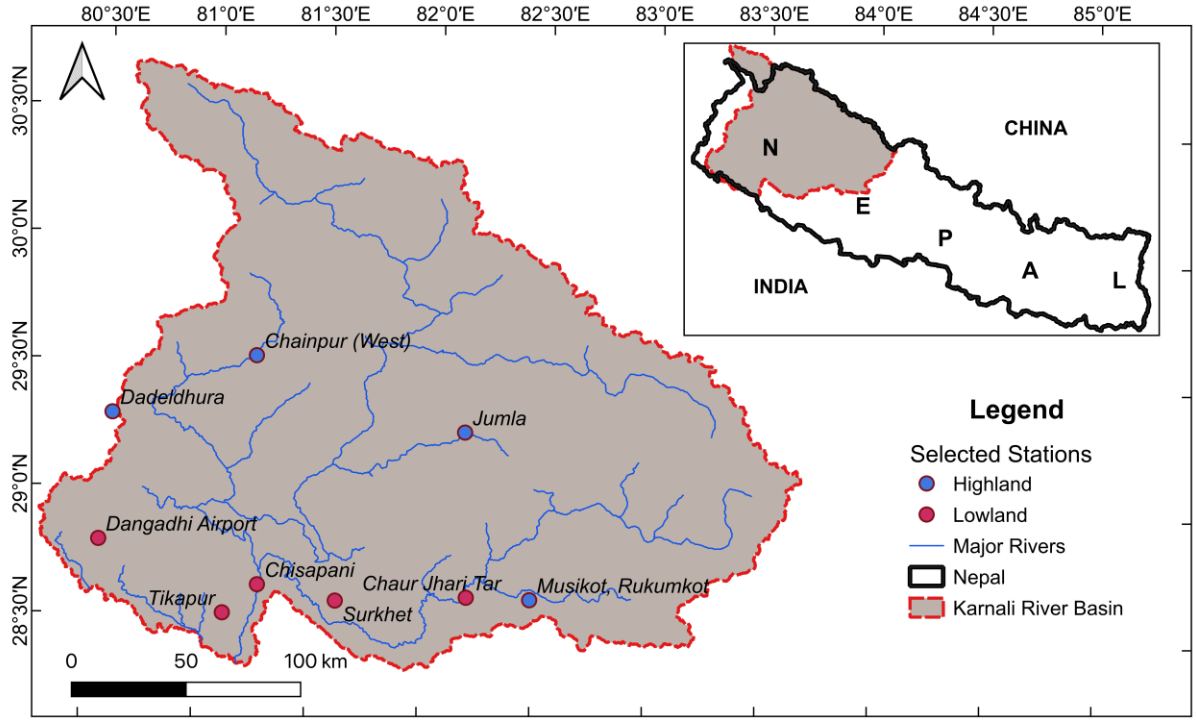

Figure 4.1: Map of the Karnali River Basin and locations of the meteorological stations selected for this study.

Western Nepal has over 336,927 ha of agricultural land, of which nearly 49% remains to be irrigated (CBS 2020). Similarly, Karnali has a run-off river-type hydropower potential of 15,660 MW because of the major rivers and steep slopes in the highlands (Jha 2010). Nearly 127 projects, including some of the country's largest hydropower and irrigation projects, are in various stages of development in this basin (IWMI 2018). Karnali is also a biodiversity hotspot, with approximately 14% of the area under protection, and is comprised of four national parks, one wildlife reserve, one hunting reserve, two buffer zones, and three Ramsar sites (Khatiwada and Pandey 2019; DNPWC 2020). Overall, Karnali remains largely rural, with sparse communities relying heavily on nature-based livelihoods, rich biodiversity and natural resources, and untapped hydropower potential spread throughout the basin. These characteristics of Karnali provide a suitable background for a multi-sectoral climate impact assessment on a relatively pristine basin.

4.2.2. Bias-corrected ensemble projection

An overview of our research design and methodology is presented in Fig. 4.2. We started with the ensemble projections developed by Dhaubanjar et al. (2020) for nine meteorological stations based on 19 RCMs in CORDEX-SA. Dhaubanjar et al. (2020) first use quantile mapping to bias-correct the 19 RCMs and then apply the climate futures framework (Clarke et al. 2011) to generate application-specific projections for climate impact assessment (see Table A4.1 in appendices for details on the stations and Table A4.2 for details on the RCMs). Ensemble projections are available for three future risk scenarios (low risk, consensus and high risk) for long-term water management of which we only consider the consensus case, i.e., projections based on an ensemble of RCMs that show consensus in the magnitudes of change in precipitation and temperature. More specifically, we use the consensus case data from Dhaubanjar et al. (2020) for the historical (1981–2005) period and three future timeframes (near: 2021–2045, mid: 2046–2070, and far: 2071–2095) under two global representative concentration pathways (RCP4.5 and RCP8.5). Details on data quality control, bias correction using the quantile-mapping approach, evaluation of the bias correction performance, and generation of the climate ensembles are provided in Dhaubanjar et al. (2020).

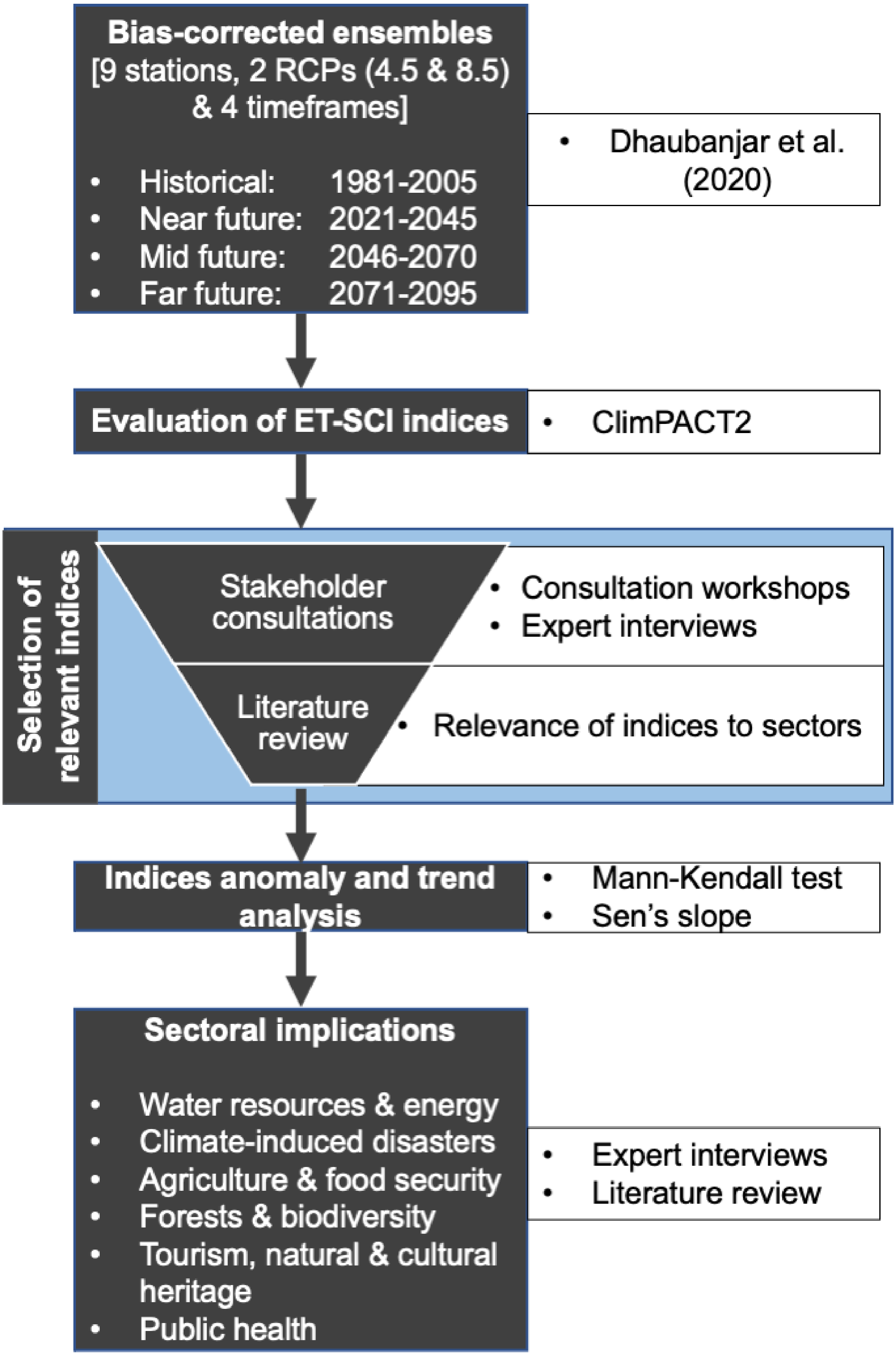

Figure 4.2: Methodological framework for unpacking future climate extremes in Karnali and their sectoral implications.

4.2.3. Evaluation of ET-SCI indices

The ClimPACT2 program, developed by ET-SCI (2016) in the R programming language, was used to evaluate 34 core and 29 non-core ET-SCI indices at both annual and monthly time-steps. For each station, we prepared single time-series combining bias-corrected historical (1981–2005) and future (2006–2100) time series for each of the six RCM ensembles as inputs to ClimPACT2. The bias-corrected historical data for 1981–2005 were therefore inserted as the base period for the evaluation of all the percentile-based indices. To allow for cross-comparisons with global studies, default values were used for indices with absolute thresholds. The evaluated index values were then sliced for the respective historical and future timeframes.

4.2.4. Selection of sector-relevant indices

The National Adaptation Plan (NAP) process in Nepal was initiated in 2015 to determine medium- and long-term adaptation needs, which identified seven sectors as the most climate-sensitive in Nepal (MoPE 2017). These sectors include (i) water resources and energy, (ii) climate-induced disasters, (iii) agriculture and food security, (iv) forests and biodiversity, (v) tourism and natural and cultural heritage, (vi) public health, and (vii) urban settlements and infrastructure. We considered six of these sectors in this study to identify the relevant indices and study the sectoral implications in Karnali. Urban settlement and infrastructure was not considered as a separate sector here because Karnali is a largely rural region.

To determine the relevance of the ET-SCI indices to the climate-sensitive sectors, we gathered qualitative inputs from stakeholders in two rounds of consultations. We conducted a hands-on workshop with 39 participants, largely practitioners and policymakers from all sectors, as shown in Fig. A4.1 in appendices. Participants engaged in group discussions followed by a survey asking for their perception of climate characteristics or types of extreme climate that posed risks to their sectors. Note that the climate indices were not directly referenced in the questionnaire; instead, real-life examples were presented to make participants consider what-if climate scenarios and their impacts on their sectors. Very few participants were able to consider climate characteristics beyond means and minimum and maximum values, providing a limited basis to consider the specialized ET-SCI indices.

To further unpack the stakeholder's perspectives, we followed up with more targeted key-expert interviews. We explicitly discussed the relevance of the ET-SCI indices with at least two experts from each sector (the list of consulted experts is given in Table A4.3). In addition, we reviewed the literature to identify the reported relationship between the climate characteristics and the sectoral impacts. Finally, considering the inputs from the stakeholders and literature, the type of indices and thresholds used, and our experiences working in Karnali, we selected 26 of the ET-SCI indices for this study. We grouped the indices by type into mean-based, absolute-value-based, percentile-based, threshold-based, and duration-based indices that characterize the average and extreme statistical features of the climate data. Details of the selected indices are summarized in Table 4.1.

Table 4.1: List of selected climate indices for this study (adapted from ET-SCI (2016)).

Index type	S. No.	ID	Name	Definition	Unit
Mean temperature indices	1.	TNm	Mean TN	Annual mean daily minimum temperature	°C
	2.	TXm	Mean TX	Annual mean daily maximum temperature	°C
Absolute-value-based extreme temperature indices	3.	TNn	Min TN	Annual coldest daily TN	°C
	4.	TNx	Max TN	Annual warmest daily TN	°C
	5.	TXn	Min TX	Annual coldest daily TX	°C
	6.	TXx	Max TX	Annual warmest daily TX	°C
Percentile-based extreme temperature indices	7.	TN10P	Amount of cold nights	Annual percentage of days when TN < 10^{th} percentile	%
	8.	TN90P	Amount of warm nights	Annual percentage of days when TN > 90^{th} percentile	%
	9.	TX10P	Amount of cool days	Annual percentage of days when TX < 10^{th} percentile	%
	10.	TX90P	Amount of hot days	Annual percentage of days when TX > 90^{th} percentile	%
Duration-based extreme temperature indices	11.	CSDI	Cold spell duration indicator	Annual number of days contributing to events where six or more consecutive days experience TN < 10^{th} percentile	days

	12.	WSDI	Warm spell duration indicator	Annual number of days contributing to events where six or more consecutive days experience TX > 90^{th} percentile	days
	13.	GDDgrow10	Growing degree days	Annual sum of the daily mean temperature (TM) − 10	degree-days
	14.	SU	Summer days	Annual number of days when TX > 25°C	days
	15.	TR	Tropical nights	Annual number of days when TN > 20°C	days
Magnitude-based precipitation indices	16.	PRCPTOT	Total precipitation	Sum of daily precipitation ≥ 1.0 mm	mm
	17.	WDAYS	Number of wet days	Annual number of days when precipitation is ≥1.0 mm	days
	18.	SDII	Simple Daily Intensity Index	PRCPTOT divided by the WDAYS	mm/day
Absolute-value-based extreme precipitation indices	19.	RX1day	Max 1-day precipitation	Maximum annual 1-day precipitation total	mm
	20.	RX5day	Max 5-day precipitation	Maximum annual 5-day precipitation total	mm
Threshold-based extreme precipitation indices	21.	R10mm	Number of heavy rain days	Annual number of days when precipitation is ≥10 mm	days
	22.	R30mm	Number of very heavy rain days	Annual number of days when precipitation is ≥30 mm	days
Percentile-based extreme precipitation indices	23.	R95pTOT	Contribution from very wet days	Fraction of total wet-day precipitation that comes from very wet days	%

	24.	R99pTOT	Contribution from extremely wet days	Fraction of total wet-day precipitation that comes from extremely wet days	%
Duration-based extreme precipitation indices	25.	CDD	Consecutive dry days	Maximum annual number of consecutive dry days (when precipitation is <1.0 mm)	days
	26.	CWD	Consecutive wet days	Maximum annual number of consecutive wet days (when precipitation is ≥1.0 mm)	days

4.2.5. Index anomaly and trend analyses

For the selected indices, we analyzed the projected index trend and their anomalies to evaluate the spatio-temporal variation across the regions. The widely used non-parametric Mann-Kendall test (Mann 1945; Kendall 1975) was used to investigate the trend significance for the near-, mid-, and far-future timeframes. The trend value was estimated using Sen's slope (Sen 1968) method. Only trend values significant at 95% confidence interval ($p < 0.05$) are reported in this paper unless otherwise stated. Nevertheless, the count of the trend significance cases for each index is summarized in Fig. 4.3. The index anomaly or the projected change from the historical average was calculated by subtracting the mean of the bias-corrected historical value from the equivalent projected future value. To capture the altitudinal difference, the five stations located below an altitude of 1000 m were grouped as the lowland stations and the four stations above an altitude of 1000 m were grouped as the highland stations. Trends across the four seasons (pre-monsoon: March–May, monsoon: June–September, post-monsoon: October–November, and winter: December–February) were further assessed for relevant indices based on the monthly values.

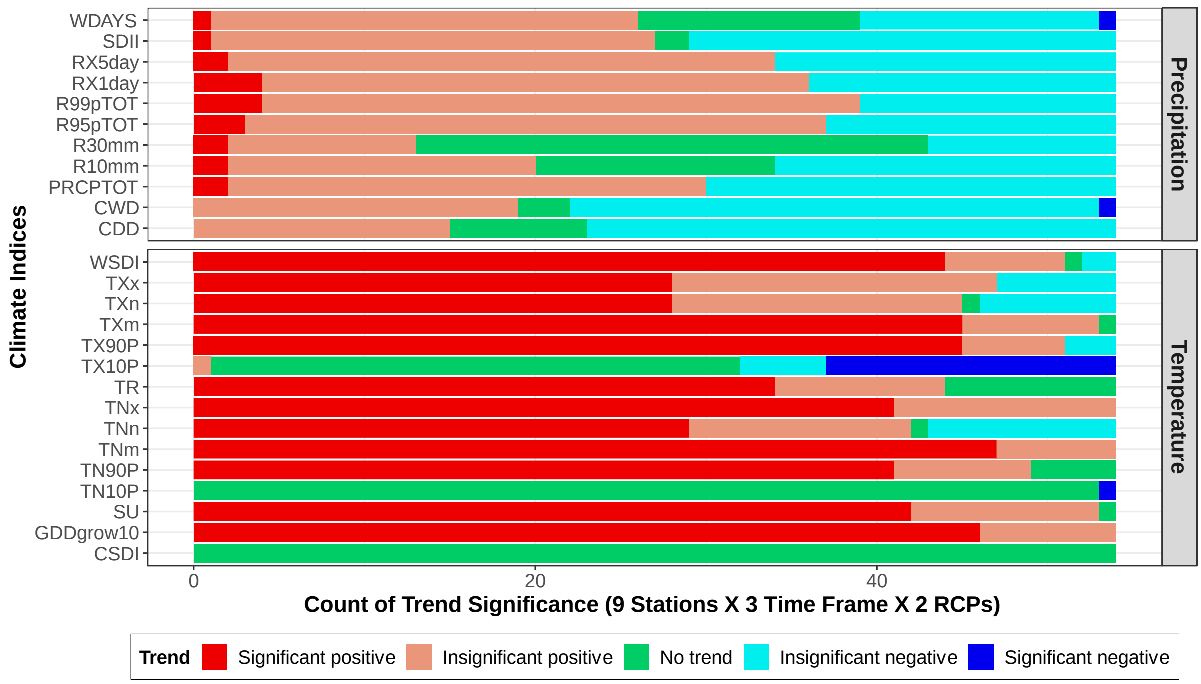

Figure 4.3: Future trends of the selected climate indices defined in Table 4.1. The horizontal axis represents the count of the index trend significance cases out of 54 cases from the nine stations, three future timeframes, and two RCPs.

4.2.6. Characterization of sectoral implications

The projection results of the selected indices were shared with experts from all of the studied sectors in the third round of expert interviews. The experts were asked to share their opinions concerning the potential implications of the projected index trends on their sectors. Received inputs were supplemented by a literature review to characterize the potential implications of the projected changes to the six sectors.

4.3. Results and discussion

4.3.1. Projected changes in temperature

4.3.1.1. Mean temperature indices

Our projections show an increase in the annual mean daily minimum and maximum temperatures (mean TN and TX, respectively) in Karnali; these increases are more pronounced in the highlands and during winter (Fig. 4.4). In the near future, the annual mean TN and TX are both projected to increase on average by 0.03 °C/year in RCP4.5 and by 0.04 °C/year in RCP8.5. This increasing trend slows in the mid future and is not significant in the far future in RCP4.5 (Fig. A4.2). Conversely, in RCP8.5, the trends for mean TN and TX are 0.06° C/year and 0.05 °C/year, respectively, in the lowlands in the mid future. Both indices increase at a rate of 0.07 °C/year in the highlands. The winter shows the highest warming rate from the near future with the mean TX increasing as fast as 0.1 °C/year in the highlands in the mid future. The warming rate is highest during the pre-monsoon in the lowlands. The annual mean TN and TX are projected to continue to increase by 0.06 °C/year and 0.04 °C/year, respectively, in the lowlands in the far future. In the highlands, the trends of the mean TN and TX are 0.06 °C/year and 0.05 °C/year, respectively. The monsoon shows the highest warming rate in the far future. The higher rate of the mean TN than the mean TX indicates that the nighttime temperature will increase faster than the daytime temperature and that the diurnal temperature range will narrow in the future.

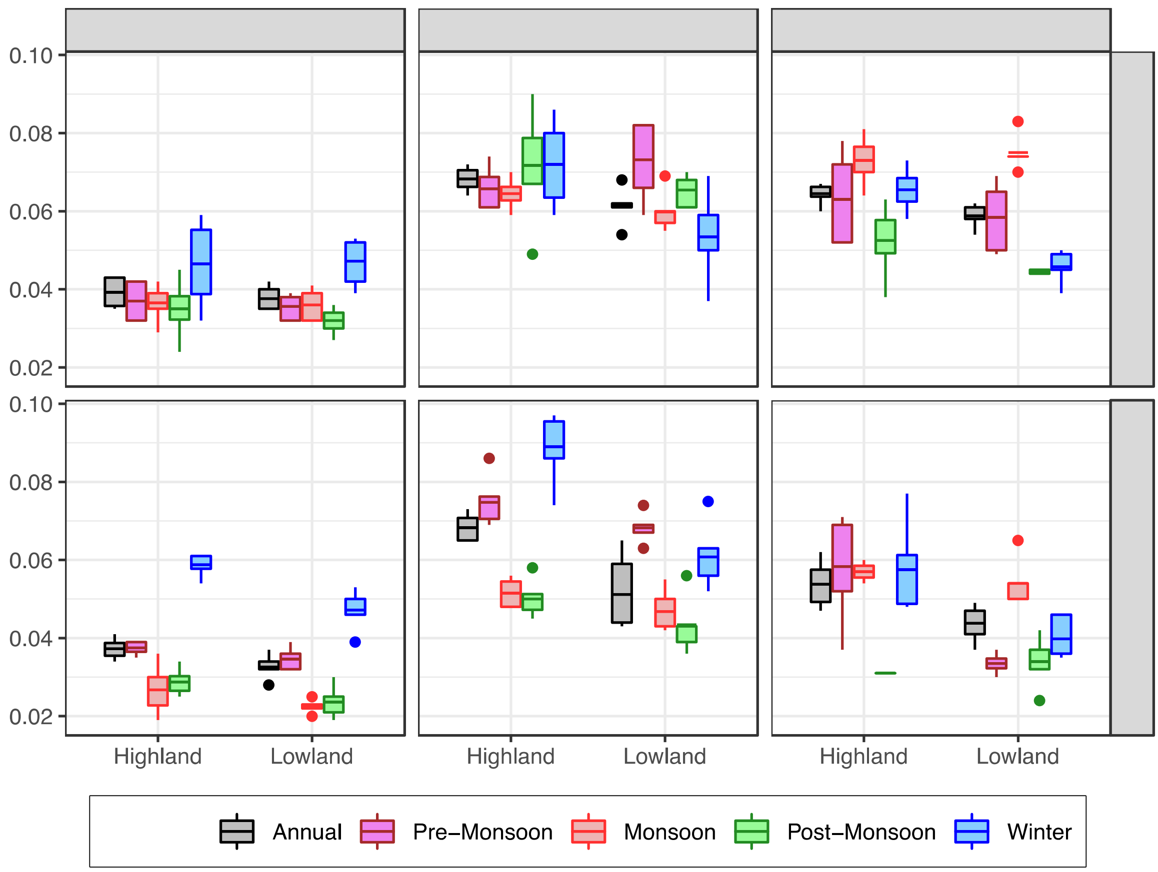

Figure 4.4: Projected annual and seasonal mean TN and mean TX trends for Karnali by future timeframe and geographical region in the RCP8.5 scenario. The middle dark lines represent the mean; the boxes represent the interquartile range; the whiskers represent the minimum and maximum values; and the dots represent outliers.

In RCP8.5, by the end of the century, the annual mean TN and TX are projected to be 4–5 °C and 3.5–4.5 °C warmer, respectively, in the lowlands and 4.5–6.0 °C and 4.5–5.0 °C warmer, respectively, in the highlands than the historical average (Fig. 4.5). However, these values could exceed 6 °C during the winter and pre-monsoon in the highlands. In RCP4.5, the annual mean TN and TX will be approximately 1.5–2.5 °C and 1.0–2.5 °C warmer, respectively, in the lowlands and 2.0–2.5 °C and 2.5–3.0 °C warmer, respectively, in the highlands.

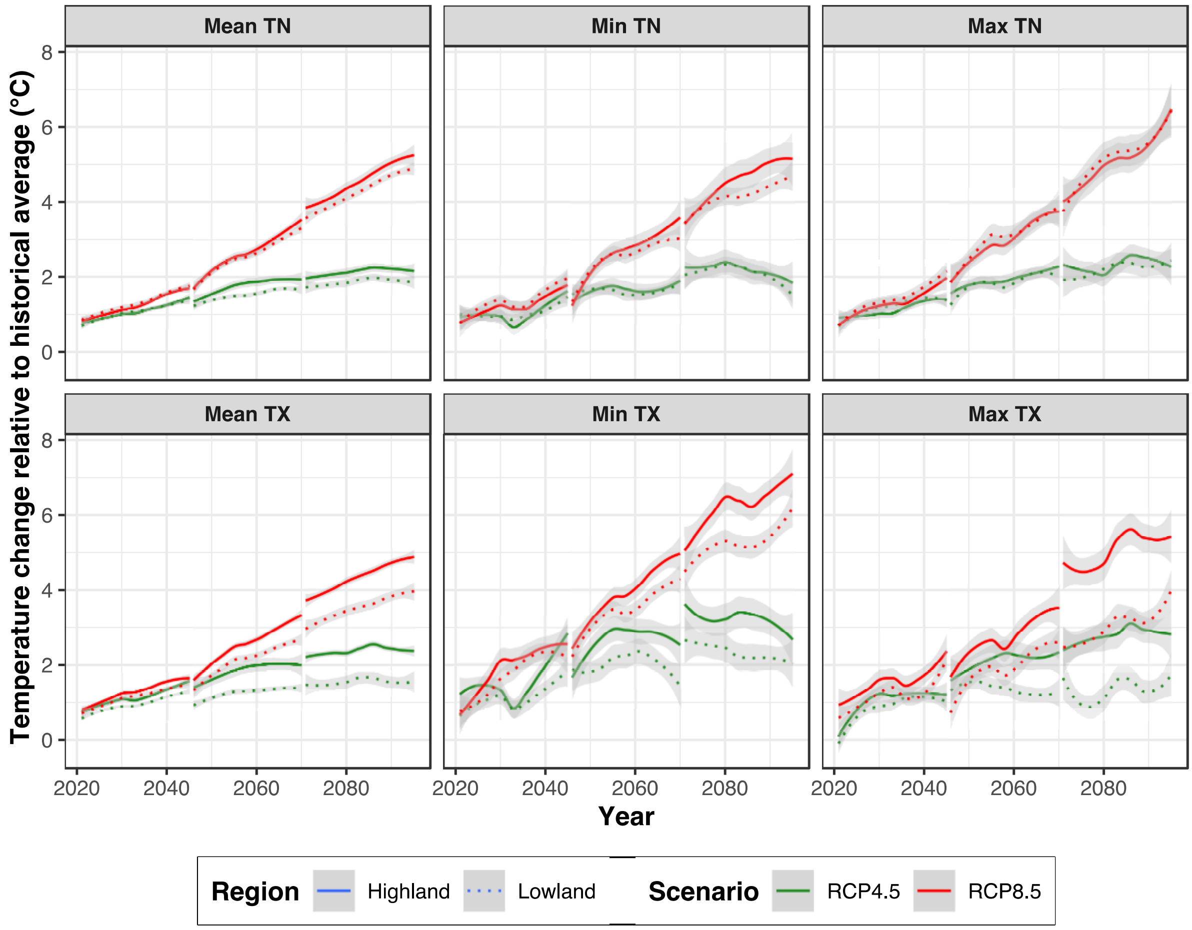

Figure 4.5: Projected mean and extreme temperature index anomalies (base period 1981–2005) for Karnali by future timeframe, scenario, and geographical region. The dark lines represent the locally smooth values, and the gray bands represent the 95% confidence intervals.

4.3.1.2. Absolute-value-based extreme temperature indices

The annual coldest and warmest daily minimum temperature (min and max TN) and maximum temperature (min and max TX) show higher warming than their respective means (mean TN and mean TX) discussed in section 4.3.1.1. Relative to the historical average, the min and max TN will be 1.5 °C and 2.5 °C higher, respectively, in RCP4.5 but 4.5 °C and 6.5 °C higher, respectively, in RCP8.5 in both the lowlands and the highlands (Fig. 4.5). The min and max TX will be 1.5 °C and 2.5 °C higher, respectively, in the lowlands and 2 °C and 3 °C higher, respectively, in the highlands in RCP4.5. In RCP8.5, the min and max TX will be 6 °C and 4.5 °C higher, respectively, in the lowlands and 6.5 °C and 6 °C higher, respectively, in the highlands. The trends of the absolute-value-based extreme temperature indices for Karnali are presented in Fig. A4.3 in appendices.

4.3.1.3. Percentile-based extreme temperature indices

The amount of hot days (TX90P) and warm nights (TN90P) steeply increases in the range of 1.3–1.9 percentage points/year in the near future in both RCPs (Fig. 4.6 and Fig. A4.4). This leads to nearly 100% and 80–90% of the days in the year being warmer than the historical hot days and warm-night threshold by the end of the mid future in RCP8.4 and RCP4.5, respectively. Consequently, the amount of cool days (TX10P) and cold nights (TN10P) is already very low in the near future and declines showing no statistically significant trend (Fig. 4.3). Nearly no days will be below the historical cool days and cold-night threshold in all future scenarios. Such projections, therefore, suggest an alarming increase in extreme temperatures both during the daytime and at night compared to the historical thresholds. A new normal will be necessary to classify extreme temperature thresholds in future contexts.

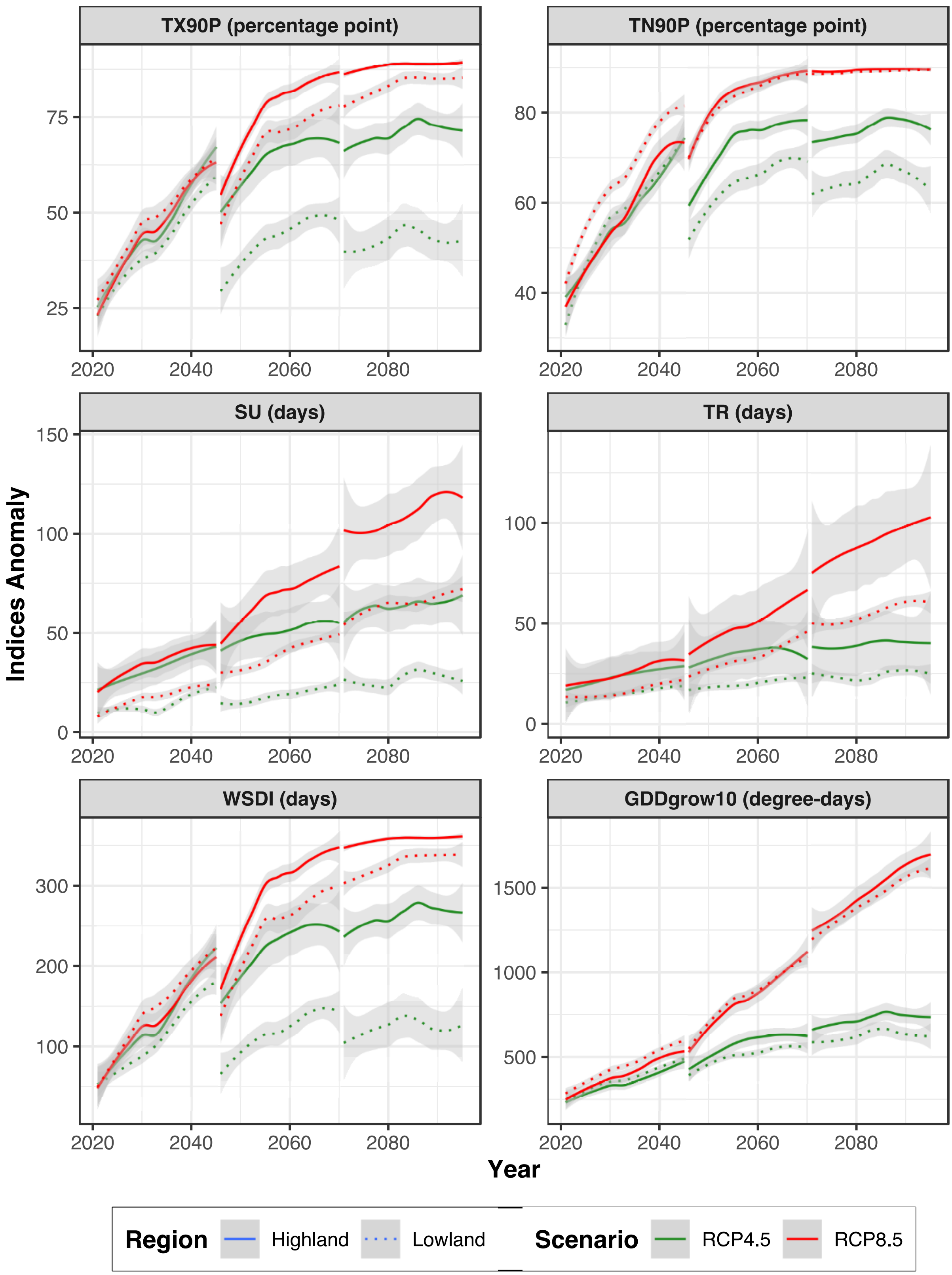

Figure 4.6: Projected percentile- and duration-based extreme temperature index anomalies for Karnali by future timeframe, geographical region, and emission scenario (different y-axis scales are used for each index). Base period, lines, and shading are as in Fig. 4.5.

4.3.1.4. Duration-based extreme temperature indices

Both the number of summer days (SU) and the number of tropical nights (TR) are increasing, similar to the trends of the amount of hot days and warm nights in section 4.3.1.3 (Fig. 4.6). However, higher rates are seen for the highlands. For example, SU will increase by 0.5–1.4 days/year in the highlands but by 0.4–0.9 days/year in the lowlands in the near future for both RCPs (Fig. A4.4). The rate will slow in RCP4.5 but will increase to 1.2–2.3 days/year in the highlands and 0.7–1.2 days/year in the lowlands in RCP8.5. In the far future, there is no significant trend for RCP4.5; however, SU will increase by 0.7–1.3 days/year in the highlands, while nearly all 365 days of the year will be summer days in the lowlands. TR shows a similar increasing trend to SU.

The warm spell duration indicator (WSDI) is increasing fastest in the near future at a rate of 5–8 days/year (Fig. 4.6 and Fig. A4.4) in both RCPs and both regions. In RCP4.5, the increasing rate slows to 2–5 days/year in the mid future, while the trend is not significant in the far future. In RCP8.5, the increasing rate is 5–7 days/year in the mid future resulting in nearly 365 days of the year being classified as a warm spell in both the highlands and the lowlands in the far future. Subsequently, the cold spell duration indicator (CSDI) has zero values in all future scenarios and shows no trend (Fig. 4.3).

The growing degree days (GDDgrow10) is a measure of the heat accumulation used to predict plant developmental rates. This index will increase at a rate of 7–10 degree-days/year in RCP4.5 and 9–14 degree-days/year in RCP8.5 in the near future in both regions (Fig. A4.4). This increasing rate will slow in the mid future, and no significant trend is observed in the far future in RCP4.5. In RCP8.5, GDDgrow10 is projected to increase by 18–25 degree-days/year in the mid future and 17–22 degree-days/year in the far future, with a slightly higher rate in the highlands. By the end of the century, GDDgrow10 will be higher by 1500–2000 degree-days in RCP8.5 and 500–1000 degree-days in RCP4.5 compared to the historical average (Fig. 4.6).

4.3.2. Projected changes in precipitation

4.3.2.1. Magnitude-based precipitation indices

Unlike temperature, the precipitation indices do not show statistically significant future trends in most cases (Fig. 4.3). The spatial differences and the differences between the future emission scenarios in precipitation are also not as stark as those seen for temperature. This suggests a higher uncertainty in precipitation trends than in temperature trends. However, the change in annual total precipitation (PRCPTOT) from the historical average is positive in most scenarios (Fig. 4.7). Therefore, Karnali is projected to receive more annual rainfall than the historical average in all future scenarios. Even though the PRCPTOT trends are not significant, they are mostly positive in the near and far future and negative in the mid future. Similar to the annual total, the changes in the pre-monsoon, monsoon, and post-monsoon precipitation are mostly positive. The largest percentage change from the historical average is projected for the post-monsoon precipitation. However, the percentage change in the winter precipitation, particularly in RCP8.5, is mostly negative. This indicates the occurrence of drier winters in the future.

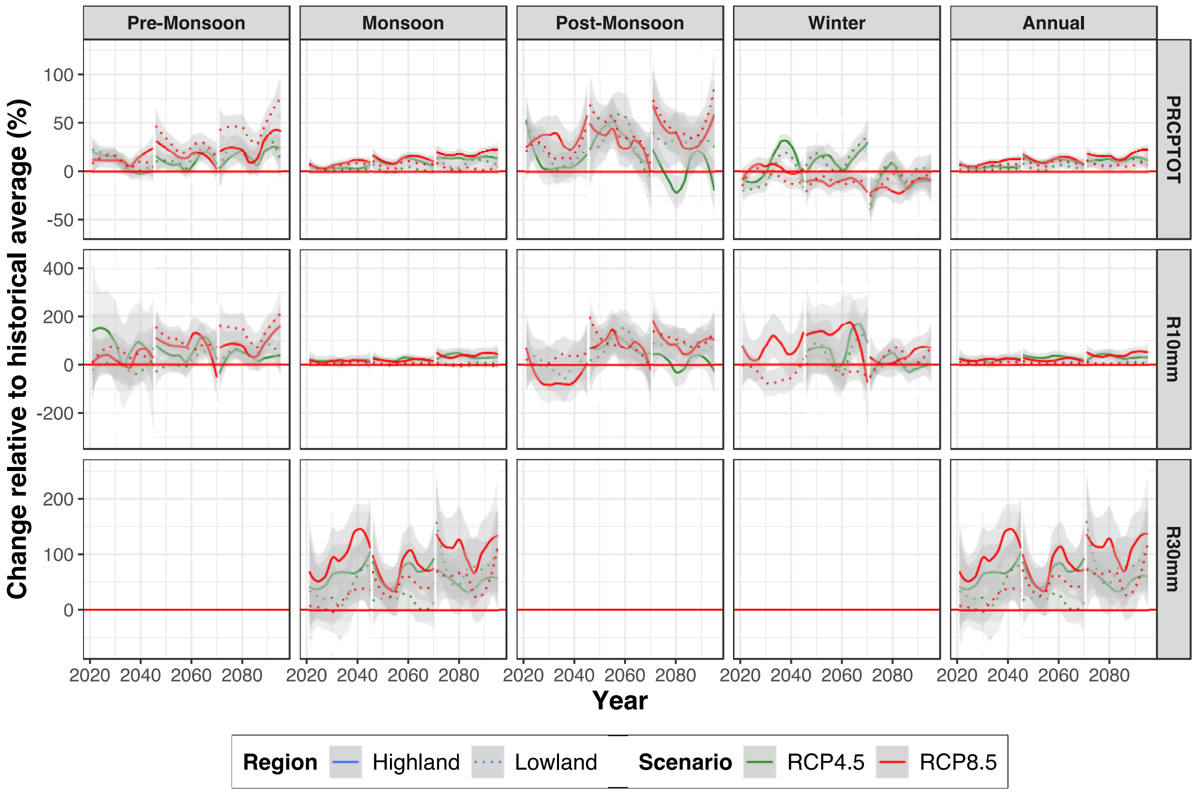

Figure 4.7: Projected percentage change in annual and seasonal total precipitation (PRCPTOT) and number of heavy and very heavy rain days (R10mm and R30mm) for Karnali by future timeframe, geographical region, and emission scenario. Base period, lines, and shading.

The simple daily intensity index (SDII) is also mostly positive in the future (Fig. 4.8). However, the projected annual number of wet days (WDAYS) shows a relatively unchanged pattern in the future. Therefore, the future annual precipitation change is projected to be dominated by higher intensity precipitation than in the past.

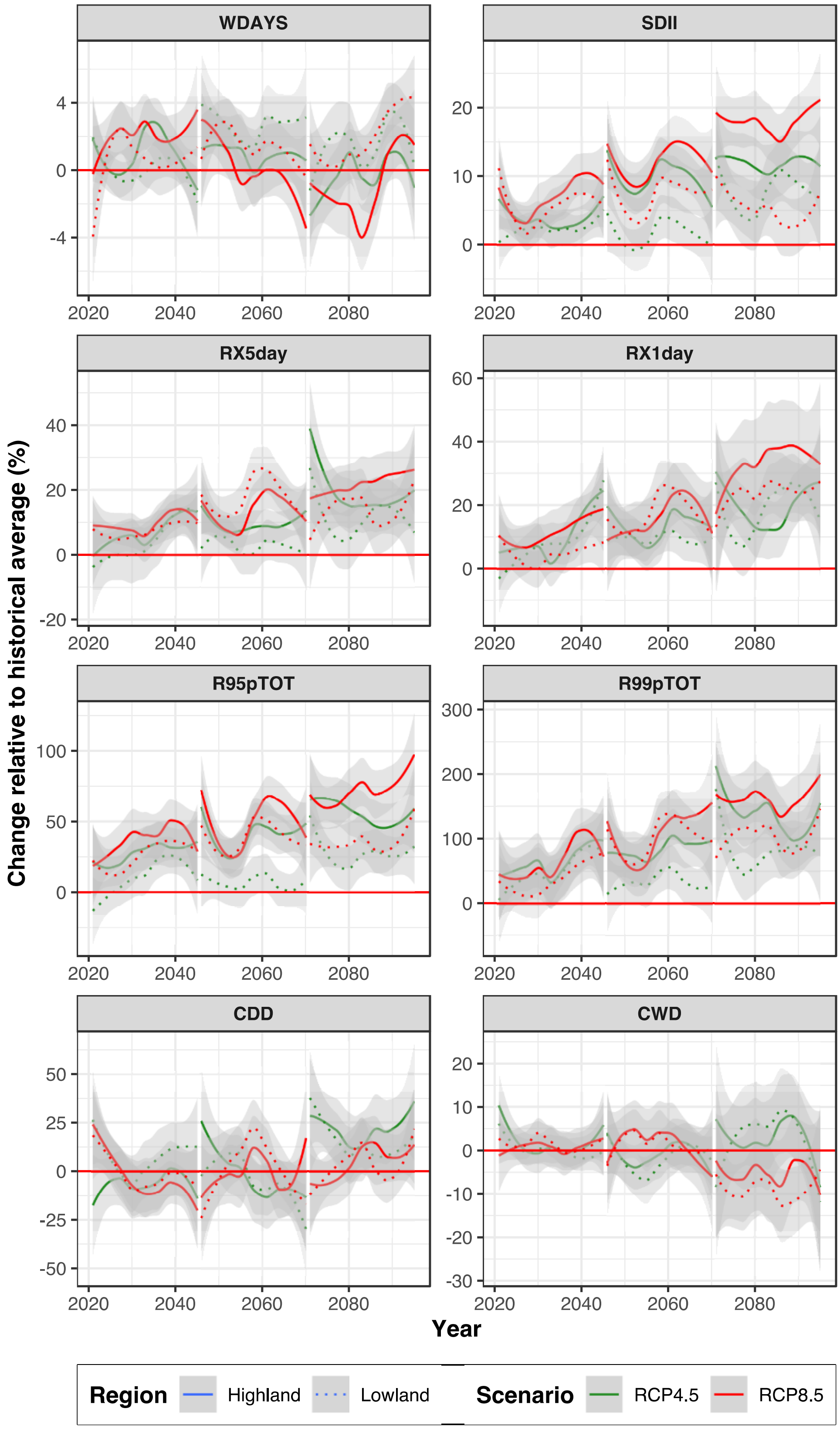

Figure 4.8: Projected percentage change in the extreme precipitation indices from the historical average for Karnali by future timeframe, geographical region, and emission scenario. Base period, lines, and shading are as in Fig. 4.5.

4.3.2.2. Absolute-value-based extreme precipitation indices

Corroborating the increasing SDII values, the changes in the maximum annual 1- and 5-day precipitation totals (RX1day and RX5day, respectively) are also positive for the future scenarios (Fig. 4.8). The index trends are also positive, although not significant, in both regions for a majority of the scenarios and negative in some, especially in the far future (Fig. 4.3). Similarly, the RX1day shows a higher change than the RX5day. The intensities of 1- and 5-day extreme precipitation events could be up to 60% and 40% higher, respectively, than the historical average in the highlands in the far future.

4.3.2.3. Threshold-based extreme precipitation indices

The numbers of heavy and very heavy rain days (R10mm and R30mm, respectively) show a strong positive change in the future (Fig. 4.7). The annual R10mm could double in some regions, while the R30mm could increase two- to three-fold by the far future. R30mm are rarer events but show a much higher increase in percentage relative to the historical average than R10mm. The trend values of both indices in most scenarios are not statistically significant. Karnali is projected to experience more heavy rain days in all seasons and more very heavy rain days in the monsoon in the future. Even during the pre- and post-monsoon, Karnali may experience some very heavy rain days in the mid and far future, which was not normal in the past (not shown in Fig. 4.7 due to extremely high percentage change).

4.3.2.4. Percentile-based extreme precipitation indices

The percentage changes in the contributions from very wet and extremely wet days (R95pTOT and R99pTOT, respectively) are mostly positive in future scenarios (Fig. 4.8). This is due to the increase in the rainfall intensities, as shown by RX1day and RX5day, and the frequency, as shown by R10mm and R30mm, of extreme precipitation days. The index trends are mostly positive in the near and mid future and both positive and negative in the far future (Fig. 4.3). The contribution from very wet days could double and the contribution from extremely wet days could triple compared to the historical average by the far future.

4.3.2.5. Duration-based extreme precipitation indices

Similar to the annual WDAYS, the percentage changes in consecutive dry and wet days (CDD and CWD, respectively) are also equally distributed in negative and positive sides in the near and mid future (Fig. 4.8). However, the CDD changes are positively skewed, and the CWD changes are negatively skewed, indicating a potential increase in CDD in the far future. The inter-annual and spatial variability of CDD and CWD might also increase in the future.

4.3.3. Projection results with respect to historical trends and other future projections

Our projection results are largely in agreement with the observed historical trends in the region and with other comparable projections. The projected warming in the highlands and lowlands in Karnali by the end of the century is slightly higher than the GCM-based projected national average for the respective regions and scenarios by MoFE (2019) but similar to the projections made for Karnali by Dahal et al. (2020). MoFE (2019) projected average warming of 3.69 °C and 3.44 °C in middle mountain and lowlands respectively in the RCP8.5 scenario by 2071-2100. Nevertheless, MoFE (2019) also projected that western Nepal would warm faster than eastern Nepal and that the pre-monsoon and winter would warm the most. The projected higher warming trends in the highlands are consistent with the elevation-dependent warming (EDW) trends observed across Nepal (Khatiwada et al. 2016; DHM 2017; Karki et al. 2019; Thakuri et al. 2019; Dahal et al. 2020). Such EDW in southern Himalaya could be attributed to the weakening monsoon and the reduced cloud cover in the region (Yang et al. 2018; Karki et al. 2019; Thakuri et al. 2019). The faster increase in the mean TN than the mean TX, however, is opposite to the historical warming pattern in Nepal. The weakening winter monsoon in western Nepal could be a cause for higher winter warming leading to a faster increase in mean TN (Wang et al. 2013; Karki et al. 2017; Yang et al. 2018). The projected extreme temperature index trends are largely consistent with the projected increase in warm extremes and decrease in cold extremes across Nepal (Rajbhandari et al. 2017; MoFE 2019; Singh et al. 2021). For example, MoFE (2019) projected that the hot days in Nepal will increase by 87% in RCP4.5 and 125% in RCP8.5 by the end of the century. Similarly, the cold nights will decrease by 53% and 74% in the respective scenarios. Nevertheless, it is hard to make one-to-one comparison of these indices due to the underlying differences such as baseline period, location, and climate models used. A similar increasing trend of hot extremes and decreasing trend of cold extremes was observed in the historical period (DHM 2017; Bohlinger and Sorteberg 2018; Karki et al. 2019; Poudel et al. 2020).

The projected increase in the annual total precipitation in Karnali agrees with the historically observed increasing annual precipitation trend in western Nepal (Khatiwada et al. 2016; Karki et al. 2017; Sharma et al. 2020), even though some studies (Khatiwada et al. 2016; Pokharel et al. 2019; Dahal et al. 2020) also reported a decreasing trend, mainly in the lowlands. In the future, Dahal et al. (2020), MoFE (2019), and Pokharel et al. (2019) all project an increase in the annual total precipitation but a decrease in winter precipitation similar to the projection in our study. A decreasing trend in the winter precipitation in western Nepal has already been observed in the historical period (Khatiwada et al. 2016; Karki et al. 2017). Wang et al. (2013) argue that the decreasing winter precipitation in western Nepal is linked with the warming sea surface temperature in the Indian Ocean, alteration of Arctic Oscillation, and rise in anthropogenic aerosols. High-intensity extreme precipitation events are more common in Karnali compared to other parts of Nepal (Karki et al. 2017; Bohlinger and Sorteberg 2018; Talchabhadel et al. 2018; Pokharel et al. 2019). Furthermore, these studies reported an increasing trend in extreme precipitation in the past. The projected increase in the frequency and intensity of the extreme precipitation indices is in line with other projections for Nepal (MoFE, 2019; Rajbhandari et al., 2017; Singh et al., 2021). MoFE (2019) projected that there will be around 20% more very wet days but 60% more extreme precipitation days in Nepal by the end of the century in RCP8.5.

4.3.4. Sectoral implications

4.3.4.1. Water resources and energy

Projection results indicate that the Karnali region will experience a change in the precipitation patterns with wet-get-wetter and dry-get-drier. The increase in the RX1day and RX5day, R10mm and R30mm, and R95pTOT and R99pTOT will increase the peak flow. The increased peak flow may cause damage to hydropower and irrigation infrastructures and siltation. On the other hand, the decrease in the occurrence of both scattered and consecutive low-intensity rainy days will reduce the percolation of water into the subsurface affecting groundwater recharge and subsequent baseflow contribution to streams, natural springs, and aquifer storages. Such decline in base flow could affect water available for electricity generation or agriculture. The projected decrease in winter precipitation, when the water availability and river flow are lowest (Dahal et al., 2020; Khatiwada et al., 2016), followed by hot and dry pre-monsoon can increase the water stress in the region in the future. This could exacerbate migration and settlement displacement in the highlands, as observed in other parts of the country (Joshi and Dongol 2018).

4.3.4.2. Climate-induced disasters

A projected increase in both the intensity (shown by RX1day and RX5day) and the frequency (shown by R10mm and R30mm) of extreme precipitation events, mainly during the already very wet monsoon, could increase the risk of landslides and erosion in the highlands. The increase in the peak flow caused by the increase in extreme rain could exacerbate flash floods and cause the inundation of fields and settlements in the lowlands. Because the maximum 1- and 5-day precipitation is projected to increase by 40–60%, even a single extreme event could be devastating. Moreover, the increasing R10mm in all future timeframes and the occurrence of R30mm in the far future, even during the pre-and post-monsoon, indicate the possibility of these disasters occurring even during the dry season. An increase in the probability of floods and landslides in the historically dry season is alarming because such events are more likely to catch people off-guard.

The projected higher increase in temperature in the highlands could accelerate Himalayan glacier retreat and increase the size and number of glacial lakes, increasing the risk of glacial lake outburst floods. The highest warming of the mean and extreme temperatures in the lowlands during the hot pre-monsoon and monsoon and extended warm spells could increase the risk of heatwaves in the future. This risk is even higher in the growing urban areas because of the urban heat island effect.

4.3.4.3. Agriculture and food security

The spatial differences in the projected climate extremes in Karnali indicate varying implications for agriculture in the highlands and lowlands in the short and long term. The decline in cold nights and increase in mean temperatures, warm spells, and growing degree days suggest that more areas in the highlands could become favorable for agriculture. A potential increase in the annual precipitation also favors this expansion. According to some studies, current subsistence farming in Karnali could expand to grow crops such as rice, maize, bananas, and vegetables at higher altitudes, provided other conditions, such as water availability and soil fertility, are favorable (Bhatt et al. 2014; Ranjitkar et al. 2016). Nevertheless, the increasing temperature has already shown negative impacts on major cereal crop (wheat, rice, and maize) production in Karnali, Dudh Koshi, and other parts of the country (Bocchiola et al. 2019; Khatiwada and Pandey 2019), warning against a focus on the potential expansion of cultivable areas with increasing temperatures in the highlands.

The compounded effect of the changes in the temperature and precipitation patterns will directly influence crop physiological processes, crop seasons, phenology, and crop cultivation suitability, while increasing the incidence of disease, pests, and other disasters affecting crop production (Bocchiola et al. 2019; Aryal et al. 2020). Therefore, the negative consequences of the projected climate on the crop yield will most likely surpass the positive impacts in the long term, worsening food insecurity in the region. Bhatt et al. (2014) pointed out that many crops are already under temperature stress in the lowlands, with impacts likely to worsen because the mean and extreme maximum temperatures are projected to increase by as much as 6 °C by the end of the century in RCP8.5.

Any change in the precipitation patterns will challenge the existing agricultural practices in Karnali that largely remain rain-fed and will increase the uncertainties in farmer decision-making. The projected decrease in the critical winter precipitation and increase in temperature will affect winter crops such as wheat, potatoes, oilseeds, and vegetables. Similarly, the temperature increases could also increase evapotranspiration. As frequent and severe droughts observed over the last decade in Karnali have already shown, such dry conditions and decreased soil moisture will lead to a decrease in the crop yield and soil degradation over time (Wang et al. 2013; Khatiwada and Pandey 2019). The actual level of the impact on agriculture also depends on the extent to which farmers adapt their agricultural practices to the changing climate.

4.3.4.4. Forests and biodiversity

The forests and biodiversity along the south-north transect in Karnali will respond differently to the projected changes. The increasing average temperature will shift the climate boundaries northward in Nepal's Himalaya ultimately affecting the current biome and species distribution (Zomer et al. 2014; Talchabhadel and Karki 2019). Grasslands and shrublands in the highlands in Karnali include several endemic species and high-value medicinal plants, such as Yarsagumba (*Ophiocordyceps sinensis*). However, such sensitive alpine ecosystems may experience hot days and nights during 80–90% of the year by the mid future, even in the RCP4.5 scenario. Winter could be more than 6°C warmer by the end of the century in RCP8.5. The characteristic cold winter climate of the highlands could vanish in the long term because the mean and extreme temperature warming rate is highest in the highlands. Such warming will enable a future advance of tree lines, and such a shift in the tree line into treeless ecosystems could have major consequences, such as decreases in alpine diversity, carbon storage, and ecosystem services (Schickhoff et al. 2016; Bhattacharjee et al. 2017).

The projected higher temperature will favor the expansion of climatically suitable regions for invasive alien plants in the southern tropical and temperate forest and agricultural lands; this has already been observed in the region (Shrestha and Shrestha 2019; Bhatta et al. 2020). The expanded summer and warm spells may cause changes in the vegetation phenology and an early onset of the growing season, particularly in the ecoregions of higher elevations in Karnali, as indicated in the literature (Xu et al. 2009; Shrestha et al. 2012). A prolonged dry period due to the projected warmer and drier winter followed by a hot and dry pre-monsoon could aggravate the incidence of forest fires, further endangering terrestrial biodiversity. Expanded warm spells and reduced winter precipitation could also negatively impact the water availability and ecosystem in important wetlands such as Rara and Phoksundo in the highlands and Ghodaghodi in the lowlands. Changes in the river flows in response to changing precipitation patterns will also affect aquatic biodiversity (Poff and Zimmerman 2010).

4.3.4.5. Tourism and natural and cultural heritage

National parks and wildlife reserves, high-altitude wetlands, rivers, mountains, and indigenous culture are among the major tourist attractions in Karnali. The degradation of the natural heritage due to the projected changes may negatively affect the tourism industry in the future. More summer days in the highlands could have a positive impact on tourism in the short term (K.C. 2017). However, the projected increase in climate extremes, such as the mean and extreme daytime temperature, hot days, and number of heavy and very heavy rain days, will reduce favorable weather conditions for major tourist activities such as trekking, mountaineering, river rafting, and jungle safaris. Such tourist activities are highly climate-sensitive, and unfavorable climatic conditions may cause locational and seasonal shifts in tourist flows (K.C. 2017). The highest precipitation increase and increased chances of heavy and very heavy rain days during the pre- and post-monsoon, which are also the peak tourist seasons in Nepal (K.C. et al. 2020), could severely affect tourism by hindering mobility (both land and air) and increasing the probability of climate disasters. Mountaineering is very sensitive to snow cover and favorable climatic windows. Projected warming-induced snow cover loss and an uncertain climate could negatively affect mountain tourism. Temperature increases could also increase costs for tourism entrepreneurs because they will need to invest more in cooling systems in lowland areas.

4.3.4.6. Public health

The projected increase in the mean temperature will increase the risk of vector-borne diseases (such as dengue, malaria, and Japanese encephalitis), water-borne diseases (such as diarrhea and hepatitis), and other health risks in Karnali. Every unit increase in the mean TN at a lag of 2 months increases the incident rate ratio of dengue cases by more than 1% in southern Nepal (Tuladhar et al., 2019). Similarly, a 1 °C increase in the mean TN increases the malaria incidence by 27% (Dhimal et al. 2014). Water scarcity during dry and hot summers may lead to poor hygienic practices and an increase in the risk of disease prevalence (Bhandari et al., 2020; Dhimal et al., 2015; Shrestha et al., 2016; Tuladhar et al., 2019). Altogether, this indicates a higher risk of vector-borne diseases over a larger area in Karnali and an intensified risk of epidemics in the future. Water-borne diseases could also increase in the future; Bhandari et al. (2020) found that a 1 °C increase in the mean TX and a 10-mm increase in the monthly precipitation increase the monthly count of diarrhea cases in Kathmandu by 8.1% and 0.9%, respectively. A projected increase in hot extremes, hot days, and warm spells in the already hot tropical lowlands could cause heat stress, leading to an increase in morbidity and mortality, as observed by Shrestha et al. (2016).

4.4. Limitations

Future climate projections and bias corrections come with inherent uncertainties. Therefore, the projected results and sectoral implications should be interpreted with caution. To better capture the highly heterogeneous terrain in western Nepal, we use bias-corrected RCM-based projections over GCM-based projections, as RCMs are better able to resolve meso-scale climatic processes in regions with highly variable topography (Flato et al. 2013). However, bias-corrected RCM projections are provided by Dhaubanjar et al. (2020) only for a limited number of stations. Many stations were discarded due to short and poor-quality data that results in poor performance in the quantile-mapping method for bias correction. The nine stations used here are skewed toward the southern lowlands increasing the uncertainty in our interpretations for the northern mountainous regions.

In addition, we further consolidated the data across the nine stations into two geographical regions (lowlands and highlands) to interpret the index trends across the study area. Thus, the regional inferences made here by consolidating a limited number of stations are most applicable for areas closest to our study stations. Higher uncertainty should be assumed when applying our index trends and sectoral implication to areas farther away from these stations.

The selection of different indices as relevant to different sectors was a subjective iterative process. In general, sectorial experts were unfamiliar with the ET-SCI indices and struggled with defining their linkage to their sectors. More dialog are required between climatologists and sector experts to improve upon the first efforts we have made to designate and interpret sector-specific indices for Karnali. Quantifying future impacts to different sectors is difficult because there are limited studies that quantify the relationship between ET-SCI indices and sectoral activities in Nepal. Future research could develop a quantitative projection of impacts to each sector, building on the qualitative analysis we performed here.

4.5. Conclusions

The projections of the 26 ET-SCI climate indices examined here suggest that both the temperature and precipitation patterns in Karnali will already change significantly from their historical patterns in the near future, irrespective of the emission scenario. If the global emission pathways do not follow stronger emission reductions, the region will encounter a much more extreme climate in the mid and far future. The northern highlands in Karnali are projected to warm faster than the southern lowlands. Because of its highest warming rate and decrease in precipitation, winter in the highlands is expected to be warmer and dryer. The already hot and wet summer in the lowlands will be hotter with more extreme temperatures and scattered extreme precipitation events. The hottest days and nights will be hotter, summer and warm spells will be longer, and cold days will be fewer. The increasing precipitation intensity (SDII), maximum 1- and 5-day precipitation (RX1day and RX5day), and contribution from very wet and extremely wet days (R95pTOT and R99pTOT) suggest an increase in sporadic higher intensity rains and fewer days of low-intensity rains throughout the year. The frequency (R10mm and R30mm) and intensity (RX1day and RX5day) of extreme precipitation events will be much higher in all futures, even in the dry season in the far future. All these projected changes in the temperature and precipitation will have largely negative implications for the six climate-sensitive sectors in Karnali. Therefore, there is an urgent need to plan adaptation measures to reduce risks and strengthen the climate resilience of the key sectors in Karnali.

Chapter Five: Conclusion

5.1. Summary of findings

The extreme weather and climate events have increased due to anthropogenic climate change and are projected to increase further in future GHG emission scenarios. Climatic disasters and their socioeconomic impacts have also shown upward trends worldwide. Notably, the poor in low-income countries are mostly impacted by such disasters, and future risks are high. However, few studies have examined the role of climate change and socioeconomic changes in increasing disaster impacts in low-income countries. This study investigates the spatiotemporal trends of climatic disaster impacts, attribution of disaster impacts to climatic and socioeconomic changes, using Nepal as a case study. Additionally, this study further unpacked climate change impacts by assessing future scenarios of extreme climate indices and their potential implications in six key climate sensitive sectors in Karnali river basin of western Nepal.

This study starts by analyzing the spatiotemporal trends of multiple climatic disaster frequency, mortality, and human vulnerability in Nepal, using the observed disaster data at the level of the 753 subnational units during 1992–2021. More than 10,000 people lost their lives in these 30 years after ~5,000 climatic disasters in Nepal. The climatic disaster frequency and disaster mortality have also increased in the past three decades. The frequency of multiple climatic disasters has increased by about seven incidences annually, and mortality has increased by almost nine persons annually. The increase in mortality and shift in monthly mortality patterns have made the entire year more deadly than in the past. Contrary to mortality, the exposure-normalized mortality or vulnerability has decreased in Nepal, potentially because of the economic growth and progress in DRR and climate change adaptation. The multidisaster exposure-normalized mortality in Nepal has fallen at the rate of 0.15 deaths per 100,000 people exposed annually. The vulnerability decrease rate is much faster in rural than urban areas. However, rural regions remain considerably more vulnerable than urban regions due to the historical rural–urban vulnerability gap. Historically, the Mid Hills and Mountain regions of central and eastern Nepal have experienced the highest climatic disaster mortality. However, disaster vulnerability was higher in western Nepal due to poor socioeconomic conditions and development deficits.

Landslides and floods were the deadliest disasters in Nepal, accounting for 70% of all climate-related disaster mortality. Landslide mortality was the highest in the Mid Hills and Mountain regions in eastern (Province 1) and central (Bagmati and Gandaki) Nepal. Flood mortality was the highest in central Nepal (Madhesh, Bagmati, and Gandaki). Western Nepal (Lumbini, Karnali, and Sudurpashchim) experienced relatively less disaster mortality in the past three decades. This landslide and flood mortality pattern closely matched the observed spatial pattern of the mean and extreme precipitation in Nepal. However, the temporal trends of extreme precipitation indices were mainly increasing in western Nepal but mostly decreasing in central Nepal. For example, maximum 1-day precipitation (RX1day) showed increasing trends in 68% of the stations in Sudurpashchim (significant in 11%) and 58% in Lumbini (significant in 15%). However, it showed decreasing trends in 76% of the stations in Bagmati (significant in 10%). Correspondingly, the landslide and flood frequency and mortality have increased in western Nepal, but no significant trends were observed in central and eastern Nepal. Such spatiotemporal patterns show a direct association between precipitation extremes and landslide and flood mortality.

The regression results confirmed that the extreme precipitation indices, mainly the extreme precipitation intensity indices (RX1day and R95pTOT), increased flood mortality and the extreme precipitation frequency and duration indices (R10mm and CWD) increased landslide mortality. A one-unit increase in RX1day and R95pTOT raised flood mortality by 33% and 31%, respectively. A one-unit increase in R10mm and CWD raised landslide mortality by 45% and 34%, respectively. Lower vulnerability, represented by higher PCI and lower SoVI, lowered flood and landslide mortality. A one-unit increase in PCI reduced landslide and flood mortality by 30% and 45%, respectively. 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 primarily attributable to the increased precipitation extremes in these regions owing to climate change.

Projections of the 26 extreme climate indices suggest that the temperature and precipitation patterns in western Nepal will change significantly from their historical patterns already in the near future, irrespective of the emission scenario. If the global emission pathways do not follow strong emission reductions, the region will encounter a much more extreme climate in the mid and far future. The northern highlands of western Nepal are projected to warm faster than the southern lowlands. Winters in the highlands are expected to be warmer and dryer because of the higher warming rate and decreasing winter precipitation. The hot and wet summers in the lowlands will be hotter with more extreme temperatures and scattered extreme precipitation events. The intensities of 1- and 5-day extreme precipitation events (RX1day and RX5day) could increase by 40%–60% in the far future, increasing the risk of flash floods, and even a single extreme event could be devastating. The annual R10mm could double in some regions, whereas the R30mm could increase two- to threefold in the far future. Western Nepal may experience some days of very heavy rain in the mid and far future, even during the pre- and post-monsoon seasons, which was not normal in the past. Such an increase in the probability of floods and landslides in the historically dry season is alarming because these events are more likely to be surprising.

5.2. Policy relevance

SDG 11 aims to "make cities and human settlements inclusive, safe, resilient, and sustainable" (United Nations 2015). SDG 13 highlights the need to "take urgent action to combat climate change and its impacts." This aim of addressing the threat of anthropogenic climate change was elaborated and agreed upon in the Paris Agreement 2015 under the UNFCCC. In addition to the mitigation goal of pursuing efforts to limit global temperature rise to 1.5°C above the preindustrial levels in Article 2, the Paris Agreement set the global goal of adaptation (UNFCCC 2015). Article 7 of the Paris Agreement "establish(es) the global goal on adaptation of enhancing adaptive capacity, strengthening resilience and reducing vulnerability to climate change, with a view to contributing to sustainable development and ensuring an adequate adaptation response in the context of the temperature goal referred to in Article 2." The SFDRR aims for the "substantial reduction of disaster risk and losses in lives, livelihoods and health and in the economic, physical, social, cultural and environmental assets of persons, businesses, communities and countries" (UNISDR 2015). The results of this study, which shows rising climate extremes but slow progress in reducing vulnerability, indicate challenges in achieving the aforementioned goals and targets of the SDGs, Paris Agreement, and SFDRR.

One of the targets of SDG 11 is to "significantly reduce the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global GDP caused by disasters, including water related disasters, with a focus on protecting the poor and people in vulnerable situations" by 2030 (United Nations 2015). The first target of the SFDRR is also to "substantially reduce global disaster mortality by 2030, aiming to lower the average per 100,000 global mortality rate in the decade 2020–2030 compared to the period 2005–2015" (UNISDR 2015). Almost half of the 15-year period planned to achieve the SDGs and SFDRR has already passed. Nevertheless, in many countries, including Nepal, total disaster mortality has not decreased but rather increased over time. This study reported that the annual climatic disaster mortality rate in Nepal has increased by about nine persons per year in the past three decades. Furthermore, extreme precipitation events have increased, particularly in western Nepal, and are projected to increase further because of climate change. Therefore, there is an urgent and strong need for global action to mitigate GHG emissions.

With the current climate change mitigation policies, the world is exceeding the 1.5°C limit of the Paris Agreement and heading toward a 2.7°C warming (CAT 2022). Notably, the benefits of mitigation will be in the long term, starting in mid-century (Estrada and Botzen 2021).

Therefore, only adaptation and DRR can reduce the climatic disaster impacts and residual loss and damage in the following few decades (UNEP 2021). Moreover, several adaptations and DRR options are already in place, successfully reducing vulnerability to climate change and increasing community resilience (MoPE/NCCSP 2016; Mishra et al. 2017). This study observed a decreasing trend of disaster vulnerability in Nepal, potentially due to the progress in DRR, adaptation, weather forecast, early warning systems, and overall socioeconomic development. Without the progress in vulnerability reduction, disaster-related human fatality could have increased much faster than the observed trend. Despite the progress made, disaster vulnerability and mortality remain high in Nepal, particularly in the rural regions.

SDG 11 and SFDRR aimed to substantially increase the national and local DRR and adaptation strategies by 2020 (UNISDR 2015; United Nations 2015). Globally, 125 countries have developed national DRR strategies (Target E of the SFDRR), and ~84% of the countries worldwide have prepared national adaptation plans, strategies, or policies (UNDRR and WMO 2022; UNEP 2022). The number of countries with local DRR strategies almost doubled from 51 in 2015 to 98 in 2021 (United Nations 2022). However, progress still needs improvement in low-income countries, such as Nepal, mainly in developing the local DRR and adaptation plans. Only 30% of local administrative units of Nepal had local DRR strategies until 2019 (NPC 2020). These national and local plans have substantial financial and implementation gaps. The financing needs for adaptation in developing countries are five to ten times greater than the current international adaptation finance flow, and the gap continues to widen (UNEP 2022). Nepal requires USD 47.4 billion between 2021 and 2050 to implement priority adaptation programs, of which USD 8.5 billion is for the climatic disasters sector (Government of Nepal 2021). However, the average climate finance commitment received during 2013–2017 was USD 383 million USD per year, and only 53% of the commitment received was for adaptation projects (Rai et al. 2020). There has been progress in establishing multi-hazard early warning systems globally. Still, only one-third of SIDs and less than half of the LDCs are covered by early warning systems (UNDRR and WMO 2022). Such finance and implementation gaps, as well as the limits to adaptation, increase the risk of climatic disasters-induced loss and damage.

Loss and damage in this context are the residual economic and noneconomic impacts (observed) and risks (projected) due to climate change, including extreme events and slow-onset events that are beyond the adaptation limits (Mechler et al. 2019; IPCC 2022b). In the global climate negotiations, poor and vulnerable countries have been calling for a burden-sharing mechanism, including compensation for unavoidable loss and damage caused by climate change (Deubelli and Mechler 2021). In 2013, the Warsaw International Mechanism for Loss and Damage was established under the UNFCCC mechanism (UNFCCC 2015). Similarly, the importance of addressing loss and damage was agreed upon in Article 8 of the Paris Agreement in 2015. Finally, the country parties agreed in the recently adopted Sharm el-Sheikh Implementation Plan in the COP 27 and CMA 4 to establish a funding arrangement for responding to loss and damage (UNFCCC 2022). However, loss and damage is often interpreted as issues of responsibility, blame, and liability (James et al. 2019). Attribution has been the major issue in this global debate (Bouwer 2019; James et al. 2019). This is the first empirical study from the global south on the attribution of disaster mortality to climatic and socioeconomic changes using a regression-based approach. The study findings help strengthen the argument of Nepal and other climate change–impacted countries for establishing and implementing the mechanisms to address loss and damage. Therefore, the relevance of this research is very high for global climate policy, including loss and damage and international climate finance.

At the national scale, Nepal has developed the National Adaptation Plan (2021–2050) and identified 64 priority adaptation programs in eight thematic and four cross-cutting sectors in the short, medium, and long terms (Government of Nepal 2021). Disaster Risk Reduction and Management is one of the priority thematic sectors in the National Adaptation Plan. Similarly, Nepal has approved the Disaster Risk Reduction and Management Act 2017, the National Policy for Disaster Risk Reduction 2018, and the National Climate Change Policy 2019. These policies and plans aim to make the country climate-adaptive and resilient (MoHA 2018; Government of Nepal 2021). However, planning and implementing these policies and plans at the subnational scale remain a considerable challenge. This study provides critical information on high-risk and vulnerable areas to climatic disasters at the local administrative unit scale in Nepal. Similarly, this study provides the future scenarios of climate extremes and the sectoral risks in one of the most vulnerable regions Karnali. Responsible authorities, such as local administrative units, province and federal ministries, national planning commission, development partners and donors can use the results to plan and implement adaptation and DRR projects. An example of an actual application of the findings of this study is the Climate-Resilient Landscapes and Livelihoods project in western Nepal, developed by the Asian Development Bank and the Government of Nepal. A part of this study contributed to the assessment of climate change impacts, vulnerability, and adaptation options at the community and landscape scale for designing a USD 50 million project in Karnali and Sudurpashchim provinces in western Nepal.

5.3. Future research needs

This study is based on a state-of-the-art methodology and the most robust data currently available for a low-income country like Nepal. Nevertheless, climate change impacts attribution science and future risks projections are complex, dynamic, and subject to several uncertainties. Therefore, continuous research is necessary to improve the understanding of this complex global problem.

This study focuses on Nepal as a low-income country. However, the results may not be entirely true for other countries. The types of climatic disasters observed in Nepal differ from other countries because of the geographic and climatic differences. Hence, our study does not provide insights on other important climatic disasters such as coastal flooding, cyclone, and drought. Therefore, similar studies should be replicated in other countries and regions and on a global scale to understand the role of climate change in disaster and other impacts at different settings and scales. In the case of Nepal, this study focused on Landslides and Floods for the attribution study. However, similar assessments could be carried out for other disaster types, such as thunderstorms, cold and heatwaves, snowstorms, and avalanches. More national and sub-national scale studies will help improve the disaster type specific adaptation and DRR planning in the study location. It will also generate more empirical evidence to strengthen the attribution science of climate change impact. Similarly, regional and global scale studies will help compare the countries and regions. This is important to inform global policies and actions.

This study provides projections of future climate extremes in western Nepal. However, the study of their potential consequences on different sectors was limited to qualitative analysis based on expert interviews and a literature review. Therefore, another crucial research step is the application of our climate extreme indices projections as inputs in various sector specific risk assessment models to quantitatively project the future risks in various scenarios and time frames. Similarly, this study proposed statistical models to predict future risks of climate-related disaster mortality in different climate and socioeconomic scenarios. An important follow-up of this research is the use of climate projection data and socioeconomic scenarios data in our proposed statistical models to estimate the future climatic disaster mortality in Nepal. Such future projections will provide vital information about scenario-based adaptation and DRR planning.

In addition to human mortality, several other aspects of disaster impacts exist. Applying this approach to investigate the trends and attribution of other disaster impacts, such as direct and indirect economic losses, disaster morbidity and health costs, and displacement, can be of equal value. However, significant improvement in disaster impact data may be necessary because such impacts still need to be recorded and quantified compared with disaster mortality. Among the drivers of disaster impacts, hazards and exposure are relatively better incorporated in the existing literature compared to vulnerability. Future research could improve this gap by incorporating more and better measures of vulnerability, adaptation, and DRR. In the case of Nepal, CBS is soon releasing new and comprehensive socioeconomic data from the 2021 national census. This 2021 census data could be extremely valuable in estimating the updated socioeconomic vulnerability index and other indicators of vulnerability and exposure.

Finally, long-time, high-quality, and high-resolution data can improve research results. Therefore, the geocoding of disaster locations and delineation of disaster-specific exposure boundaries should be further improved. Importantly, denser networks of meteorological stations should be used for the observed climate data. Moreover, including more indicators of explanatory variables for disaster impacts, particularly vulnerability indicators, can further improve the accuracy of causality. Using new and evolving technologies, such as satellite data, artificial intelligence, and machine learning techniques for data collection and analysis, could help to fill the data gap.

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Appendices

Table A2.1: List of disaster types included in this study and respective disaster types as listed in the DesInventar and Nepal DRR Portal database.

Disaster Types		
Grouped in this study	**As listed in DesInventar**	**As listed in Nepal DRR Portal**
Landslides	Landslides	Landslides
Floods and heavy rains	Floods Rains	Floods Heavy Rainfall Flash Floods
Thunderstorms	Thunderstorms	Thunderbolt
Cold waves and frosts	Cold Waves Frosts	Cold Waves Frosts
Windstorms	Strong Wind Storms	Strong Wind Wind Storms Storms
Snowstorms and avalanches	Snow Storms Avalanches	Snow Storms Avalanches
Heat waves	Heat Waves	Heat Waves
Hailstorms	Haim Storms	Hailstones Hail Storms

Table A2.2: List of analytical dimensions of the Nepal Living Standard Survey (NLSS).

S. No.	**NLSS Analytical Dimensions**
1.	Mountains
2.	Urban-Kathmandu
3.	Urban-Hills
4.	Urban-Tarai
5.	Rural-Hills-Eastern
6.	Rural-Hills-Central
7.	Rural-Hills-Western
8.	Rural-Hills-Mid & Far Western
9.	Rural-Tarai-Eastern
10.	Rural-Tarai-Central
11.	Rural-Tarai-Western
12.	Rural-Tarai-Mid & Far Western

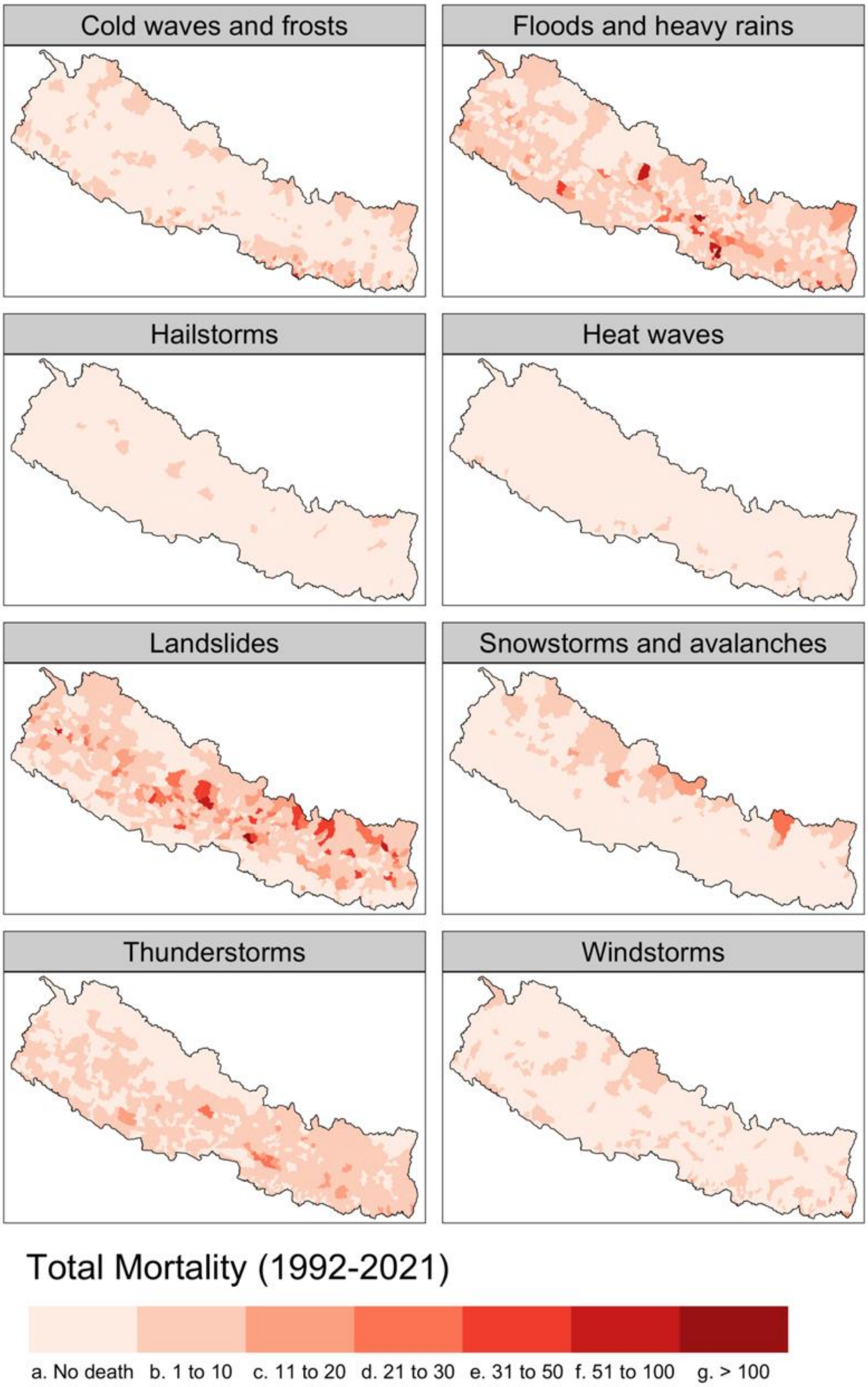

Figure A2.1: Spatial distribution of climatic disaster impacts (total mortality) by disaster types in Nepal during 1992-2021. The color code range in the maps is manually created and the range values are as shown in the legend.

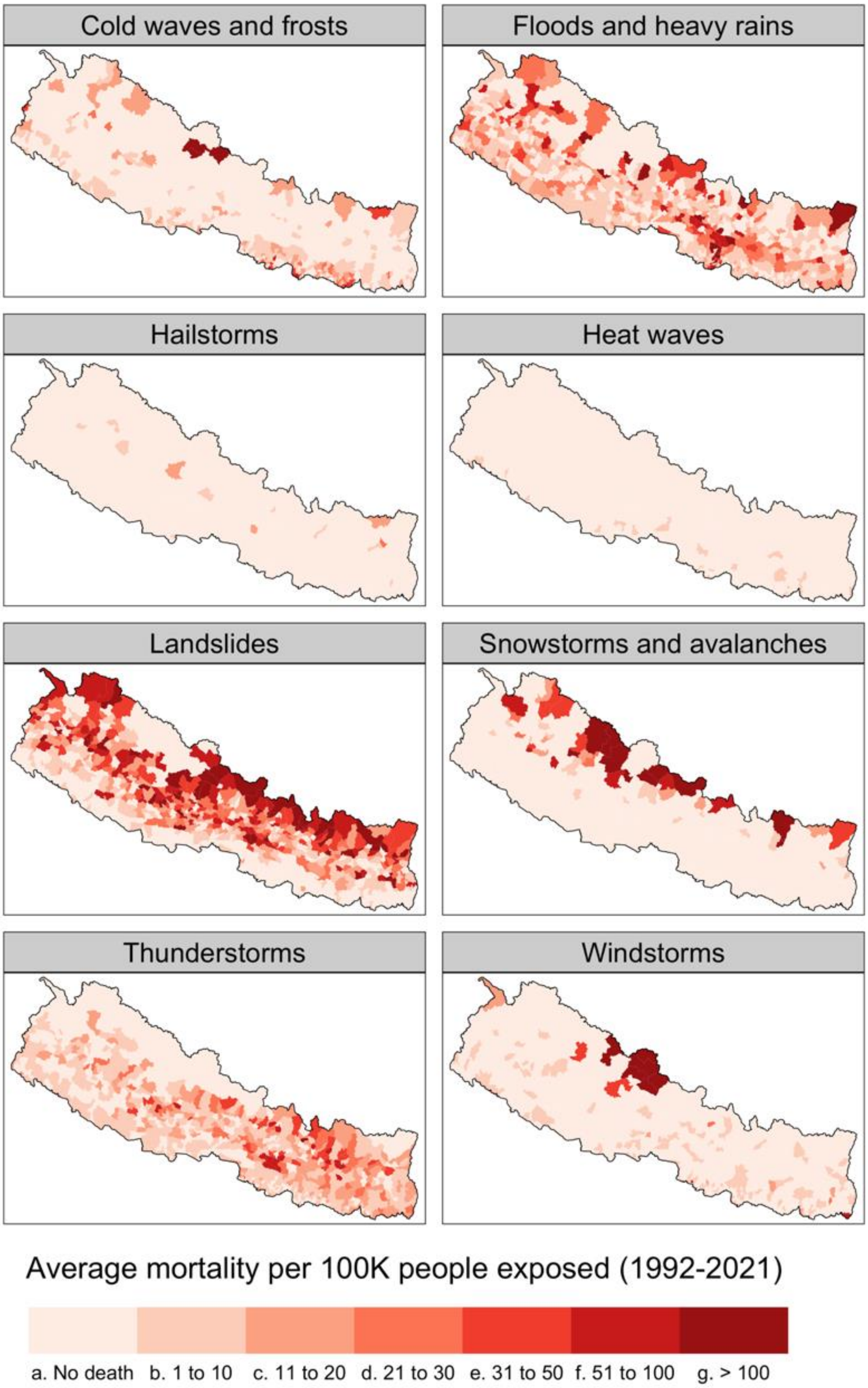

Figure A2.2: Spatial distribution of climatic disaster vulnerability (average annual mortality per 100K people exposed) by disaster types in Nepal during 1992-2021. The color code range in the maps is manually created and the range values are as shown in the legend.

Table A2.3: Results of the regression analysis.

	Dependent variable: No. of people died (log)	
	OLS model	Location fixed effect model
Constant	3.533*** (0.215)	
No. of people exposed to disaster (log)	-0.039*** (0.014)	0.039 (0.095)
No. of disaster incidences recorded (log)	1.164*** (0.025)	1.156*** (0.028)
Per capita income (log)	-0.265*** (0.021)	-0.345*** (0.030)
Observations	3,683	3,683
R^2	0.38	0.521
Adjusted R^2	0.38	0.402
Residual Std. Error	0.586 (df = 3679)	0.575 (df = 2948)
F Statistic	752.81*** (df = 3; 3679)	4.373*** (df = 734; 2948)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ Estimate std. error in parentheses	

Table A3.1: 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 (Dispersion test results for Poisson model)	12.23 (p-value = 0.0016)	70.34 (p-value = 0.0821)

Table A3.2: 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															
σ^2			3.94			1.91			3.26			0.01			0.00
τ_{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
AIC			54870.8			22536.7			11376.1			12750.5			11277.2
BIC			54915.6			22574.1			11421.0			12795.4			11326.1

Table A3.3: 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												
σ^2	0.00		0.00		0.00		0.00		0.00		0.00	
τ_{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	
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 A3.4: 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												
σ^2	0.00		0.00		0.00		0.00		0.00		0.00	
τ_{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	
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	

Table A4.1: List and details of meteorological stations selected for this study.

Station Name	Index No.	District	Latitude	Logitude	Elevation	Region
Dadeldhura	s104	Dadeldhura	29.300	80.583	1848	Highland
Chainpur (West)	s202	Bajhang	29.550	81.217	1304	Highland
Tikapur	s207	Kailali	28.533	81.117	140	Lowland
Dhangadi Airport	s209	Kaliali	28.800	80.550	187	Lowland
Jumla	s303	Jumla	29.283	82.167	2300	Highland
Chisapani	s405	Bardiya	28.650	81.267	225	Lowland
Birendranagar	s406	Surkhet	28.600	81.617	720	Lowland
Chaur Jhari Tar	s513	Rukum	28.633	82.200	910	Lowland
Musikot	s514	Rukum	28.633	82.483	2100	Highland

Table A4.2: Details of the 19 CORDEX-SA RCMs used in Dhaubanjar et al. 2020. All RCMs have 0.44° spatial resolution [adapted from Dhaubanjar et al. 2020].

S. No.	Short Name (GCM_RCM)	Driving GCM	CORDEX-SA RCM description	RCM modeling Centre	Timeframe	Coordinate system
1.	ACCESS_CCAM	ACCESS1.0	CSIRO-CCAM-1391 M: Conformal cubical atmospheric model (McGregor and Dix, 2001)	Commonwealth scientific and industrial research organization (CSIRO), marine and atmospheric research, Melbourne, Australia	Hist: 1970–2005 RCP4.5/8.5:2006–2099	Regular
2.	CNRM_CCAM	CNRM-CM5			Hist: 1970–2005 RCP4.5/8.5:2006–2099	Regular
3.	GFDL_CCAM	GFDL-CM3			Hist: 1970–2005 RCP4.5:2006–2070 RCP8.5:2006–2099	Regular
4.	MPI_CCAM	MPI-ESM-LR			Hist: 1970–2005 RCP4.5/8.5:2006–2099	Regular
5.	NorESM_CCAM	NorESM-M			Hist: 1970–2005 RCP4.5:2006–2099 RCP8.5: None	Regular
6.	HadGEM_RA	HadGEM2-AO	HadGEM3-RA: HadGEM3 regional atmospheric model (Moufouma-Okia and Jones, 2014)	Met Office Hadley Centre (MOHC), UK	Hist: 1970–2005 RCP4.5/8.5:2006–2100	Curvilinear rotated_Latitude_longitude
7.	CNRM_RCA4	CNRM-CM5			Hist: 1951–2005	Rotated pole

			SMHI-RCA4: Rossby Centre regional atmospheric model version 4 (Samuelsson et al., 2011)	Rossby Centre, Swedish Meteorological and Hydrological Institute (SMHI), Sweden	RCP: 2006–2100	
8.	ICHEC_RCA4	ICHEC-EC-EARTH			Hist: 1970–2005 RCP: 2006–2100	Rotated_latitude_Longitude
9.	IPSLMR_RCA4	IPSL-CM5A-MR			Hist: 1951–2005 RCP: 2006–2100	Rotated_pole
10.	MIROC5_RCA4	MIROC-MIROC5			Hist: 1951–2005 RCP: 2006–2100	Rotated_pole
11.	MPI_RCA4	MPI-ESM-LR			Hist: 1951–2005 RCP: 2006–2100	Rotated_pole
12.	NOAA_RCA4	NOAA-GFDL-GFDL-ESM2M			Hist: 1951–2005 RCP: 2006–2100	Rotated_pole
13.	MPI_REMO	MPI-ESM-LR	MPI-CSC-REMO2009: MPI regional model 2009 (Teichmann et al., 2013)	Climate service Centre (CSC), Germany	Hist: 1970–2005 RCP: 2006–2100	Regular
14.	CanESM2_RegCM4	CCCma-CanESM2	IITM-RegCM4	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India	Hist: 1951–2005 RCP4.5/8.5:2006–2099	Rotated_mercator
15.	CNRM_RegCM4	CNRM-CM5	The Abdus Salam International Centre for Theoretical Physics Regional Climatic Model		Hist: 1951–2005 RCP4.5:2006–2099 RCP8.5:2006–2085	Rotated_mercator
16.	CSIRO_RegCM4	CSIRO-Mk3.6			Hist: 1951–2005 RCP4.5/8.5:2006–2099	Rotated_mercator

17.	IPSLLR_RegCM4	IPSL-CM5A-LR	version 4 (Giorgi et al., 2012)		Hist: 1951–2005 RCP4.5/8.5:2006–2099	Rotated_mercator
18.	MPIMR_RegCM4	MPI-ESM-MR			Hist: 1951–2005 RCP4.5/8.5:2006–2099	Rotated_mercator
19.	NOAA_RegCM4	NOAA-GFDL-GFDL-ESM2M			Hist: 1970–2005 RCP: 2006–2099	Curvilinear_rotated_mercator

Table A4.3: List of consulted experts during indices selection process and study of sectoral implications.

S. No.	Name	Affiliation	Sector
1	Dipak Gyawali	Nepal Academy of Science and Technology (NAST)	Water Resource and Energy, Climate Induced Disaster, Agriculture and Food Security, Tourism
2	Dr. Khadga Bahadur Bisht	IPPAN	Water Resource and Energy
3	Anup Gurung	Nepal Kayak Club	Tourism
4	Dr. Sanjeev Bhuchar	International Centre for Integrated Mountain Development (ICIMOD)	Tourism
5	Dr. Ram Chandra Bastakoti	National Planning Commission, Government of Nepal	Agriculture and Food Security
6	Bishnu Prasad Paudel	Nepal Agricultural Research Council (NARC), Government of Nepal	Agriculture and Food Security
7	Dr. Madhav Karki	IUCN Commission on Ecosystem Management	Forest and Biodiversity, Agriculture and Food Secutiry
8	Sadiksha Rai	Department of Water Resources and Irrigation, Government of Nepal	Water Resource and Energy, Climate Induced Disaster
9	Dr. Sailesh Ranjitkar	Honghe Center of Mountain Futures, China/Mid-Western University, Nepal.	Agriculture and Food Security, Forest and Biodiversity
10	Anup KC	Clemson University, USA	Tourism
11	Rajan Thapa	Oxford Policy Management	Climate Induced Disaster

12	Dr. Rocky Talchabhadel	Texas A&M University, USA	Climate Induced Disaster
13	Jeeban Panthi	University of Rhode Island, USA	Water Resources and Energy, Climate induced Disaster
14	Dr. Meghnath Dhimal	Nepal Health Research Council (NHRC)	Public Health
15	Dr. Uttam Khanal	Queensland University of Technology, Australia	Agriculture and Food Security

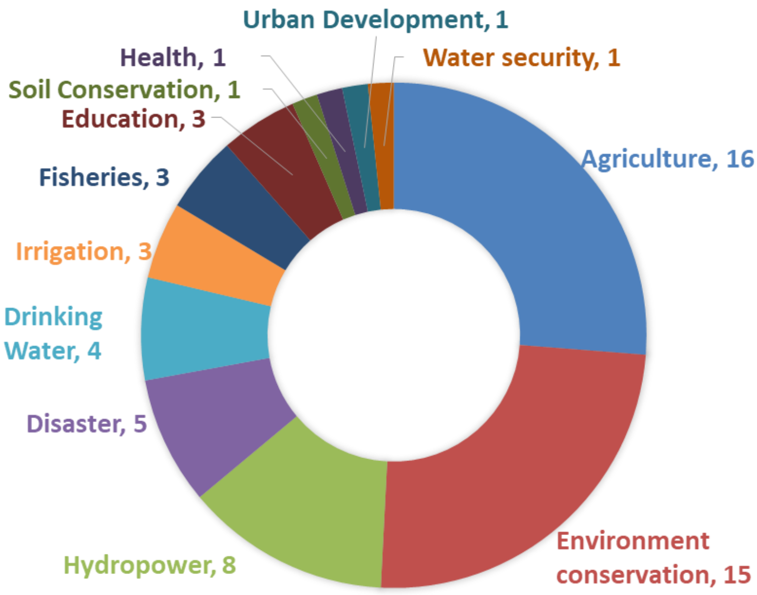

Figure A4.1: Sectoral background of participants in stakeholder consultation workshop.

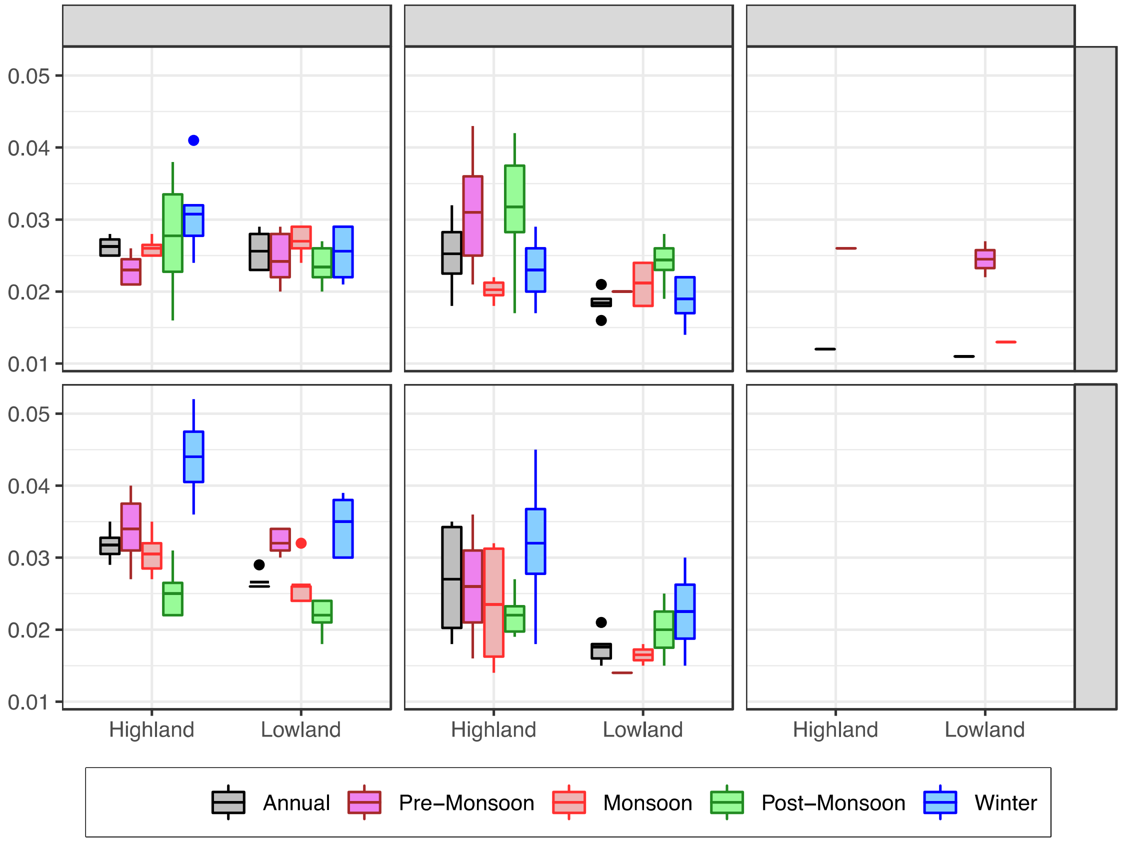

Figure A4.2: Projected annual and seasonal mean temperature index trends for Karnali by future timeframe and geographical region in the RCP4.5 scenario. The middle dark lines represent the mean; the boxes represent the interquartile range; the whiskers represent the minimum and maximum values; and the dots represent outliers.

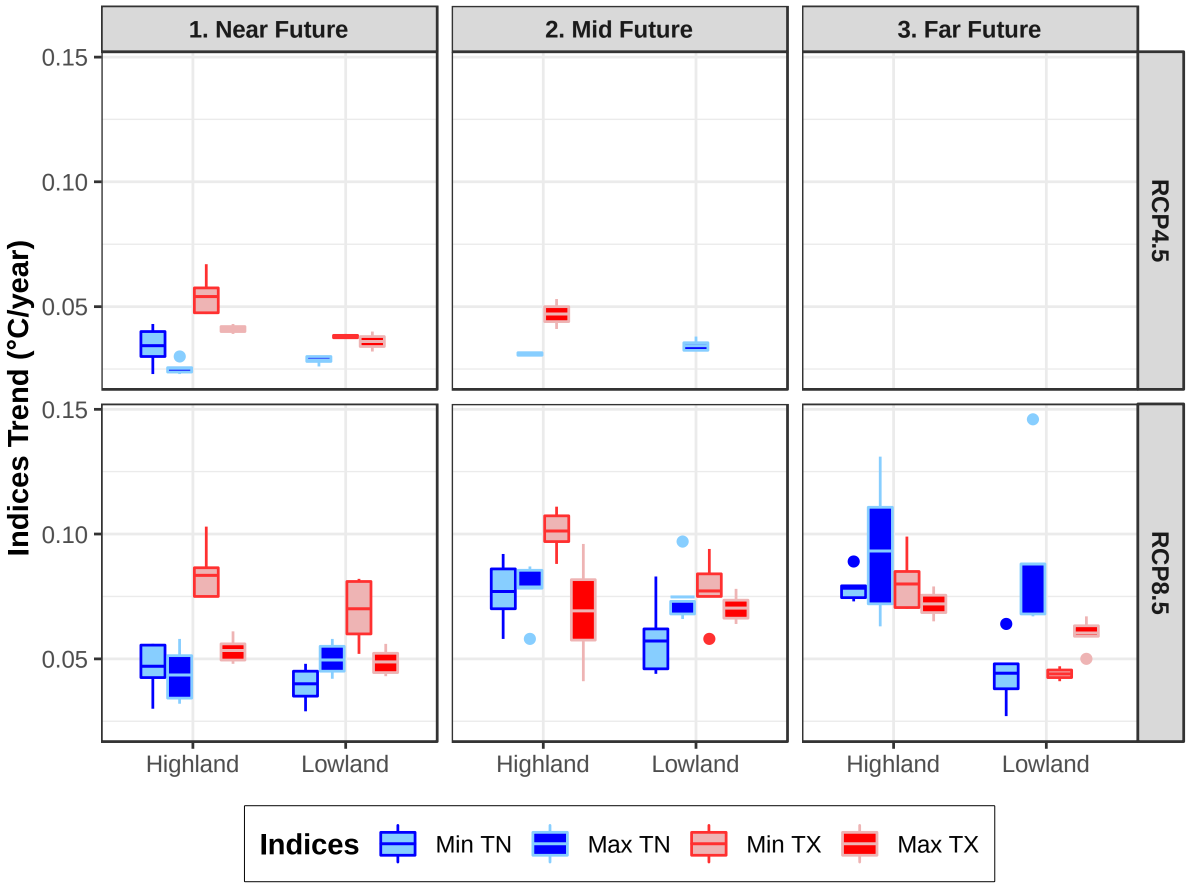

Figure A4.3: Projected absolute-value-based extreme temperature index trends for Karnali by future timeframe, geographical region, and emission scenario. Symbols are as defined in Fig. S2.

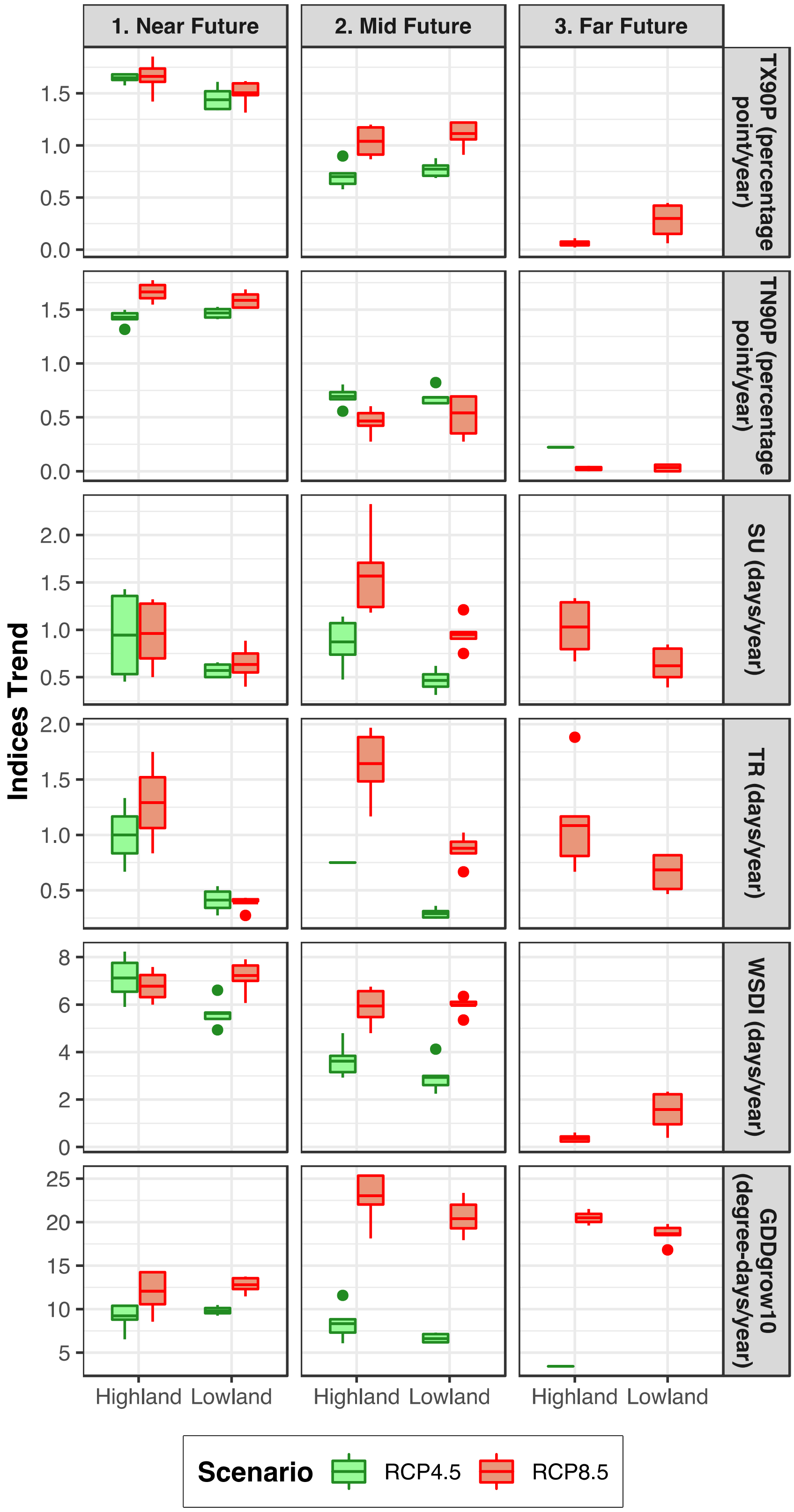

Figure A4.4: Projected percentile- and duration-based extreme temperature index trends for Karnali by future timeframe, geographical region, and emission scenario (different y-axis scales are used for each index). Symbols are as defined in Fig. S2.