

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**INVESTIGATION TOPOGRAPHIC, CLIMATIC AND
ANTHROPOGENIC FACTORS CONTROLLING
FATAL LANDSLIDES ON A GLOBAL SCALE**



Ph.D. THESIS

Seçkin FİDAN

Department of Solid Earth Sciences

Geodynamics Programme

DECEMBER 2024

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Thesis Advisor: Prof. Dr. Tolga GÖRÜM

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

**KÜRESEL ÖLÇEKTE ÖLÜMCÜL HEYELANLARI
KONTROL EDEN TOPOĞRAFİK, İKLİMSEL VE
ANTROPOJENİK FAKTÖRLERİN İNCELENMESİ**

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ARALIK 2024

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To my mom,



FOREWORD

Landslides are one of the most devastating geohazards that cause substantial loss of life and socio-economic damage worldwide every year. This thesis once again demonstrates the spatial distribution of fatal landslides globally and, for the first time, holistically reveals and documents the potential effects of topographic, climatic, and anthropogenic factors. Studying a subject of such complexity and huge impact has been both challenging and highly educational for me. The road to this PhD was steep and rugged: lengthy investigations, challenging large data sets, analyses that felt never-ending, and so on. All this pushed me to my limits at times but simultaneously fuelled my passion for seeking outputs toward a better understanding of fatal landslides. Although the path sometimes seemed impossible, the idea that my research could contribute to saving human lives and minimizing damages made it all the more meaningful. Contributing to a broader understanding of fatal landslides has been an indescribable source of satisfaction for me. Looking back, I feel great satisfaction and happiness that I have had the chance to work in this field. Every challenge has taught me important lessons, and every step has shown me again how valuable this work is.

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ABBREVIATIONS

AIC	: Akaike information criterion
<i>A_{mountain}</i>	: Total mountainous area
B.H.	: Brazilian Highlands
C3S	: Copernicus Climate Change Service
CARH	: Central American Ranges and Hispaniola
CCI	: Climate Change Initiative
CDS	: Climate Data Store
CI	: Confidence interval
CTI	: Compound topographic index
DEM	: Digital Elevation Model
ESA	: European Space Agency
<i>F</i>	: Number of fatalities
<i>FD</i>	: Fatality density
GADM	: Global Administrative Areas
GDP	: Gross domestic product
GEI	: Government Effectiveness Index
GFLD	: Global Fatal Landslide Database
Gini	: Income inequality
GLM	: Generalized Linear Model
GNI	: Per capita gross national income
GRV	: Great Rift Valley
H	: High-income
H.R.	: Himalayan Range
HDI	: Human Development Index
HFI	: Human footprint
HILDA+	: HIsToric Land Dynamics Assessment
ICDR	: Intermediate Climate Data Records
IND	: Indonesia
KDE	: Kernel Density Estimation
<i>KDE_{sub-basin}</i>	: Mean of the Kernel Density Estimation grid cells

L	: Low-income
L	: Number of landslides
LD	: Landslide density
LM	: Lower-middle-income
LTAF	: Landslides triggered by anthropogenic factors
LTNF	: Landslides triggered by natural factors
LULCC	: Land use and land cover change
<i>LULCCR_{score}</i>	: Total land use and land cover change rate
<i>LULCCR_{scoreN}</i>	: Normalized total land use and land cover change rate
<i>LULCC_{total}</i>	: Total land use and land cover change
Max	: Maximum
Mdn	: Median
Min	: Minimum
N.A.	: Northern Andes
NEIB	: North East India and Bangladesh
NLD	: Normalized landslide density
P.T.	: Philippines and Taiwan
PCR	: Population change rate
<i>PCR_N</i>	: Normalized population change rate
<i>Pop_{sub-basin}</i>	: Total population in each sub-basin
RQs	: Research questions
Std	: Standard deviation
SWIID	: Standardized World Income Inequality Database
UM	: Upper-middle-income
UNDP	: United Nations Development Programme
V.T.	: Vietnam
WGSL	: Western Ghats and Sri Lanka

SYMBOLS

km²	: Kilometer square
km	: Kilometer
m	: Meter
mm	: Millimeter
elev-std	: Elevation standard deviation
m a.s.l	: Meters above mean sea level
°	: Degree
R²	: Coefficient of determination
%	: Percentage
~	: Around/on the order of
\$	: US Dollar
<i>p</i>	: <i>p</i> -value (Statistical significance)
n	: Sample size or frequency of observations



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INVESTIGATION TOPOGRAPHIC, CLIMATIC, AND ANTHROPOGENIC FACTORS CONTROLLING FATAL LANDSLIDES ON A GLOBAL SCALE

SUMMARY

Landslides are a common global geohazard that lead to substantial loss of life and socio-economic damage annually. They are becoming more common due to extreme weather events and the impacts of anthropogenic disturbance, and thus, they are threatening sustainable development in many vulnerable areas. Previous studies on fatal landslides have focused on inventory development; spatial and temporal distributions; the role of precipitation or seismic forcing; and human impacts. However, climatologic, topographic, and anthropogenic variables featuring fatal landslides at a global scale have been mostly neglected.

In this thesis, using the Global Fatal Landslide Database (GFLD), we evaluate the characteristics of landslides induced by natural and anthropogenic factors with respect to topographic, climatic, and anthropogenic factors, drawing attention to their persistent spatial patterns. The majority of natural (69.3%) and anthropogenic (44.1%) landslides occur in mountainous areas in tropical and temperate regions, which are also characterized by the highest casualty rates per group, 66.7% and 43.0%, respectively. However, they significantly differ in terms of their morphometric footprint. Fatal landslides triggered by natural variables occur mostly in the highest portions of the topographic profile, where human disturbance is minimal. As for their anthropogenic counterpart, these failures cluster at much lower altitudes, where slopes are gentler, but human intervention is higher due to a higher population density. This observation points towards land cover changes being a critical factor in landscape dynamics, stressing the human pressure as a discriminant cause/effect term for natural vs. human-induced landslide fatalities.

This thesis also investigates the relationship between increasing population pressure, land use/cover change (LULCC) in mountainous areas, and fatal landslides. Anthropogenic disturbance is a direct contributor to landslide occurrence in mountainous environments and a potential threat to sustainable development. Population pressure and associated land cover changes are also expected to increase the frequency and impacts of landslides. The role of LULCC on landslides is recognized, but research that considers the differences between countries in mountainous regions having different development ranks is lacking. Here, we address the interactions between land cover and income level, population change, landslides, and fatalities across mountainous areas in 46 countries. Using a 59-year-long land cover and a 45-year-long population change rate dataset, we develop linear regression models to assess their relationship with landslides and fatalities. Our results show a significant relationship between land cover and population changes in mountainous areas. LULCC in lower-middle and low-income countries, where the degree of change and human intervention is notably higher, occurs at a greater rate and intensity compared to other income groups. Furthermore, our findings indicate higher landslides and fatality densities in low- and lower-middle-income countries, where human

disturbance and LULCC rates are greater. Our findings highlight the LULCC as a critical factor in landscape dynamics and human pressure as a pre-condition/trigger factor for landslides.

The final part of the thesis examines the impact of socioeconomic factors on fatal landslides. Differences in socioeconomic conditions, such as the level of economic and human development, income inequality and governance, vary across countries but have the potential to substantially affect communities vulnerable to landslides as a natural hazard. However, only a small number of studies have investigated this potential impact at a global scale. Thus, there is still a lack of understanding of how the combination of socioeconomic factors across the world affects fatal landslides in countries with different income levels. Here, we investigate the relationship between landslide fatalities and socioeconomic factors in 62 countries by income level. For this purpose, we build negative binomial generalized linear regression models. Our results show that in high-income countries, a one-unit increase in the population potentially exposed to landslides was associated with a 42% increase in fatalities. In upper-middle-income countries, a one-unit increase in the Gini index was associated with a 16% increase in mortality, while an increase in the potentially exposed population resulted in a 21% increase in fatalities. In addition, a one-unit increase in the Government Effectiveness Index (GEI) is associated with a 37% reduction in fatalities. In low-middle-income countries, an increase in the potentially exposed population corresponds to a 33% increase in fatalities. Similarly, in low-income countries, an increase in the exposed population is associated with a 33% increase in fatalities. However, a higher Human Development Index (HDI) has been observed to reduce landslide-related fatalities by 99%. As a result, countries with lower levels of economic and human development, as well as those with higher income inequality and weaker governance, tend to experience higher landslide fatalities. Notably, the protective effect of increasing gross domestic product (GDP) and governance disappeared when accounting for income inequality and population in landslide-affected areas were included in the model. These findings emphasize the need to pay more attention to socioeconomic factors in landslide fatalities reduction or prevention studies.

Overall, this thesis provides a comprehensive, holistic assessment of the complex interplay of topographic, climatic, and anthropogenic factors that control fatal landslides on a global scale. Fatal landslides triggered by natural factors tend to occur at higher altitudes and steeper slopes, while their anthropogenic counterparts are found to occur at lower slopes and in densely populated areas. Additionally, population pressure and LULCC have been shown to play a significant role in fatal landslide occurrence and fatalities, especially in low- and lower-middle-income countries. Moreover, the impact of socioeconomic factors on landslide fatalities was also examined, and the effects of economic development, income inequality, and governance on landslide fatalities were clarified. The thesis results show that socioeconomic development, income inequality, and quality of governance are critical factors in preventing and reducing landslide-related fatalities, especially in low-income countries.

KÜRESEL ÖLÇEKTE ÖLÜMCÜL HEYELANLARI KONTROL EDEN TOPOĞRAFİK, İKLİMSEL VE ANTROPOJENİK FAKTÖRLERİN İNCELENMESİ

ÖZET

Heyelanlar, her yıl önemli ölçüde can kaybına ve sosyo-ekonomik zarara yol açan yaygın bir küresel jeo-tehlikedir. Aşırı hava olayları ve antropojenik bozulmanın etkileri nedeniyle daha yaygın hale gelmektedirler ve bu nedenle birçok hassas bölgede sürdürülebilir kalkınmayı tehdit etmektedirler. Ölümcül heyelanlarla ilgili önceki çalışmalar, envanter geliştirme, mekânsal ve zamansal dağılımlar, yağış, deprem ve insan etkileri üzerine odaklanmıştır. Ancak, küresel ölçekte ölümcül heyelanları içeren topoğrafik, iklimsel ve antropojenik değişkenler çoğunlukla ihmal edilmiştir.

Bu tezde, küresel ölümcül heyelan veri tabanını kullanarak, doğal ve antropojenik faktörlerin neden olduğu heyelanları topoğrafik, iklimsel ve antropojenik faktörler açısından değerlendiriyor ve kalıcı mekânsal modellerine dikkat çekiyoruz. Doğal (%69,3) ve antropojenik (%44,1) heyelanların çoğunluğu tropikal ve ılıman bölgelerdeki dağlık alanlarda meydana gelmektedir ve bu bölgeler aynı zamanda grup başına sırasıyla %66,7 ve %43,0 ile en yüksek kayıp oranlarıyla karakterize edilmektedir. Bununla birlikte, morfometrik özellikler bakımından önemli ölçüde farklılık göstermektedirler. Doğal faktörlerin tetiklediği ölümcül heyelanlar çoğunlukla insan müdahalesinin en az olduğu topoğrafik profilin en yüksek alanlarında meydana gelmektedir. Antropojenik muadillerine gelince, bu heyelanlar eğimlerin daha düşük olduğu, ancak daha yüksek nüfus yoğunluğu nedeniyle insan müdahalesinin daha fazla olduğu çok daha düşük rakımlarda kümelenmektedir. Ayrıca, arazi örtüsü değişikliklerinin peyzaj dinamiklerinde kritik bir faktör olduğuna işaret etmekte ve insan baskısını doğal ve insan kaynaklı heyelan ölümleri için ayırt edici bir neden/sonuç terimi olarak vurgulamaktadır.

Bu tez aynı zamanda artan nüfus baskısı, dağlık alanlardaki arazi kullanımı/örtüsü değişimi (LULCC) ve ölümcül heyelanlar arasındaki ilişkiyi de araştırmaktadır. Antropojenik bozulma, dağlık ortamlarda heyelan oluşumuna doğrudan katkıda bulunur ve sürdürülebilir kalkınma için potansiyel bir tehdittir. Nüfus baskısı ve buna bağlı arazi örtüsü değişikliklerinin de heyelanların sıklığını ve etkilerini artırması beklenmektedir. LULCC'nin heyelanlar üzerindeki rolü kabul edilmektedir, ancak farklı gelişmişlik düzeylerine sahip dağlık bölgelerdeki ülkeler arasındaki farklılıkları dikkate alan araştırmaların eksikliği söz konusudur. Bu çalışmada, 46 ülkedeki dağlık alanlarda arazi örtüsü ile gelir düzeyi, nüfus değişimi, heyelanlar ve ölümler arasındaki etkileşimler ele alınmaktadır. 59 yıllık arazi örtüsü ve 45 yıllık nüfus değişim oranı verileri kullanarak, bunların heyelan ve ölümlerle ilişkisini değerlendirmek için doğrusal regresyon modelleri geliştiriyoruz. Tez kapsamında, ülkeler gelir seviyelerine göre gruplandırılmış ve LULCC her bir grup için ayrı ayrı incelenmiştir. Yüksek gelir grubundaki ülkelerde arazi örtüsündeki değişim sınırlı kalmış ve orman örtüsünde %1,7'lik bir artış gözlenmiştir. Bununla birlikte, kentsel alanlar %80

oranında artış göstermiştir. Üst-orta gelir grubundaki ülkelerde de benzer şekilde küçük çaplı değişiklikler meydana gelmiştir. Bu grupta otlak alanları %6,9 artarken, çalı ve çayır alanlarında %17,5'lik bir azalma gözlenmiştir. Alt-orta gelir grubundaki ülkelerde ise değişiklikler daha belirgindir; otlak alanları %27,8 oranında artarken, kentsel alanlar da iki katına çıkmıştır. Düşük gelirli ülkelerde ise LULCC oranları daha yüksek olup, orman örtüsü %20 oranında azalmıştır. Aynı zamanda, tarım arazilerinin üç katına çıkması dikkat çekici bir bulgudur. Ayrıca, kentsel alanlarda on kattan fazla bir genişleme ile diğer gelir gruplarına kıyasla dağlık alanlarda en yüksek kentsel genişleme oranını göstermiştir. Sonuçlarımız, dağlık alanlarda arazi örtüsü ve nüfus değişiklikleri arasında önemli bir ilişki olduğunu göstermektedir. Değişim derecesinin ve insan müdahalesinin belirgin şekilde daha yüksek olduğu alt-orta ve düşük gelirli ülkelerdeki LULCC, diğer gelir gruplarına kıyasla daha yüksek bir oranda ve yoğunlukta gerçekleşmektedir. Ayrıca bulgularımız, insan müdahalesi ve LULCC oranlarının daha yüksek olduğu düşük ve alt-orta gelirli ülkelerde daha yüksek heyelan ve ölüm yoğunluğuna işaret etmektedir. Bulgularımız, LULCC'nin peyzaj dinamiklerinde kritik bir faktör olduğunu ve insan baskısının heyelanlar için bir tetikleyici faktör olduğunu vurgulamaktadır.

Tezin son bölümünde sosyoekonomik faktörlerin ölümcül heyelanlar üzerindeki etkisi incelenmektedir. Ekonomik ve insani kalkınma düzeyi, gelir eşitsizliği ve hükümet etkinliği gibi sosyoekonomik koşullardaki farklılıklar ülkeden ülkeye değişmekle birlikte, doğal bir tehlike olarak heyelanlara karşı savunmasız toplulukları önemli ölçüde etkileme potansiyeline sahiptir. Ancak, sadece az sayıda çalışma bu potansiyel etkiyi küresel ölçekte araştırmıştır. Dolayısıyla, dünya genelinde sosyoekonomik faktörlerin kombinasyonunun farklı gelir düzeylerine sahip ülkelerdeki ölümcül heyelanları nasıl etkilediğine dair hâlâ bir anlayış eksikliği bulunmaktadır. Burada, 62 ülkede gelir düzeyine göre heyelan ölümleri ile sosyoekonomik faktörler arasındaki ilişkiyi araştırıyoruz. Bu amaçla, negatif binom genelleştirilmiş doğrusal regresyon modelleri kuruyoruz. Sonuçlarımız, yüksek gelirli ülkelerde, potansiyel olarak heyelana maruz kalan nüfustaki bir birimlik artış, ölümlerde %42'lik bir artışa yol açmıştır. Üst-orta gelirli ülkelerde ise Gini endeksinde bir birimlik artış, ölümlerde %16'lık bir artışla bağlantılıyken, potansiyel olarak maruz kalan nüfustaki artış ölümlerde %21'lik bir artışla sonuçlanmıştır. Ayrıca, Hükümet Etkinliği İndeksi'ndeki (GEI) bir birimlik artış, ölümlerde %37'lik bir azalmaya işaret etmektedir. Düşük-orta gelirli ülkelerde, potansiyel olarak maruz kalan nüfusun artışı, ölümlerde %33'lük bir artışa karşılık gelmektedir. Düşük gelirli ülkelerde de benzer şekilde, maruz kalan nüfusun artışı ölümlerde %33'lük bir artışla ilişkilendirilmiştir. Bununla birlikte, daha yüksek bir İnsani Gelişim Endeksi'nin (HDI) heyelan kaynaklı ölümler üzerinde %99'luk bir azalma sağladığı gözlemlenmiştir. Sonuç olarak, daha düşük ekonomik ve insani kalkınma düzeyine sahip ülkelerin yanı sıra daha yüksek gelir eşitsizliği ve daha zayıf yönetişime sahip ülkeler daha yüksek heyelan ölümlerine maruz kalma eğilimindedir. Özellikle, artan gayrisafi yurtiçi hasıla (GSYH) ve hükümet etkinliğinin koruyucu etkisi, gelir eşitsizliği ve heyelandan etkilenen bölgelerdeki nüfus yoğunluğu modele dahil edildiğinde ortadan kalkmıştır. Bu bulgular, heyelan ölümlerini azaltma veya önleme çalışmalarında sosyoekonomik faktörlere daha fazla dikkat edilmesi gerektiğini vurgulamaktadır.

Genel olarak bu tez, küresel ölçekte ölümcül heyelanları kontrol eden topoğrafik, iklimsel ve antropojenik faktörlerin karmaşık etkileşiminin kapsamlı ve bütünsel bir değerlendirmesini sunmaktadır. Doğal faktörlerin tetiklediği ölümcül heyelanlar daha yüksek rakımlarda ve daha dik yamaçlarda meydana gelme eğilimindeyken,

antropojenik muadillerinin daha düşük eğimli yamaçlarda ve yoğun nüfuslu alanlarda meydana geldiği tespit edilmiştir. Ayrıca, nüfus baskısı ve LULCC'nin, özellikle alt-orta ve düşük gelirli gelirli ülkelerde, ölümcül heyelan oluşumunda ve ölümlerde önemli bir rol oynadığı gösterilmiştir. Ayrıca, sosyoekonomik faktörlerin heyelan ölümleri üzerindeki etkisi de incelenmiş ve ekonomik kalkınma, gelir eşitsizliği ve hükümet etkinliğinin heyelan ölümleri üzerindeki etkileri açıklığa kavuşturulmuştur. Tez sonuçları, sosyoekonomik kalkınma, gelir eşitsizliği ve hükümet etkinliği kalitesinin, özellikle düşük gelirli ülkelerde heyelan kaynaklı ölümlerin önlenmesi ve azaltılmasında kritik faktörler olduğunu göstermektedir.



1. INTRODUCTION

1.1 Motivation

Landslides are one of the most widespread geohazards that globally cause significant loss of life and environmental damage (Froude and Petley, 2018; D. Kirschbaum et al., 2015; D. Petley, 2012). Impacts of landsliding are exacerbated by more frequently occurring extreme weather events and increased human occupation of vulnerable mountainous landscapes (Grima et al., 2020). Specifically, the growing demographic pressure and land use/cover changes are expected to increase the frequency and impacts of landslides in both rural (Froude and Petley, 2018; Guns and Vanacker, 2014; Maki Mateso et al., 2023) and urban (Froude and Petley, 2018; Gariano and Guzzetti, 2016; Ozturk et al., 2022) areas.

Therefore, developing a better understanding of variables controlling landslide occurrence is a critical element in landslide disaster prevention. In this context, the recording, monitoring, and analysis of landslides form essential elements in developing more robust predictive models.

Digital documentation and archiving of landslides have become increasingly common, most notably in the last two decades (e.g., Tanyaş et al., 2017; Emberson et al., 2022). Despite the expanding literature, financial losses and fatalities are rarely reported as part of landslide event inventories. And yet, a relatively large literature has been constructed that targets climatic and anthropogenic influences on fatal landslides across different spatial and temporal domains, including national (e.g., Petley et al., 2007; Lin and Wang, 2018; Görüm and Fidan, 2021; Garcia-Delgado et al., 2022), regional (e.g., Petley 2010; Sepúlveda and Petley, 2015; Haque et al., 2016, 2019), and global (e.g., Kirschbaum et al., 2010, 2015; Petley, 2012; Froude and Petley, 2018; Haque et al., 2019) scale assessments.

The contextual effect of human stress on slopes under extreme weather conditions has already been noticed in a number of global studies, emphasizing hotspots in Central and Southeast Asia; Central and South America; as well as East Africa (Kirschbaum

et al., 2012, 2015; Froude and Petley 2018; Haque et al., 2019). Such occurrences have also been responsible for a proportional increase in fatalities (Haque et al., 2019). A closer look at fatal landslide hotspots highlights South Asia as the most affected region, mainly driven by the summer monsoon, and East Asia, driven by landfalling tropical cyclones and a monsoonal climate. These aspects have been explored in depth by Petley (2010), which also highlights Southeast Asia (mainly the Philippines and Indonesia) as a landslide fatality hotspot, albeit without linking them to a specific climatic regime. Similar studies have also been conducted in other parts of the world. Sepúlveda and Petley (2015) examine fatalities in the Caribbean region, Central America, Colombia, and southeastern Brazil. They emphasize the role of large-scale hurricanes, with the El Niño/La Niña cycle as an additional disturbance, potentially leading to more fatalities. In another study focusing on the European landscape, Haque et al. (2016) argue that human activities may exert a minor effect with respect to extreme natural agents.

Similar studies have also been carried out at finer spatial scales, being tailored to specific countries such as the Democratic Republic of Congo (Depicker et al., 2021), Nepal (Petley et al., 2007), and Türkiye (Görüm and Fidan, 2021), where the spatial distribution of landslides has been associated with land use changes, civil wars or economic and political influences, respectively. This implies that anthropogenic influences seem to be more apparent in a finer-resolution review. For instance, Garcia-Delgado et al. (2022) refer to low income, high corruption, and inequality effects as factors increasing the vulnerability against landsliding in Colombia.

Considering the studies that human activities and land cover changes are important drivers of landslides, these effects are particularly alarming in mountainous regions. Covering 27% of the world's land surface (Sayre et al., 2018), mountains are topographically complex regions formed by the interplay of tectonic and volcanic processes, rising prominently with steep slopes and considerable local relief (Antonelli et al., 2018; Rahbek et al., 2019). They are host to ecosystems that are rich in climatic and ecological diversity (Antonelli et al., 2018; Makino et al., 2019; Rahbek et al., 2019; Rixen et al., 2018). These environments also play a key role in providing essential living resources such as water, food, and energy to communities within and around, as well as beyond their geographical boundaries (Leister et al., 2019; Makino et al., 2019; Nogués-Bravo et al., 2007; Sayre et al., 2018; Thornton et al., 2022).

However, mountain areas are fragile landscapes, their fragility exacerbated by an increasing frequency of extreme weather events due to anthropogenic climate change, increasing human occupation and subsequent land use land cover change (LULCC), and the socioeconomic marginalization of their settler populations (Fidan et al., 2024; Grima et al., 2020; Leister et al., 2019; Li and Jenkins, 2022). Although this relationship remains to be entirely ascertained, growing human pressure and changes in land use/cover are expected to increase the frequency and impact of landslides as they are associated with environmental degradation processes in steep terrain (Depicker et al., 2021; Guns and Vanacker, 2014; Maki Mateso et al., 2023; Pisano et al., 2017).

Globally, about 26% to 31% of the human population lives in mountainous areas (Meybeck et al., 2001; Thornton et al., 2022), approximately 60% of which are under intense human pressure, particularly at low elevations (Elsen et al., 2020). The number of people exposed to natural hazards has nearly doubled between 1975 and 2015 (Ehrlich et al., 2021; Thornton et al., 2022). Although human pressure is generally highest at lower elevations, about 30% of the land above 4500 meters also experiences intense human activity (Elsen et al., 2020). Population growth in many mountainous areas is associated with strong urbanization (Thornton et al., 2022), and increasing human settlements on unstable slopes enhance the risk of fatal landslides (Depicker et al., 2021; Froude and Petley, 2018; Oreye et al., 2022; Ozturk et al., 2022).

The main impact of human pressure on mountainous areas is the alteration of land use/cover, an important environmental driver controlling the incidence of landslides (Depicker et al., 2021; Guns and Vanacker, 2014; Oreye et al., 2022). Clear-cutting, or transition of forests to pasture and cropland, has been shown to vary hydrological processes, resulting in decreased slope stability and increased shallow landsliding (Depicker et al., 2021; Glade, 2003; Guns and Vanacker, 2014; Montgomery et al., 2000; Vanacker et al., 2003). Mining, infrastructure, and road construction activities also increase the terrain's susceptibility to landslides (Froude and Petley, 2018; Tanyaş et al., 2022), while adding to the vulnerability of mountain communities that are already disadvantaged by accessibility, poverty, and inadequate infrastructure (Gentle and Maraseni, 2012; Kirschbaum et al., 2020; Li and Jenkins, 2022).

Increased precipitation and extreme weather events due to anthropogenic climate change may also destabilize hillslopes and increase the frequency of landslides

(Kirschbaum et al., 2012, 2015). It is predicted that climate change, specifically changes in the intensity and duration of precipitation, coupled with anthropogenic interferences on the landscape, will leave more people dangerously exposed to the potential increase in the frequency and intensity of landslides (Crozier, 2010; Gariano and Guzzetti, 2016). In sum, the combined effects of climate change, increasing population pressure, and LULCC create an insecure and high-risk environment for mountain communities.

Wealthier nations may experience fewer deaths from disasters (e.g., earthquakes, floods, hurricanes, extreme temperatures, and landslides) as they often have the required resources and protection infrastructure already in place (Kahn et al., 2005). In contrast, countries with lower income levels often lack the resources and infrastructure to mitigate and respond to such hazards effectively (Lindersson et al., 2023), making them more vulnerable to their impacts (Froude and Petley, 2018). Despite numerous long-standing studies on the importance of increasing human pressure and LULCC on landslides (Depicker et al., 2021; Guns and Vanacker, 2014), there has been no global assessment of how the combination of these factors varies across mountain ranges in countries with different income levels.

Less developed countries experience more severe humanitarian impacts than developed countries, while developed countries suffer greater economic losses. In addition, more people are adversely affected in countries with higher income inequality than in more equal societies (Tselios and Tompkins, 2019). Some studies have indicated that landslide-related fatalities tend to increase as GDP per capita decreases (Froude and Petley, 2018; D. Kirschbaum et al., 2015) and in countries with low human development (Sepúlveda and Petley, 2015). Also, countries with better governance and stronger state capacity, particularly in democratic contexts, tend to experience fewer deaths from natural disasters due to the more effective exercise of political power at all levels of government, which helps reduce the population's exposure to hazard impacts (T. H. Lin, 2015; Tierney, 2012; Tselios and Tompkins, 2021). As a result, although studies include the effects of socioeconomic factors on landslide fatalities, there are still gaps in understanding how the combination of socioeconomic factors on a global scale varies across countries with different income levels.

1.2 Research Objectives and Structure

This thesis consists of a total of six chapters, including three main chapters (Figure 1.1) that address the following three main Research Questions (RQs):

Chapter one presents an introduction that includes a concise literature review, identifies the research gap, outlines the thesis objectives, and delineates the framework and research questions.

Chapter two outlines the thesis's methodological framework, focusing on the analysis of topographic, climatic, and anthropogenic factors affecting fatal landslides, the impact of land use land cover change (LULCC) in mountainous areas, and the socioeconomic factors influencing landslide fatalities.

Chapter three describes **RQ 1: “How do macro-landforms, their morphometric characteristics, climatic regimes, and anthropogenic pressure affect the distribution of fatal landslide events?”** The overall perspective on fatal landslides is a complex phenomenon that has lacked a holistic examination of how macro-landforms and their morphometric characteristics, anthropogenic pressure, and climatic regimes interplay to generate landslide-related losses. The research reported in this thesis aims to start to fill this specific gap. With this idea in mind, we accessed the Global Fatal Landslide Database (GFLD) and initially aggregated the records at the basin scale. Then, we examined the persistent spatio-temporal occurrence of landslide fatalities against a number of morphologic and climatic features, aiming at capturing variations between landslides driven by natural or anthropogenic variables. This chapter is based on the paper “Fidan, S., Tanyaş, H., Akbaş, A., Lombardo, L., Petley, D. N., & Görüm, T. (2024). Understanding fatal landslides at global scales: a summary of topographic, climatic, and anthropogenic perspectives. *Natural Hazards* 120, 6437–6455”

Chapter 4 explores **RQ 2: “How does land use land cover change (LULCC) affect the occurrence of fatal landslides in mountainous areas of countries at different income levels?”** To address the gaps in the impact of LULCC on fatal landslides, we adopted the K1 mountain characterization (Kapos et al., 2000) and focused on mountainous areas of 46 countries categorized by income level. Initially, we calculated a 59-year-long LULCC and a 45-year-long population change rate dataset and analyzed how these two variables are related. We then evaluated their relationships with landslides, fatalities, and environmental variables. Finally, we built a statistical

model to determine whether or not LULCC and population growth are associated with observed landslides and fatalities in mountainous areas.

Chapter 5 investigates **RQ 3: “Can socioeconomic differences such as economic and human development, income inequality, and governance explain variations in landslide fatalities?”** To answer this question, we investigate to what extent countries experience higher landslide fatalities. We collected data on the level of economic and human development, income inequality, and political stability in 62 countries from 2004 to 2017. By examining these socioeconomic factors, we aimed to determine whether they play an important role in explaining the observed differences in landslide-related fatalities. We also used statistical models to identify potential relations, thus providing an understanding of how socioeconomic conditions affect landslide fatalities.

Finally, chapter six presents a conclusion summarising the main findings of this thesis in light of the three main RQs.

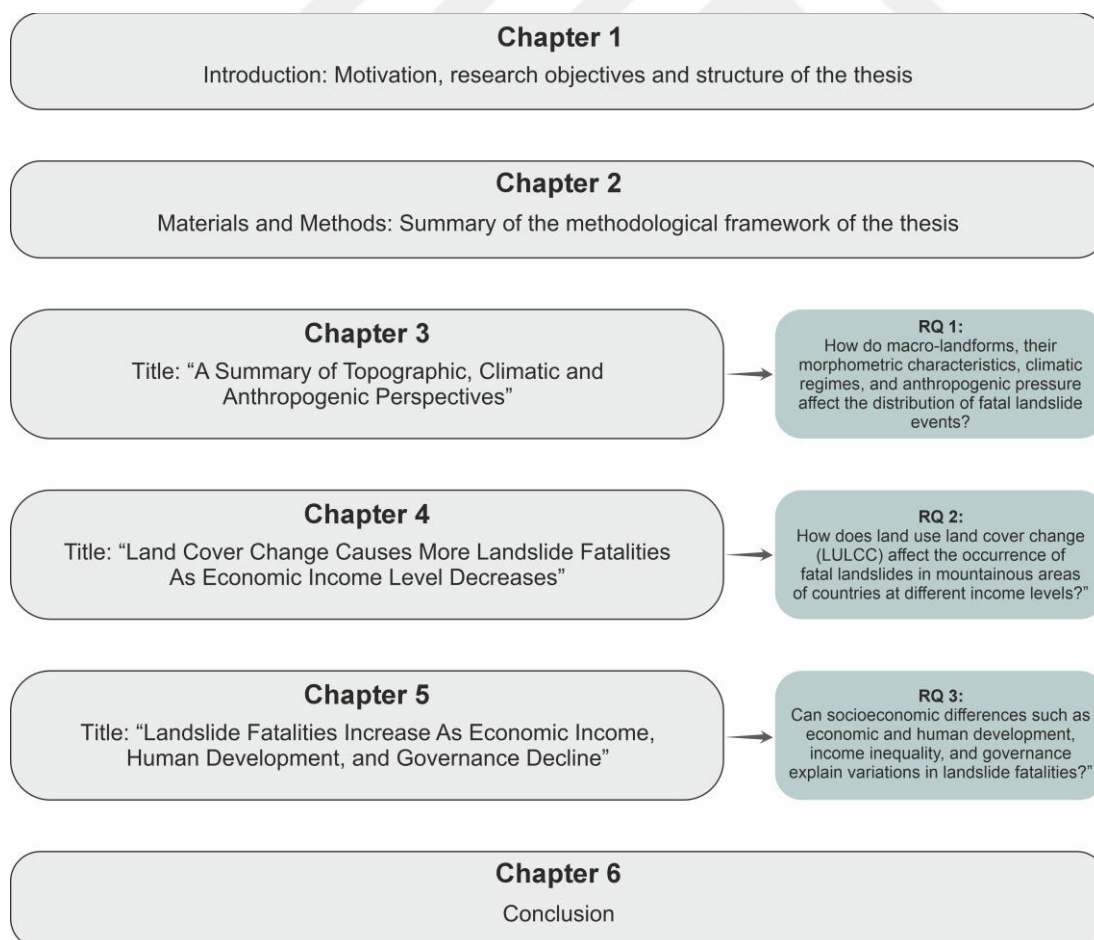


Figure 1. 1: Overview of the thesis structure

2. MATERIALS AND METHODS

2.1 Framework for Analyzing Topographic, Climatic, and Anthropogenic Factors

In this thesis, we selected a total of 12 potential controlling factors in five categories: topographic (elevation, slope, elevation standard deviation, compound topographic index, and macro landforms), climatic (climate classification and precipitation), hydrographic (sub-basins), economic (GDP per capita) and anthropogenic (population, human footprint, and land cover change) variables from a variety digital sources (Table 2.1).

2.1.1 Potential controlling factors

We used the GFLD information collected from 2004 to 2017 (Froude and Petley, 2018), which exclusively reports fatal landslides triggered by non-seismic causes, such as precipitation and human activities. The GFLD compiles landslide records in news reports, scientific studies, and government reports. In addition, the database provides information about location and associated accuracy, occurrence date, type, cause, and number of victims. Also, the location accuracy in GFLD is addressed based on administrative units such as villages or states. To carry out the assessment in this manuscript, we selected all fatal landslides with a location accuracy of 10 km or less. Such a level of accuracy is suited to a global scale analysis, particularly because the data aggregation (presented in the following Sections) has been performed over catchments with a mean planimetric extent of 130 km² and a variation of 69 km² measured in one standard deviation.

Most landslide-related deaths and economic damage are clustered in urban areas and, specifically, in countries with low GDP per capita (Froude and Petley, 2018). In low to middle-income countries, fatal landslides are more frequent on slopes where people live in shanty towns (Alexander, 2005; Sepúlveda and Petley, 2015). In this overall scenario, if we were to include high-income countries in the analysis – for instance, with a 2017 GDP per capita (World Bank, 2017) of more than \$20,000 – the results

would potentially be biased. Therefore, we excluded nations fulfilling the above criterion and focused on the fatal landslide information about low- and middle-income countries.

Table 2. 1: The list of potential controlling factors used in this research.

Data category	Data type	Spatial resolution	Reference
Landslide	Fatal landslide	location accuracy <10 km	Froude and Petley (2018)
Economic	GDP per capita	Country-based	World Bank (2017)
Hydrography	Sub-basins	~450 m	Lehner and Grill (2013)
	Elevation	~90 m	Yamazaki et al., (2017)
	Elevation standard deviation (elev-std)	90 m	Amatulli et al., (2020)
Topographic	Slope	90 m	Amatulli et al., (2020)
	Compound topographic index (CTI)	90 m	Amatulli et al., (2020)
	Macro landform	~55 km	Amatulli et al., (2020)
Climatological	Köppen-Geiger climate classification	1 km	Beck et al. (2018)
	Precipitation	~1 km	Karger et al., (2017)
	Population density	1 km	Bright et al. (2004, 2017); Bright and Coleman (2001, 2003); Rose et al. (2018, 2021)
Anthropogenic	Human Footprint Index (HFI)	1 km	Mu et al. (2022)
	Land cover (only forest and settlement)	300 m	Climate Data Store (2019)

To eliminate the effect of uncertainty regarding the point representation of landslides, we spatially represented landslides at the basin scale, making use of the HydroBASINS dataset. This dataset was created from hydrologically corrected DEMs (~30 m), and fed to a flow path routing method. The resulting hydrological basins were computed and stored across different spatial scales. These correspond to 12 levels of hierarchically nested global sub-basins (Lehner and Grill, 2013). In the remainder of the manuscript, all analyses refer to the 12th level.

We used the MERIT-Digital Elevation Model (DEM) created by Yamazaki et al. (2017) as the baseline elevation data for topographic analysis. MERIT DEM is a worldwide terrain elevation dataset with a 3-arcsecond resolution (~ 90 m at the equator) that covers land regions between 90N-60S concerning the EGM96 geoid. The high-accuracy global MERIT DEM was developed by removing multiple errors, including absolute bias, stripe noise, speckle noise, and tree height bias. For other topographic parameters associated with landslides, we used the Geomorpho90m global dataset, which consists of different geomorphometric features also derived from the MERIT DEM (Amatulli et al., 2020). These features correspond to slope, elevation standard deviation (elev-std), and compound topographic index, and their use as part of our analyses will be described in the data pre-processing section.

To further characterize catchment characteristics associated with fatal landslide information, we also used a macro-landform description (Meybeck et al., 2001) aggregated into five diagnostic classes: (1) plains, (2) lowlands, (3) platforms, (4) plateaus, and (5) mountains.

For climate analyses, we used the 1 km resolution Köppen-Geiger climate classification of Beck et al. (2018). The authors group the world's climates into five main classes: (A) tropical, (B) arid, (C) temperate, (D) continental, and (E) polar. To this generic description, we added a more precipitation-oriented one using the CHELSA v2.1 climate dataset (Karger et al., 2017, 2021). This dataset is expressed at a 30-arcsecond (~ 1 km) spatial resolution, and from it, we extracted the mean annual precipitation layer (i.e., BIO12) over the last 30 years (1981-2010).

To examine the role of anthropogenic factors, we used three different proxies. First, we used global population data from 2000 to 2020. Because the GFLD dataset has both spatial and temporal dimensions, we extracted the information related to the population for the period when the fatal landslide occurred. The population data was accessed through the LandScan Global Population Distribution Dataset, a 1 km resolution product (Bright et al., 2004, 2017); Bright and Coleman, 2001, 2003); Rose et al., 2018, 2021). Also, we considered the 1 km resolution Human Footprint (HFI, hereafter) dataset (Mu et al., 2022), which is expressed into eight different human pressure variables. These correspond to the intensity of human activities from 2000 to 2018, associated with built-up environments, population density, night-time lights, croplands, pastures, roads, railways, and navigable waterways.

Ultimately, to understand the temporal change trends and possible impacts of forest and settlement areas in the considered basins, we used the land cover data accessed from The Copernicus Climate Change Service (C3S). This is a 300 m resolution product referred to as Climate Data Store (CDS), generated by the European Space Agency (ESA) Climate Change Initiative (CCI). It summarised Land Cover (LC) data from 1992 to 2015 (Defourny et al., 2017) and Intermediate Climate Data Records (ICDR) Land Cover data from 2016 to 2020 (Defourny et al., 2021). Notably, ICDR LC data from 2016 to 2020 are consistent with the ESA CCI LC data from 1992 to 2015 to ensure continuity (Defourny et al., 2021).

2.1.2 Data pre-processing

We prepared two different landslide datasets corresponding to *i*) landslides triggered by natural factors (LTNF; i.e., precipitation) and *ii*) landslides triggered by anthropogenic factors (LTAF; i.e., construction, mining activities, hill cutting, and other human activities).

Using the information on the geolocation accuracy, we created a buffer zone around each fatal landslide of 10 km. We then selected all sub-basins intersecting these buffers and represented landslide locations by them. This procedure was repeated for LTNF and LTAF. This has led to a total of 6744 sub-basins intersected by LTNF and 2081 sub-basins hosting LTAF.

While aggregating landslide information over sub-basins, we also aggregated corresponding environmental characteristics. The first aggregation step applies to the continuous characteristics. We calculated the mean values of *i*) elevation, *ii*) slope, *iii*) elev-std, *iv*) CTI, *v*) precipitation, *vi*) the annual rate of change for HFI, and *vii*) population. Furthermore, we computed the total population and calculated the trend of forest and settlement planimetric extents from land cover data.

We utilized Kernel Density Estimation (KDE, Silverman 1986) to define hotspots worldwide. First, we merged the LTNF and LTAF sub-basins and converted them to points. Next, we computed KDE within a moving window of a 100 km radius to obtain a continuous density surface. We then defined hotspots along the spatially coherent density surfaces by considering topographic and climatic characteristics. Moreover, to determine the landslide density for each sub-basin, we computed the KDE within a moving window with a radius of 10 km. Each sub-basin was then assigned with a fatal

landslide density value corresponding to the mean of the KDE grid cells ($KDE_{sub-basin}$). The total population in each sub-basin ($Pop_{sub-basin}$) was also produced. This information allowed us to obtain the normalized landslide density (NLD) as the proportion of the last two parameters:

$$NLD = \frac{KDE_{sub-basin}}{Pop_{sub-basin}} \quad (2.1)$$

2.1.3 Bivariate spatial descriptors

Traditionally, maps represent the variation of a given parameter across the geographic space. Because the aim of this work is to examine the contextual effect of multiple parameters and check whether they can be used as discriminant tools between natural and anthropogenic fatal landslides, we opted for an exploratory step based on bivariate maps. These are maps where the distribution of two parameters is grouped into a finite number of classes, and the combination of the two is then plotted via a two-dimensional color bar (Robertson and O’Callaghan, 1986; Trumbo, 1981). We initially applied this graphical technique to combine the spatial signals of the Köppen-Geiger climate classification together with a macro landform representation. Then, the frequency of LTNF and LTAF is calculated for each of the combined classes mentioned above. We also repeated the same operation for the two types of fatal landslides falling in a combined classification map showing landslide fatalities and their relative spatiotemporal persistence.

Moreover, we also computed the summary statistics of topographic, climatic, and anthropogenic proxies for each fatal landslide type. This information is summarised in a suite of scientific illustrations from which we base our interpretation and further discussions.

2.2 Framework for Analyzing Land Cover Change in Mountainous Areas

2.2.1 Study extent and landslide data

We only focused on mountainous areas worldwide and calculated land use land cover change (LULCC) from 1960 to 2019. We also examined the relationship between the rate of LULCC and fatal landslides at the country level by income class to shed light on the role of economic income level -high income, upper middle income, lower middle income, and low income-. However, the income classifications of countries

categorized by the World Bank change over time due to economic conditions (World Bank, 2024). Therefore, we identified the predominant income class using a frequency-based method to create a consistent income classification representing relative living standards that have changed over time. This income classification for all countries is reported in the source data file. To do this, we use the income class based on per capita gross national income (GNI), according to the Atlas method (World Bank Open Data, n.d.). Moreover, we considered the median value (5.5) to ensure comparability across countries and only included countries with six or more fatal landslide events. This approach resulted in 46 countries grouped by income class, which allowed for a more reliable comparison across countries: seven high-income countries, eight upper-middle-income countries, 15 lower-middle-income countries, and 16 low-income countries.

We obtained landslide records from the Global Fatal Landslide Database (GFLD), which includes information collected between the years 2004 and 2017 (Froude and Petley, 2018). This database has been described in detail above (see 2.1.1). We used landslides triggered by natural factors (i.e., precipitation and snow melt) and anthropogenic factors (i.e., construction, mining activities, hill cutting, and other human activities) corresponding to mountainous areas in the database. We aggregated landslide and fatality information using a repeated procedure for the mountain area of each country. We also calculated landslide density (*LD*) and fatality density (*FD*) by dividing the number of landslides and deaths by the mountainous area of that country. This calculation allowed us to obtain a normalized measure of how concentrated landslides and fatalities are in different mountainous areas.

2.2.2 Global mountainous data and analysis

We used the K1 layer, a previously published (Kapos et al., 2000) comprehensive dataset describing mountainous areas on a global scale (Figure 1a). The K1 layer classifies 24% of the Earth's land area as mountainous using a combination of elevation, slope, and relative relief at 1 km resolution worldwide. All areas above 2500 meters are considered mountainous regardless of relative relief, while areas below 2500 meters are assigned as mountainous if their elevation and relative relief exceed 300 meters. It also provides comprehensive data appropriate for calculating forested areas in mountains and other land cover (Sayre et al., 2018).

We split the mountainous areas by country borders to understand how land use changed among countries with different income levels. We then analyzed the LULCC in mountainous areas of countries with six or more fatal landslide events at the country level based on income. Our analyses were performed over the mountainous areas of each country with a mean planimetric extent of 365,483 km² and a variation of 784,341 km² measured in one standard deviation.

2.2.3. Land cover data and change rate calculations

To explore the LULCC, we used HILDA+ (HISTORIC Land Dynamics Assessment+), a global land cover dataset at 1 km spatial resolution between 1960 and 2019 (Winkler et al., 2021). HILDA+ is based on a data-driven reconstruction approach and combines many open data sources, such as high-resolution remote sensing and long-term land cover reconstructions. This database includes six land cover types: urban, cropland, pasture, forest, grass and shrubland, and sparse and non-vegetated areas. We calculated each land cover transition to capture differences in country-specific patterns and rates of change across these categories for the 59-year period from 1960 to 2019. In addition, to visualize the change between land cover types, we created Sankey diagrams in R-Studio using the 'networkD3' package (Allaire et al., 2017) to visualize the persistence of land cover over the specified time interval and transitions between land cover classes.

To calculate the LULCC rate, this method follows four main steps. In the first step, we derived absolute areas in urban, cropland, pasture, forest, grass and shrubland, and sparse and non-vegetated regions from the HILDA database for the years 1960 and 2019, respectively. We then generated a transition matrix $T(t)$ representing the change between the six land cover types from 1960 to 2019. In this matrix, each cell $T_{ij}(t)$ represented the area moving from land cover type i to land cover type j in year t . In the second step, we used this transition matrix to obtain the total areas of change for each land cover type between 1960 and 2019. We calculated the total transition areas between each land cover type using equation (2.2),

$$LULCC_{total} = \sum_{i=1}^6 \sum_{j=1}^6 T_{ij}(t), \quad (2.2)$$

where $LULCC_{total}$ represents the total LULCC. Repeating this procedure for 46 countries provided the basis for analyzing the dynamics of LULCC at the country level by income class.

As the third step, we assigned a score corresponding to the dynamics of LULCC in each of the 46 countries to obtain a total LULCC rate. For this, we classified transitions between all land cover categories into change (e.g., conversion to another type) and non-change events (e.g., unchanged areas and conversions to forest) and converted area transitions into percentages. Since in many mountainous areas, forests help prevent landslides by providing slope stability (Brang et al., 2006; Grima et al., 2020), and we categorized them as non-change events. The rate of change (which is the sum of the percentages of conversion from one land cover type to another) was calculated by equation 2.3,

$$LULCCR_{score} = \sum_{\substack{i=1 \\ i \neq j \\ j \neq forest}}^6 \sum_{j=1}^6 P_{ij}(t), \quad (2.3)$$

where $LULCCR_{score}$ represents the total LULCC rate, $P_{ij}(t)$ represents the percentage of area transitioned from land cover type i to land cover type j , $i \neq j$ excludes unchanged areas, and $j \neq forest$ excludes transitions to forests. A higher $LULCCR_{score}$ value indicates that the land cover in a specific country's mountainous areas is considerably changing, while a lower $LULCCR_{score}$ value means minimal change and less intervention (Table 4.1-4.2).

Finally, we normalized the total rate of LULCC by each country's mountainous area to calculate the intensity of its change by area and obtain a comparable measure. For each country and its associated LULCC, we apply the following equation (2.4):

$$LULCCR_{scoreN} = \frac{LULCCR_{score}}{A_{mountain}}, \quad (2.4)$$

where $LULCCR_{scoreN}$ represents the normalized $LULCCR_{score}$, and $A_{mountain}$ represents the total mountainous area of the country. In addition, we performed a normalization to $LULCCR_{scoreN}$ in the range 0 to 1 (Table 4.1-4.2).

2.2.4 Population data and analysis

To estimate population pressure in potentially mountainous areas, we utilized population grids at 30-arcsecond (~ 1 km) spatial resolution (GHS-POP R2023A, a product of Global Human Settlement). GHS-POP R2023A provides the distribution of the human population expressed as the number of people per cell (Schiavina et al., 2023). Due to the lack of historical population data going back to 1960 (the year from which land cover data became available), we used data from 1975 onwards, and using population data from the GHS-POP product, we obtained the total number of individuals for each country's mountainous area for 1975 and 2020 (Figure 4.7). We then calculated the population change rate (PCR) as follows in equations (2.5) and (2.6):

$$PCR = ((Mountain_{pop2020} / Mountain_{pop1975}) - 1), \quad (2.5)$$

$$PCR_N = \frac{PCR}{A_{mountain}}, \quad (2.6)$$

where $Mountain_{pop2020}$ is the total population in 2020 and $Mountain_{pop1975}$ is the total population in 1975. We also normalized this by each country's mountainous area ($A_{mountain}$) to obtain a comparable measure (PCR_N), and this procedure was repeated for each country to a range of 0 to 1. Details per country can be found in Table 4.3-4.4.

2.2.5 Topographic relief and precipitation analysis

To estimate local topographic relief, we calculated the difference in elevation between the highest and lowest elevations within a 2.5 km radius using the MERIT-Digital Elevation Model (DEM) data at a 1 km pixel resolution (Yamazaki et al., 2017). For precipitation analysis across mountain regions, we used the CHELSA v2.1 climate dataset (Karger et al., 2017), which offers a 30-arcsecond (~ 1 km) spatial resolution. We extracted the average annual precipitation layer (BIO12) over the last 30 years (1981-2010) to account for the spatial precipitation gradient.

2.2.6 Regression models

We use a Generalized Linear Model (GLM) in which the dependent (response) variables are assumed to have a Gaussian distribution. To do so, we designed two versions of GLM. The models were fitted using the `glm()` function with the R package MASS (Faraway, 2004; James et al., 2013). All variables were centered, and two highly skewed variables were log-transformed.

First, we created a GLM to estimate the association between the LULCC and population change rates. This simple linear model is based on the following equation (2.7):

$$\log (LULCCR_{scoreN}) = \beta_0 + \beta_1 \log (PCR_N) + \epsilon \quad (2.7)$$

where the dependent variable, $LULCCR_{scoreN}$, represents the normalized total LULCC rate. β_0 is the mean model intercept, β_1 is the regression coefficient for the predictor variable $-PCR_N$ is accounting for the normalized population change rate-, and ϵ is the error term.

Second, we fitted GLMs trained to explain the spatial variability in landslide and fatality density as a function of LULCC and population change rate. These models to be estimated are given by equations (2.8) and (2.9):

$$\log (LD) = \beta_0 + \beta_1 \log (LULCCR_{scoreN}) + \beta_2 \log (PCR_N) + \epsilon \quad (2.8)$$

$$\log (FD) = \beta_0 + \beta_1 \log (LULCCR_{scoreN}) + \beta_2 \log (PCR_N) + \epsilon \quad (2.9)$$

The dependent variable LD represents landslide density, and FD represents fatality density. The predictor variables included the normalized total LULCC rate ($LULCCR_{scoreN}$) and normalized population change rate (PCR_N). β_0 is the mean model intercept, β_{1-2} are the regression coefficients for each predictor variable, and ϵ is the error term.

To verify the model's functionality, we performed residual analysis for the models using the R package stats (R Core Team, 2013). We tested the residual analyses using histograms, Q-Q plots, and plots of residuals versus fitted values.

2.3 Framework for Analyzing Socioeconomic Factors

2.3.1 Study extent and landslide data

We utilized the Global Fatal Landslide Database (GFLD), which records landslides and associated fatalities from 2004 to 2017 (Froude and Petley, 2018). This database has been described in detail above (see 2.1.1).

We used only landslides triggered by precipitation, which are more persistent among natural triggers in the database. We excluded landslide events triggered by anthropogenic factors (e.g., construction, mining activities, hill-cutting, and other human activities) as they are associated with economic conditions (Froude and Petley, 2018; Sepúlveda and Petley, 2015) and could potentially bias our study, which focuses on socioeconomic factors. Initially, we aggregated landslides using a repeated procedure for each country and considered the median value (5) to ensure comparability across countries. We then compiled the number of fatalities, taking into account countries where five or more fatal landslide events were recorded. Moreover, we examined the association between landslide fatalities and socioeconomic factors at the country level by income class to emphasize the role of economic income level (i.e., high income, upper middle income, lower middle income, and low income). For this purpose, we use the Atlas method (World Bank Open Data) to calculate the income class based on per capita gross national income (GNI). Overall, this study covers 62 countries, including 10 high-income, 21 upper-middle-income, 18 lower-middle-income, and 13 low-income countries (Figure 2.1).

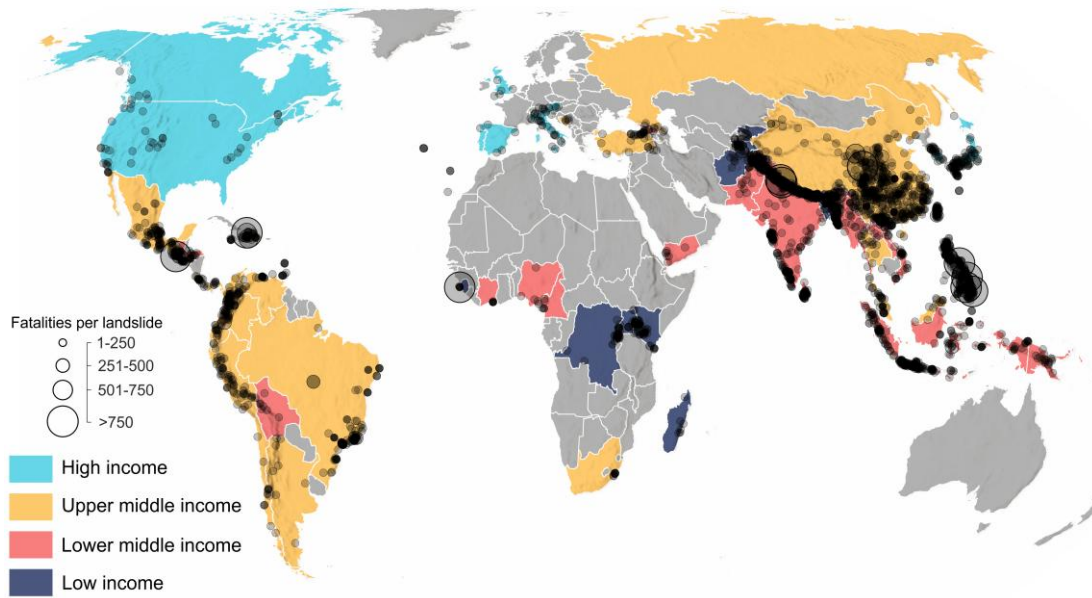


Figure 2. 1: This map shows the spatial distribution of fatal landslides used in this study between 2004 and 2017. The size of the dots indicates the number of reported landslide fatalities, and the color of the countries indicates the economic income level. Grey areas show countries that are masked out.

2.3.2 Datasets and analysis

To examine and compare relative living standards across different countries and over time, we employed expenditure-side real gross domestic product (GDP) data at constant 2017 prices in US dollars, sourced from Penn World Table v.10.0, which is adjusted for price changes such as inflation (Feenstra et al., 2015, 2021). We used national population totals from the same database to calculate GDP as per-capita income. For the years in which landslide events occurred, we considered each country's GDP measure for that year. Also, we considered the Gini index of disposable (post-tax, post-transfer) household income from the Standardized World Income Inequality Database (SWIID) v.9.1 to obtain country-year data of income inequality (Solt, 2019; Solt, 2020). We selected the SWIID as our data source because it provides estimates of disposable income inequality with a data-collection protocol designed to maximize both the comparability of data across countries and years, ensuring broad coverage and reliable predictions (Solt, 2020). Although this data source is annual, some countries may have missing year records. We addressed the missing values to the nearest available year to overcome this. Thus, each country is assigned an indicator of economic income inequality.

To estimate the number of potentially exposed people, we used global population data from 2000 to 2020 based on the LandScan Global Population Distribution Dataset (Bright et al., 2004, 2017; Bright and Coleman 2001, 2003; Rose et al., 2018, 2021) mentioned above (see 2.1.1). The accuracy of location data in GFLD is determined based on administrative divisions ranging from village to state level according to spatial databases of Global Administrative Areas (GADM; <https://gadm.org/>). We, therefore, extracted population information from LandScan using these administrative boundaries and calculated the total number of potentially exposed individuals for each landslide record, considering the population in the year of the landslide event. We also calculated fatality rates for all registries by dividing the number of deaths recorded by the number of individuals living in the landslide-affected area in the year of the event.

For our analysis of human impact, we selected two proxies: the Human Footprint Index (HFI) and the Human Development Index (HDI). The first proxy, the HFI, represents a measure of human activity from 2000 to 2018 (Mu et al., 2022). We used this previously detailed dataset (see 2.1.1.6) to examine the intensity of human activities. Similar to our approach with population data, we applied a repetitive procedure for each landslide event, taking into account the year of occurrence and computing the total HFI within the administrative boundaries.

We have also included the second proxy, the HDI, to enrich our understanding of human impact further. The HDI from the United Nations Development Programme (UNDP) summarises average achievement across key dimensions of human development: a long and healthy life, knowledge, and a decent standard of living (UNDP, 2022). It is calculated by taking the geometric mean of the normalized indices for each of these three dimensions. Unlike the population and HFI data, which were analyzed at the administrative boundary level, the HDI was assigned at the national level. For each landslide event, we matched the HDI of the respective country with the year the event occurred, ensuring that our analysis reflects the socioeconomic conditions at the time of each landslide.

In addition to economic, demographic, and human impact factors, we included the Government Effectiveness Index (GEI) (Kaufmann and Kraay, 2023) to assess the impact of political stability and governance quality on landslide fatalities. GEI captures perceptions of the quality of public services, the degree of independence from political pressures, the quality of policy formulation and implementation, and the credibility of

the government's commitment to those policies. The values of this indicator range from approximately -2.5 (weak) to 2.5 (strong) governance performance. In this context, political data may provide valuable insights into countries' institutional structures and the functioning of their governments. We followed a similar procedure to the HDI for government effectiveness data. For each landslide event, we assigned the GEI value of the respective country to the year in which the event occurred and assigned this value to the landslide record.

2.3.3 Approach

To assess the relationship between socioeconomic factors and landslide fatalities at the country level, we collected data on economic conditions, human exposure to landslides, and government effectiveness from international databases. To ensure comparability, we conduct our analysis based on the World Bank's country classification by income level. We then developed a regression model with these data to test for event-based landslide fatalities at the country level. We examined whether and how landslide fatalities varies by country, time, income inequality, and levels of economic development. We also analyzed whether landslide fatalities levels in terms of absolute numbers of deaths and fatalities rates changed over the study period. For this purpose, we also used the non-parametric Mann-Kendall test to detect trends.

2.3.4 Regression models

To assess the association between independent variables and landslide fatalities, we used a negative binomial generalized linear regression model. Negative binomial regression was selected due to its suitability for over-dispersed census data, i.e., where the conditional variance is higher than the conditional mean (Scott Long, 1997). The models were fitted using the `glm.nb` function in the MASS package (Zeileis et al., 2008). We present histograms illustrating the distribution of the response variable for the entire dataset as well as for each income group (Figure 2.2). To further support our analysis, we provide summary statistics for variables across all countries and at each income level in Tables 2.2 and 2.3, respectively.

Table 2. 2: Summary statistics of variables across all countries. The unit of analysis is landslide events that occurred between 2004 and 2017. The outcome variable is landslide fatalities per event. The covariates use values from the year in which each event occurred.

Variable	Mean	Mdn	Std	Min	Max
All countries: 4026 landslides in 63 countries.					
Fatalities per event (<i>Variance: 14378.7</i>)	13.2	3	119.9	1	5748
Country Gini index (%)	42.9	42.7	5.6	27.1	63.6
Country GDP/cap (1,000 US\$)	8.9	6.02	9.07	0.6	60.8
Potentially exposed population	319754.7	40664	850070.1	6	12397093
Human Footprint Index (HFI)	14,604.24	4,440.99	21,754.52	14	249,004.0
Human Development Index (HDI)	0.65	0.65	0.09	0.4	0.93
Government Effectiveness Index (GEI)	-0.14	-0.08	0.56	-2.09	1.88

Note. Mdn: Median. Std: Standard deviation.

To explore the relationship between the dependent variable, landslide fatalities, and socioeconomic factors, we designed five different regression models. Our first model covers all countries, while the other models were designed according to *i)* high, *ii)* upper-middle, *iii)* lower-middle, and *iv)* low-income groups. All variables were centered, and the two highly skewed variables, potentially exposed population and per-capita real GDP, were log-transformed (Figure 2.3). We repeated this procedure for each model for all income groups: high (Figure 2.4), upper-middle (Figure 2.5), lower-middle (Figure 2.6), and low (Figure 2.7). We also performed collinearity analysis on the independent variables for each model. If the correlations between independent variables in the analysis were greater than 0.70, we included only one of the variables in the model (Figure 2.8).

Table 2. 3: Summary statistics of variables across income groups.

Variable	Mean	Mdn	Std	Min	Max
High Income: 225 landslides in 10 countries.					
Fatalities per event (<i>Variance: 64.9</i>)	3.4	1	8.05	1	74
Country Gini index (%)	33	32	3.1	27.1	42.2
Country GDP/cap (1,000 US\$)	40.4	38.6	7.3	20.8	60.8
Potentially exposed population	223.9	19.7	1168.3	29	10143.4
Human Footprint Index (HFI)	13494.3	3356.4	31398.9	38.5	224280.2
Human Development Index (HDI)	0.88	0.89	0.03	0.75	0.93
Government Effectiveness Index (GEI)	1.25	1.43	0.43	0.11	1.88
Upper middle income: 1177 landslides in 21 countries.					
Fatalities per event (<i>Variance:4113.4</i>)	12.9	4	63.9	1	1765
Country Gini index (%)	44.4	42.9	3.9	32.7	63.6
Country GDP/cap (1,000 US\$)	12.3	11.8	4.2	6.02	29
Potentially exposed population	574179.2	227019	1205983.4	479	12397093
Human Footprint Index (HFI)	24239.2	18295.3	22622.4	84.5	212834.5
Human Development Index (HDI)	0.71	0.71	0.04	0.62	0.85
Government Effectiveness Index (GEI)	0.04	0.03	0.34	-	1.23
Lower middle income: 1913 landslides in 20 countries.					
Fatalities per event (<i>Variance:21706.8</i>)	14.5	3	146.7	1	5748
Country Gini index (%)	44.4	46.5	5.2	33.7	56.5
Country GDP/cap (1,000 US\$)	5.6	5.2	2.2	1.9	12.3
Potentially exposed population	275663.9	45860	601893.3	6	6186329
Human Footprint Index (HFI)	12863.3	3377.7	19508.3	14	249004
Human Development Index (HDI)	0.62	0.63	0.06	0.45	0.79
Government Effectiveness Index (GEI)	-0.15	-0.07	0.32	-	0.69
Low income: 711 landslides in 12 countries.					
Fatalities per event (<i>Variance:16201.8</i>)	14.6	3	129.3	1	3006
Country Gini index (%)	39.5	38	4.8	31.7	54
Country GDP/cap (1,000 US\$)	2.2	2.03	0.8	0.6	4.9
Potentially exposed population	47537.6	7814	302767.7	42	7457.1
Human Footprint Index (HFI)	3689.8	572.2	14751.2	17.9	219472.8
Human Development Index (HDI)	0.54	0.55	0.04	0.4	0.69
Government Effectiveness Index (GEI)	-0.87	-0.89	0.26	-	0.01

Note. Mdn: Median. Std: Standard deviation.

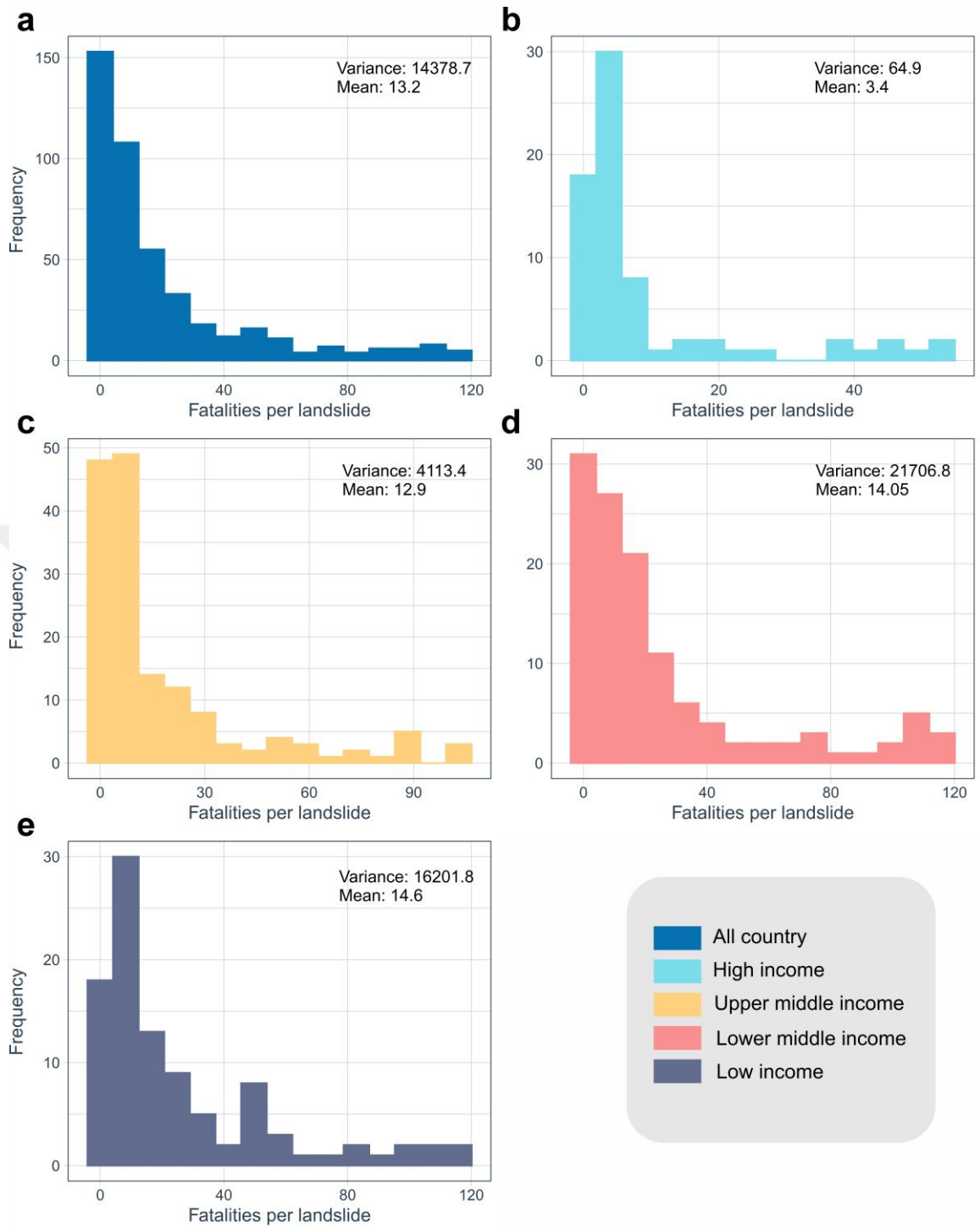


Figure 2. 2: Histograms of the response variable distribution for the entire dataset and each income group. The over-dispersion, where the conditional variance exceeds the conditional mean, highlights the appropriateness of negative binomial regression for modeling the data.

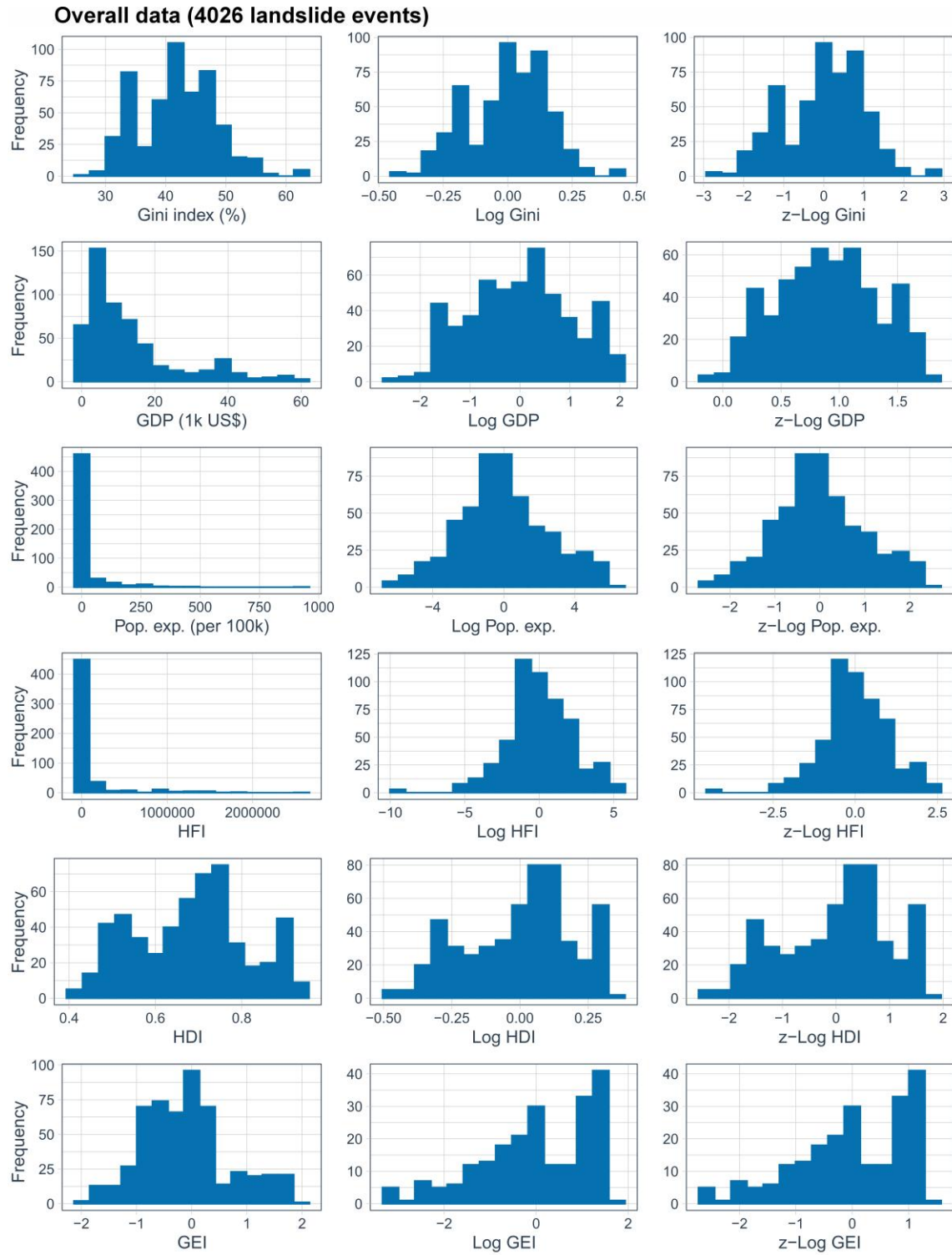


Figure 2. 3: Histograms show the distributions of independent variables for the entire sample in their original units, log-transformed, and standardized forms.

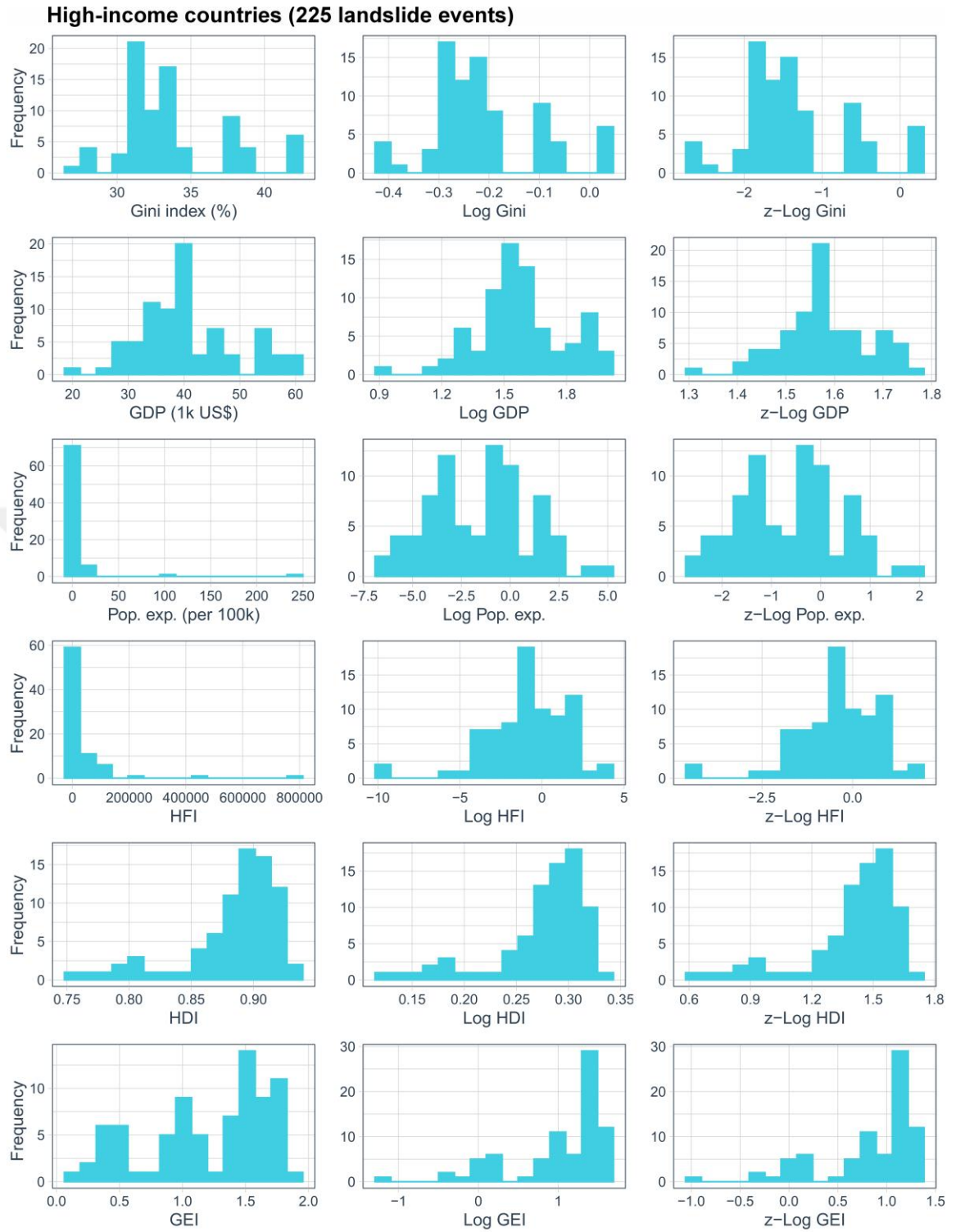


Figure 2. 4: Histograms show the distributions of the independent variables for high-income countries. The distributions are presented in original units, log-transformed, and standardized.

In this thesis, we created empirical models to explain fatalities caused by a landslide in country j at time t . Equation 2.10 shows the model for all countries, while equation 2.11 shows the model applied separately to each of the four income groups.

$$LF_i = (\beta_0 + b_{0,j}) + \beta_1 Gini_{jt} + \beta_2 \log(GDP_{jt}) + \beta_3 \log(Pop_{exp_{it}}) + \beta_4 Year_i + \epsilon \quad (2.10)$$

$$LF_i = (\beta_0 + b_{0,j}) + \beta_1 Gini_{jt} + \beta_2 \log(GDP) + \beta_3 \log(Pop_{exp}) + \beta_4 GEI_{jt} + \beta_5 Year_i + \epsilon \quad (2.11)$$

To account for differences in baseline landslide fatalities across countries, we included a random intercept term ($b_{0,j}$) for each country. This approach helps the model account for differences in landslide-prone between countries and the non-independence of data from the same country, offsetting the effects of differences not represented by our data. The response variable, LF_i , represents the number of reported fatalities from each landslide event. The independent variables include the Gini index of disposable income ($Gini_{jt}$), the per-capita real GDP (GDP_{jt}), the number of individuals potentially exposed to the landslide event ($Pop_{exp_{it}}$), the effect of government effectiveness in the country (GEI_{jt}) and a time dummy variable ($Year_i$) to control for temporal changes. β_0 is the mean model intercept, β_1 through β_5 are the regression coefficients for each independent variable, and ϵ is the error term. In addition to the negative binomial regression assessment, we conducted residual diagnostics for the models using the R package DHARMA (Hartig, 2022). For all models, we performed residual diagnostics with 250 iterations.

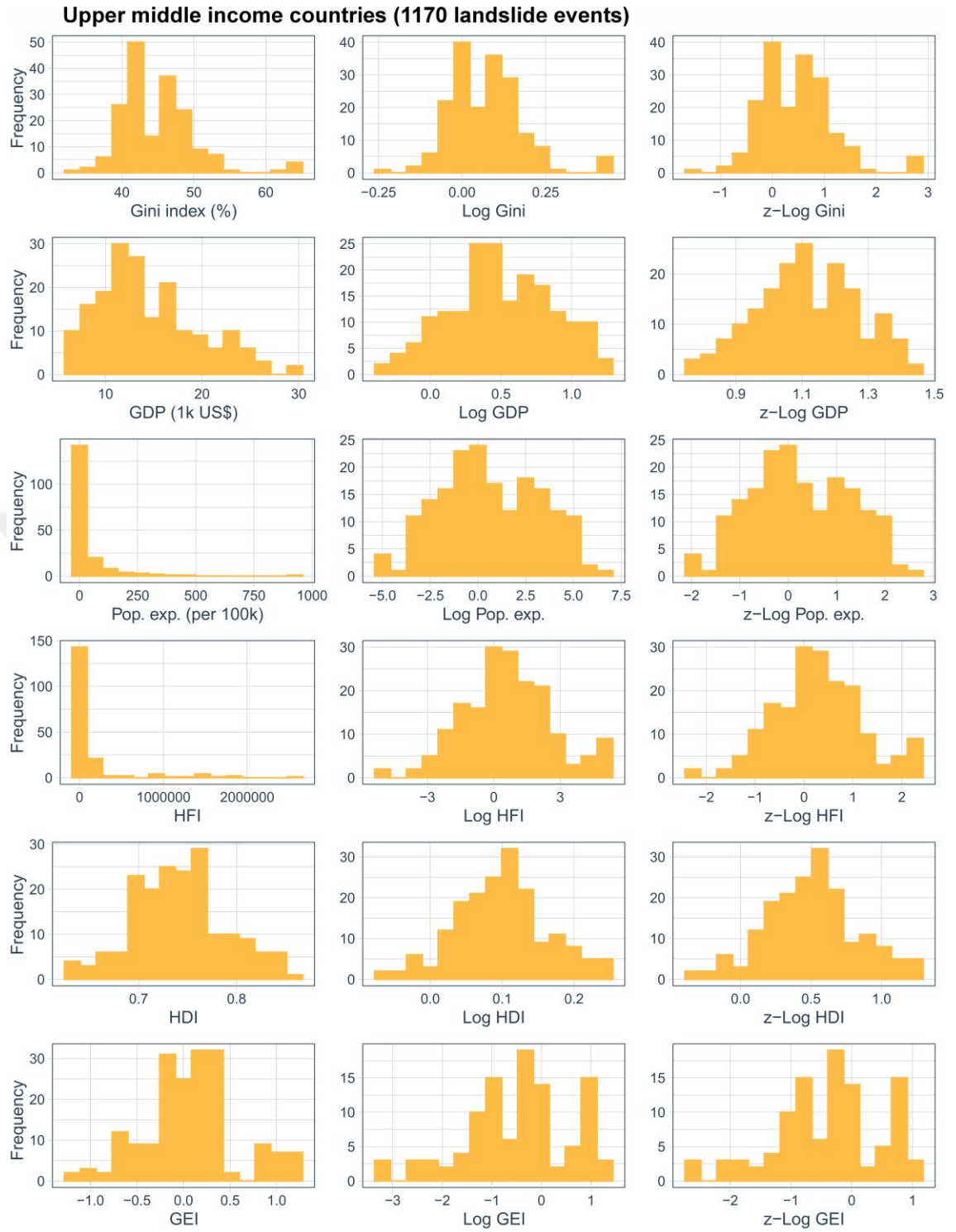


Figure 2. 5: Histograms show the distributions of the independent variables for upper-middle-income countries. The distributions are presented in original units, log-transformed, and standardized.

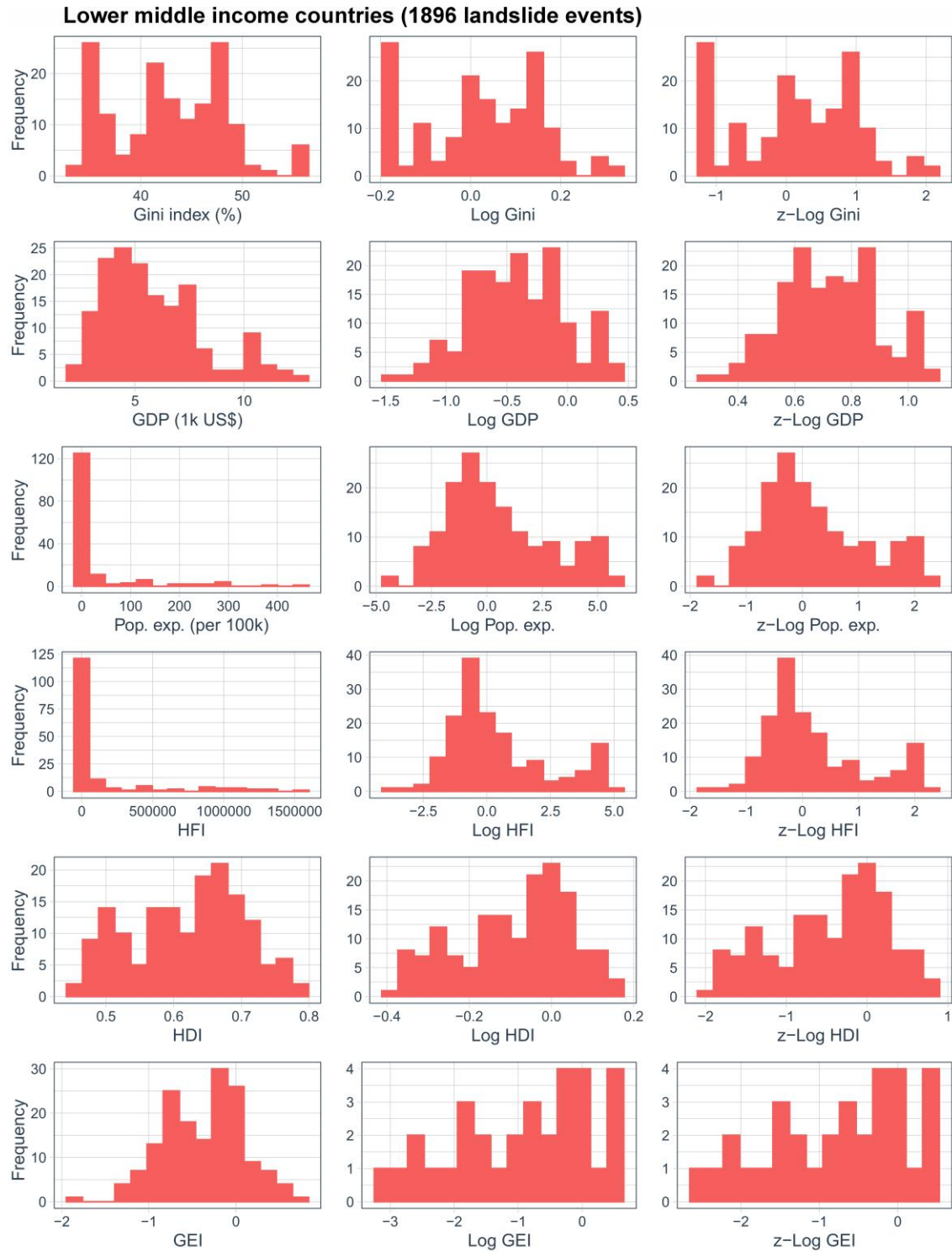


Figure 2. 6: Histograms show the distributions of the independent variables for lower-middle-income countries. The distributions are presented in original units, log-transformed, and standardized.

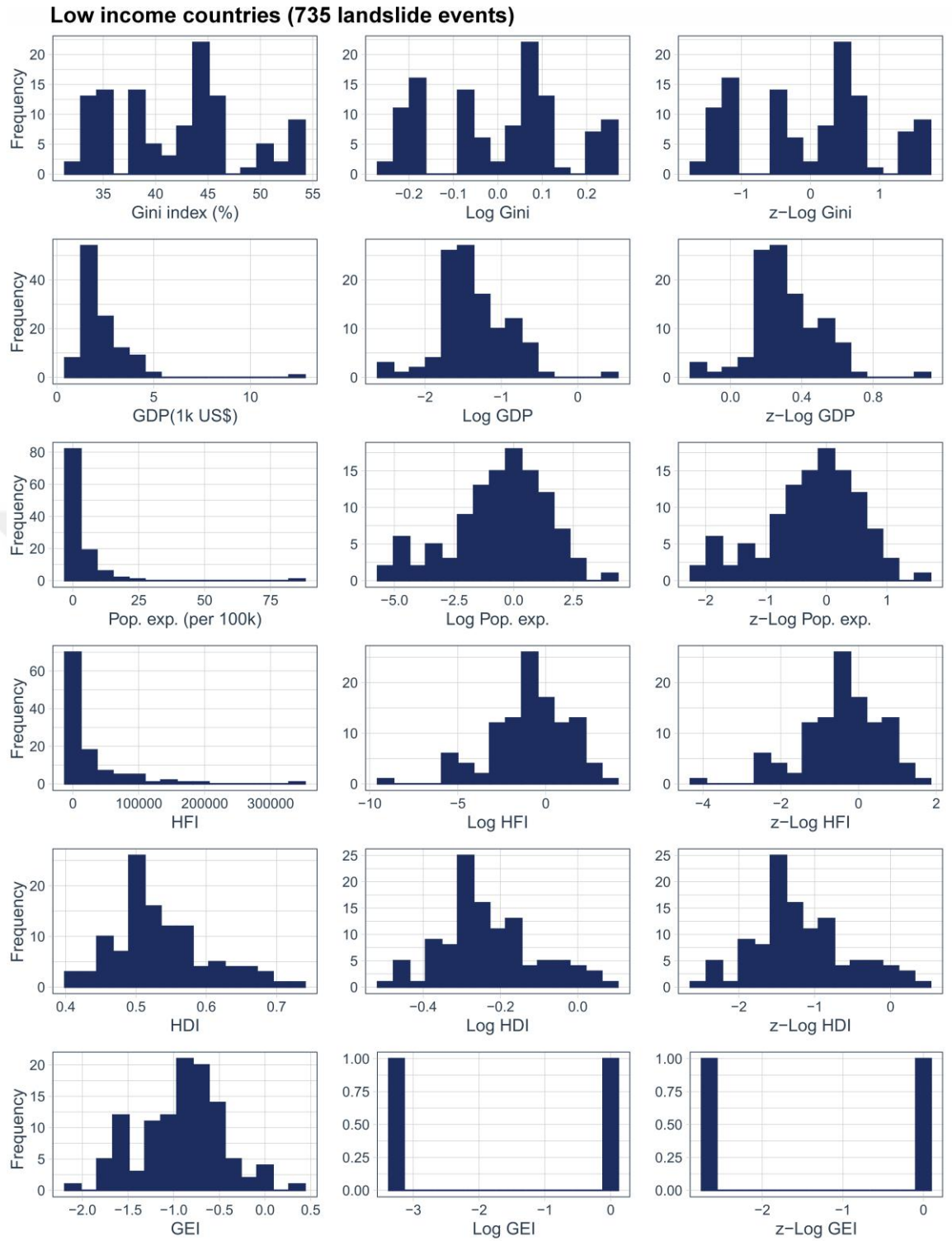


Figure 2. 7: Histograms show the distributions of the independent variables for low-income countries. The distributions are presented in original units, log-transformed, and standardized.

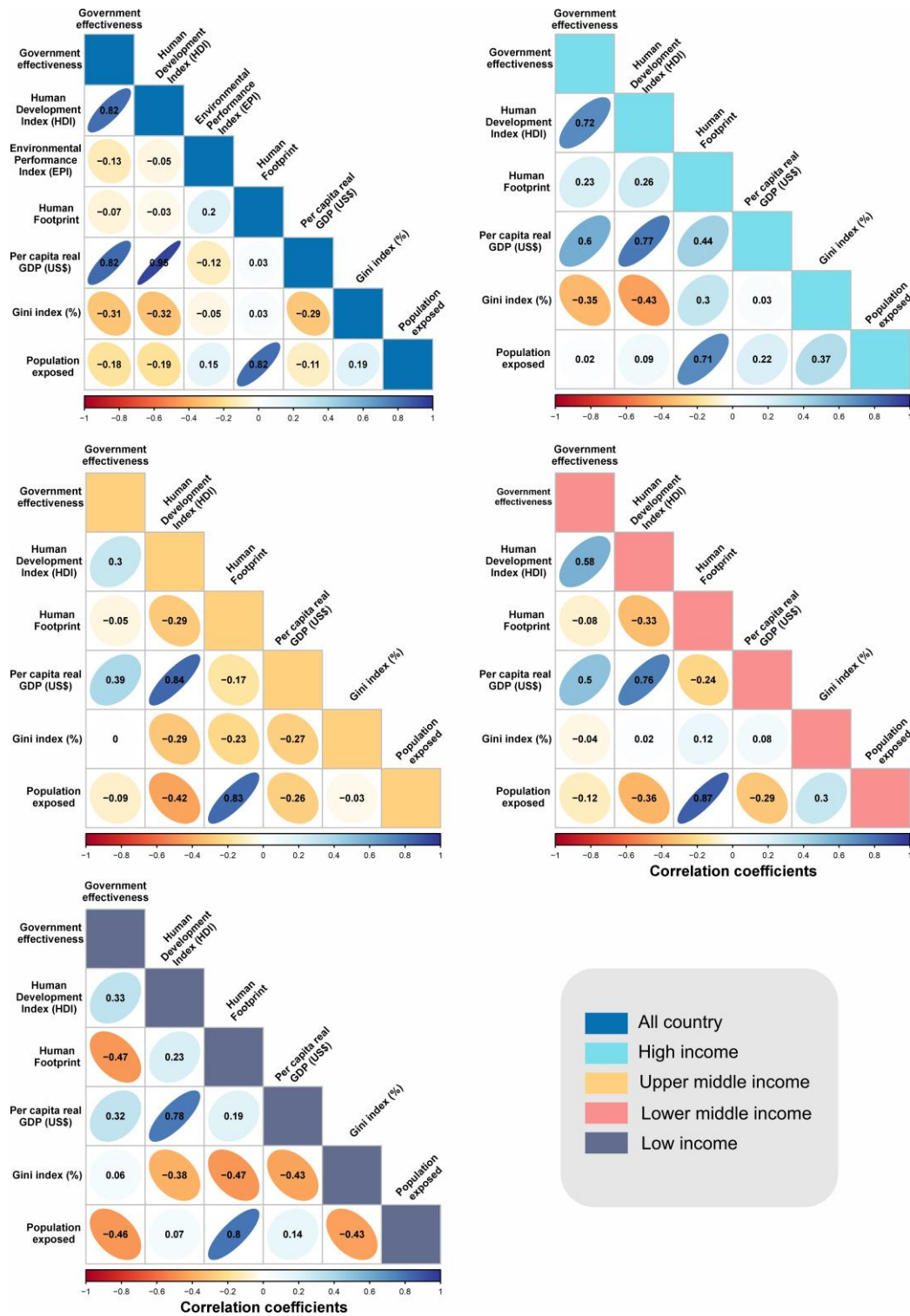


Figure 2. 8: Collinearity analysis of the independent variables. This figure shows the results of the collinearity analysis, which assesses the multicollinearity between the independent variables used in the models.

3. A SUMMARY OF TOPOGRAPHIC, CLIMATIC AND ANTHROPOGENIC PERSPECTIVES

3.1 Results

3.1.1 Bivariate analysis

We examined the spatial distribution of selected fatal landslides over various climatic and landform conditions (Figure 3.1a). We presented landslides triggered by natural and anthropogenic factors in Figure 3.1b and 3.1c, respectively. After filtering out landslide locations due to the economic (GPD>\$20,000) and spatial accuracy (>10 km) criteria mentioned above, the resultant GFLD dataset has 2231 landslides, 1886 LTNF resulting in 18,301 deaths, and 345 LTAF causing 1162 deaths.

The major landslide concentration occurs around tropical (A, see Figure 3.1) and temperate (C) regions quite similarly for both LTNF (A: 49.7% and C: 44.3%) and LTAF (A: 50.4% and C: 37.7%), respectively (Table 3.1). In terms of fatalities, the highest number is also recorded in the tropical and temperate climatic regions for both LTNF (A: 52.1% and C: 34.7%) and LTAF (A: 52.7% and C: 35.5%), respectively. However, the lowest number is recorded in different climatic regions. The lowest fatalities for LTNF are associated with continental regions (D: 2.8%), whereas for LTAF, polar regions constitute the lowest incidences (E: 0.2%).

As for the landform categories, both the number of landslides and fatalities have the highest amount in low and middle mountains for LTNF (62.5% and 63.4%) and LTAF (41.4% and 43.2%), respectively (Table 3.2). Notably, LTAF are about 20% lower than their naturally occurring counterparts regarding both the number of landslides and fatalities. This 20% difference appears as an increase in LTAF occurred in the plains and thus, both the number of LTAF and fatalities caused by them are approximately 20% higher compared to naturally occurring landslides.

The summary provided above is also presented in Figure 3.2 through a combined climate-landform vision of fatal landsliding (Table 3.3). Figure 3.2 shows the frequency distribution of fatal landslides (stacked barplot) and fatalities per landslide

(bubble plot) following the same color scheme of the bivariate climate-landform maps presented in Figure 3.1. Panel (a) reports a graphical summary for LTNF, whereas panel (b) shows the situation for LTAF.

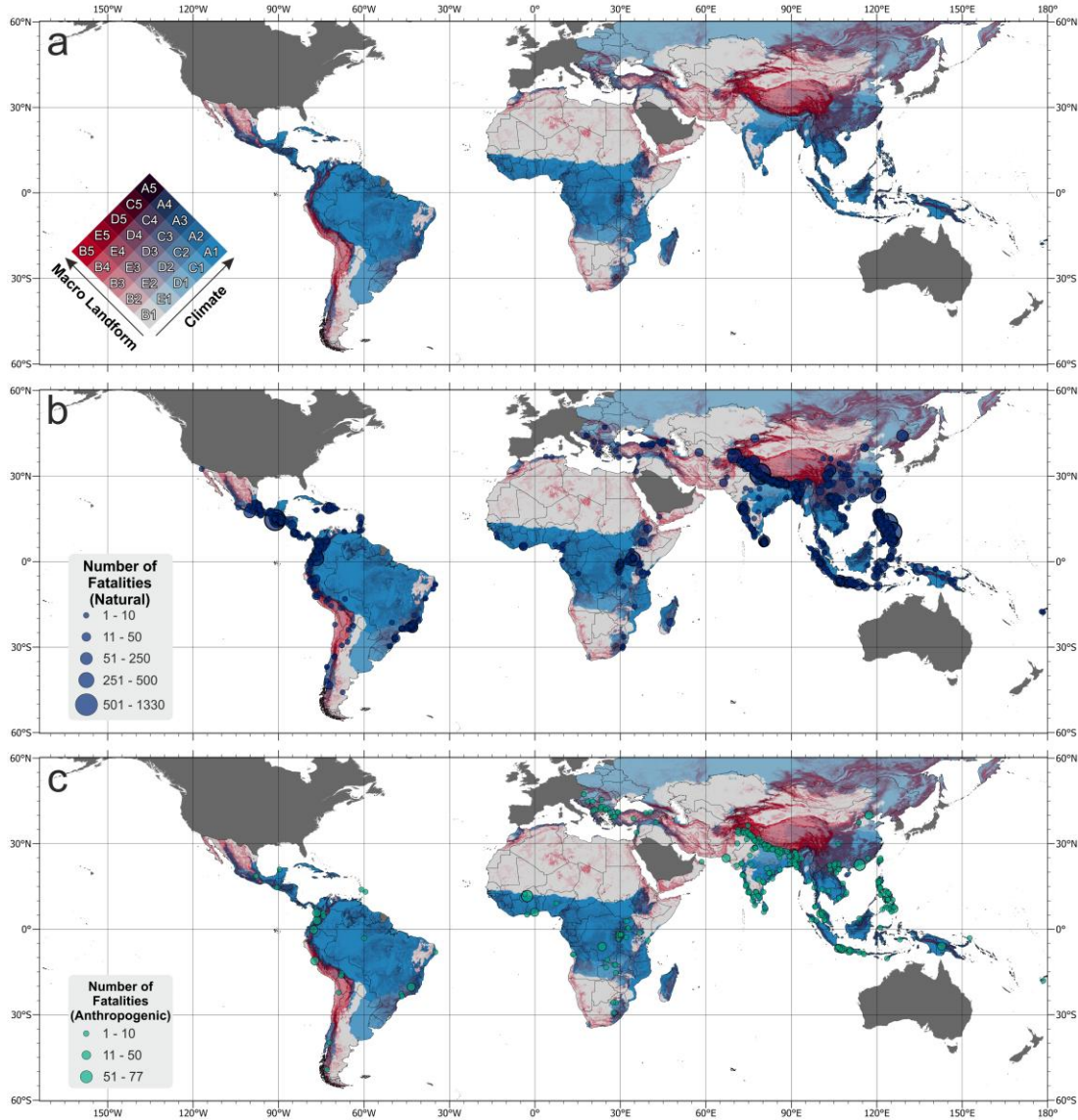


Figure 3. 1: Panels showing **a)** the climate-landform combined map and the same map overlaid by the spatial distribution of fatal landslides and fatalities triggered by **b)** natural and **c)** anthropogenic factors. Climatic information is based on (A) tropical, (B) arid, (C) temperate, (D) continental, and (E) polar regions. The macro landform information is expressed into plains (1), lowlands, platforms, and low plateaus (2), middle, high, and very high plateaus (3), low and middle mountains (4), and high and very high mountains (5). The size of the landslide point indicates the number of fatalities for each event. Grey areas indicate regions that were masked out.

Table 3. 1: Distribution of fatal landslides and fatalities by climate-landform classification.

Köppen-Geiger climate classification	LTNF					LTAF				
	Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)	Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)
Arid (B)	36	679	18.9	1.9	3.7	26	86	3.3	7.5	7.4
Polar (E)	25	1235	49.4	1.3	6.7	2	2	1.0	0.6	0.2
Continental (D)	52	518	10.0	2.8	2.8	13	49	3.8	3.8	4.2
Temperate (C)	836	6342	7.6	44.3	34.7	130	413	3.2	37.7	35.5
Tropical (A)	937	9527	10.2	49.7	52.1	174	612	3.5	50.4	52.7

Table 3. 2: Distribution of fatal landslides and fatalities by climate-landform classification.

Macro landform units	LTNF					LTAF				
	Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)	Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)
[1] Plains	213	1028	4.8	11.3	5.6	113	365	3.2	32.8	31.4
[2] Lowlands, platforms, and low plateaus	227	2564	11.3	12.0	14.0	48	197	4.1	13.9	17.0
[3] Middle, high, and very high plateaus	47	362	7.7	2.5	2.0	18	51	2.8	5.2	4.4
[4] Low and middle mountains	1179	11599	9.8	62.5	63.4	143	502	3.5	41.4	43.2
[5] High and very high mountains	220	2748	12.5	11.7	15.0	23	47	2.0	6.7	4.0

Table 3. 3: Distribution of fatal landslides and fatalities by climate-landform classification.

Köppen-Geiger climate classification	Macro landform units	Climate-landform classification	LTNF					LTAF				
			Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)	Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)
Arid (B)	[1] Plains	B1	11	94	8.5	0.6	0.5	19	62	3.3	5.5	5.3
Arid (B)	[2] Lowlands, Platforms, Low Plateaus	B2	16	561	35.1	0.8	3.1	3	17	5.7	0.9	1.5
Arid (B)	[3] Middle, High, Very High Plateaus	B3	1	3	3.0	0.1	0.0	3	6	2.0	0.9	0.5
Arid (B)	[4] Low mountains, Middle mountains	B4	6	19	3.2	0.3	0.1	1	1	1.0	0.3	0.1
Arid (B)	[5] High and Very High Mountains	B5	2	2	1.0	0.1	0.0	0	0	0.0	0.0	0.0
Polar (E)	[1] Plains	E1	14	61	4.4	0.7	0.3	6	20	3.3	1.7	1.7
Polar (E)	[2] Lowlands, Platforms, Low Plateaus	E2	2	51	25.5	0.1	0.3	3	17	5.7	0.9	1.5
Polar (E)	[3] Middle, High, Very High Plateaus	E3	32	274	8.6	1.7	1.5	2	9	4.5	0.6	0.8
Polar (E)	[4] Low mountains, Middle mountains	E4	3	124	41.3	0.2	0.7	2	3	1.5	0.6	0.3
Polar (E)	[5] High and Very High Mountains	E5	1	8	8.0	0.1	0.0	0	0	0.0	0.0	0.0
Continental (D)	[1] Plains	D1	23	1213	52.7	1.2	6.6	1	1	1.0	0.3	0.1
Continental (D)	[2] Lowlands, Platforms, Low Plateaus	D2	1	18	18.0	0.1	0.1	1	1	1.0	0.3	0.1
Continental (D)	[3] Middle, High, Very High Plateaus	D3	1	4	4.0	0.1	0.0	0	0	0.0	0.0	0.0
Continental (D)	[4] Low mountains, Middle mountains	D4	0	0	0.0	0.0	0.0	0	0	0.0	0.0	0.0
Continental (D)	[5] High and Very High Mountains	D5	0	0	0.0	0.0	0.0	0	0	0.0	0.0	0.0
Temperate (C)	[1] Plains	C1	573	4641	8.1	30.4	25.4	63	181	2.9	18.3	15.6
Temperate (C)	[2] Lowlands, Platforms, Low Plateaus	C2	37	137	3.7	2.0	0.7	11	95	8.6	3.2	8.2
Temperate (C)	[3] Middle, High, Very High Plateaus	C3	37	88	2.4	2.0	0.5	27	74	2.7	7.8	6.4
Temperate (C)	[4] Low mountains, Middle mountains	C4	156	1203	7.7	8.3	6.6	19	36	1.9	5.5	3.1

Table 3. 3 (continued): Distribution of fatal landslides and fatalities by climate-landform classification.

Köppen-Geiger climate classification	Macro landform units	Climate-landform classification	LTNF					LTAF				
			Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)	Number of landslides	Number of fatalities	Number of fatalities per event	Number of landslides (%)	Number of fatalities (%)
Temperate (C)	[5] High and Very High Mountains	C5	33	273	8.3	1.7	1.5	10	27	2.7	2.9	2.3
Tropical (A)	[1] Plains	A1	575	6318	11.0	30.5	34.5	70	283	4.0	20.3	24.4
Tropical (A)	[2] Lowlands, Platforms, Low Plateaus	A2	163	795	4.9	8.6	4.3	64	212	3.3	18.6	18.2
Tropical (A)	[3] Middle, High, Very High Plateaus	A3	185	2301	12.4	9.8	12.6	35	99	2.8	10.1	8.5
Tropical (A)	[4] Low mountains, Middle mountains	A4	11	74	6.7	0.6	0.4	5	18	3.6	1.4	1.5
Tropical (A)	[5] High and Very High Mountains	A5	3	39	13.0	0.2	0.2	0	0	0.0	0.0	0.0

Overall, our analyses show that mountainous areas of tropical and temperate climatic regions appear to be the main concentration areas of LTNF and cause considerable life losses. A similar situation with some slight differences also appears for LTAF. Specifically, they mostly concentrate around mountainous areas of tropical and temperate climatic regions as seen for natural ones. The difference is that LTAF are also located in plains of tropical and temperate climatic regions. We also note that mortality rates (i.e., average number of fatalities per landslide) are much higher for naturally triggered landslides than anthropogenically induced ones (Figure 3.2).

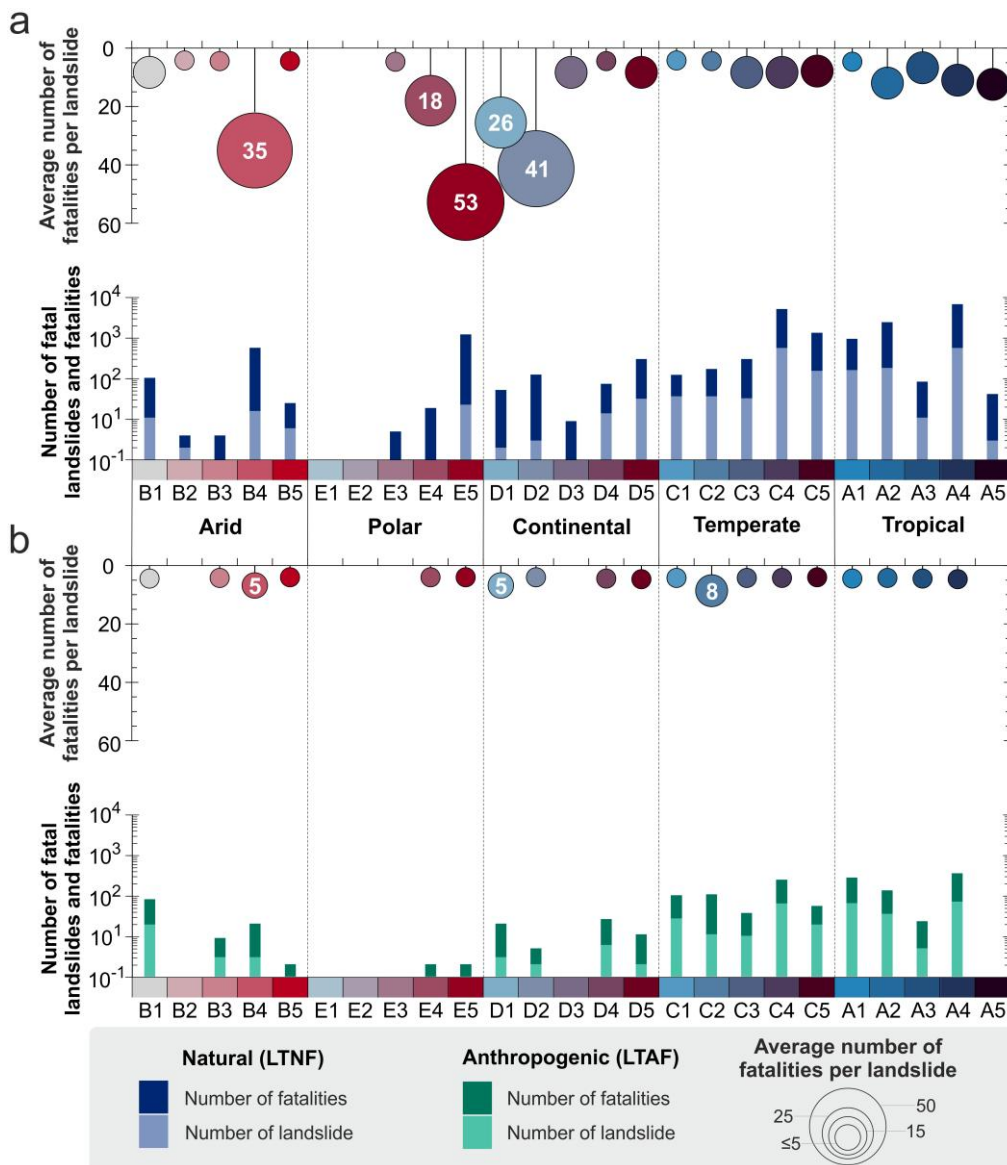


Figure 3. 2: Climate-landform regions vary in the number of fatal landslides and fatalities (bottom panel) triggered by **a)** natural triggering and **b)** anthropogenic triggering factors (in log-scale). The bubble plots (top panel) in (a) and (b) show the average number of fatalities per landslide (FpL). (see Figure 3.1a and Table 3.3 for a description of the climate-landform classification).

Figure 3.3 shows persistence and the total number of incidences (i.e., landslides or fatalities) over sub-basins. The total number of landslides or the total number of fatalities associated with a given sub-basin is referred to as incidence. We define persistence, on the other hand, in relation to the recurrence of landsliding for a given sub-basin. A higher persistence indicates a larger number of landslides occurring over time in a sub-basin.

For LTNF, Figure 3.3a summarizes this information in bivariate plots showing both the incidence (where the maximum value is 14) and their persistence (where the maximum value is 9) together. Figure 3.3b presents the same information but shows the number of victims per sub-basin and their persistence (where the maximum values are 1132 and 9, respectively). The same is reported in Figures 3.3c and 3d for LTAF.

Results show that South and Southeast Asia host sub-basins characterized by the highest incidences and persistence for fatal landslides triggered by natural agents. Sub-basins located in this region have a maximum of 14 landslides (i.e., high incidence) that occurred on up to nine different occasions (i.e., high persistence). Central and South America show a relatively high landslide incidence (the maximum value is 7), with a persistence of up to three occurrences (Figure 3.3a).

A similar spatial pattern arises when looking at fatalities from the same incidence-persistence perspective (Figure 3.3b), with a slight difference associated with incidences. Notably, landslides with many fatalities are relatively rare, which is why high incidences are rarely coupled by high persistence.

The sub-basins with the highest incidences characterized by the high persistence for landslides (Figure 3.3c) and fatalities (Figure 3.3d) associated with anthropogenic agents are also located in South and Southeast Asia. As seen in the naturally occurring landslides, events with a high number of fatalities are also rare in this case.

To further explore the link between incidence and persistence for the examined sub-basins, we created scatter plots (Figure 3.4) for incidence and persistence for each climate-landform class. Results show that in general, sub-basins exposed to fatal landslides experience these events repetitively. Specifically, tropical and temperate climatic areas host sub-basins where fatal landslides occur repeatedly and thus, Figure 3.4 indicates high persistence in those regions. Continental, polar, and arid areas, on the other hand, are dominantly characterized by low persistence.

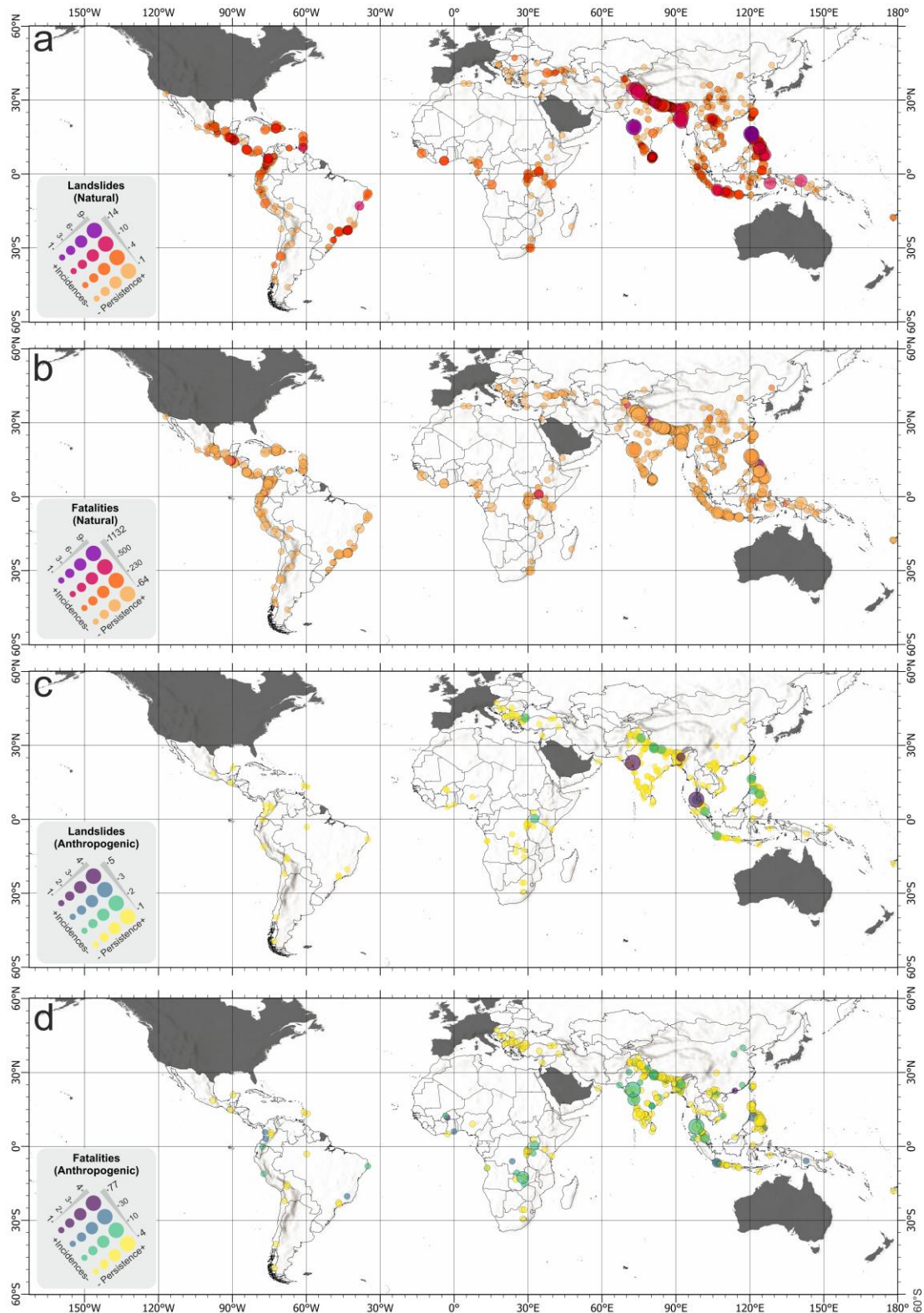


Figure 3.3: The maps illustrate the spatial persistence of **a)** landslides and **b)** fatalities associated due to natural factors, as well as **c)** landslides and **d)** fatalities due to anthropogenic factors. The darker the color of the bubbles representing the sub-basins, the higher the number of landslides and fatalities, and the larger their size, the higher the persistence.

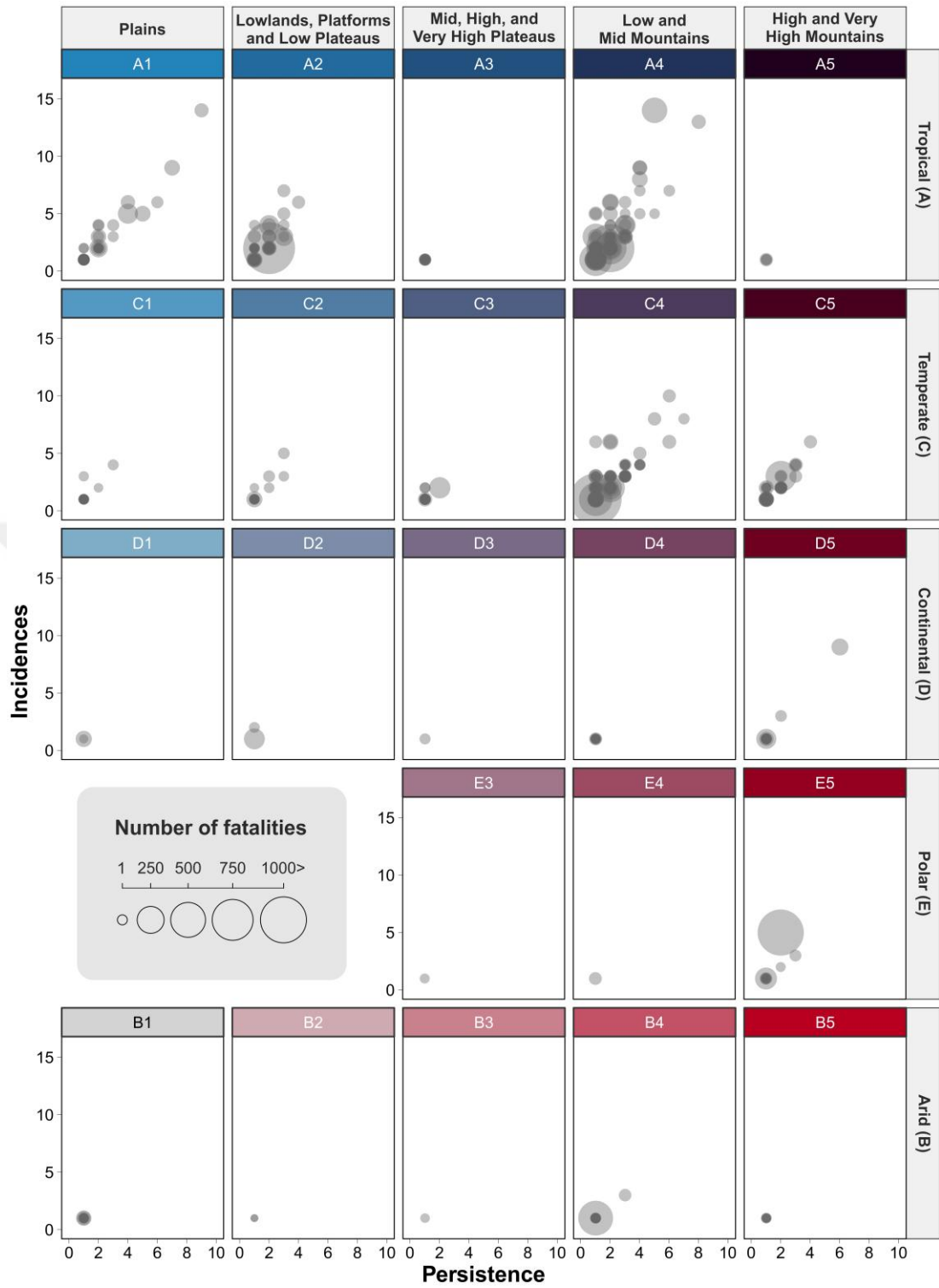


Figure 3. 4: Panels showing persistence vs incidences of fatal landslides over different climate-landform regions.

3.1.2 Controlling Factors Analysis

This section presents the summary statistics of basin characteristics that host LTNF or LTAF (Figure 3.5). To avoid repeated information, we exclude basins hosting both LTNF and LTAF.

Topographically, LTNF has a higher elevation, elev-std, and slope median values compared to the LTAF. The median values for LTNF are 724.2 m, 17.8 m, and 11.3°, respectively. As for LTAF, the median values are 372.0 m, 5.7 m, and 3.6°, respectively. A difference can also be seen in the long-term average annual precipitation, albeit less pronounced as compared to the morphometric cases. Specifically, LTNF has an annual precipitation centered at 2145 mm, while it is 1499 mm for LTAF. As for the total population, the median value is much higher for LTAF (27167) as compared to LTNF (16530).

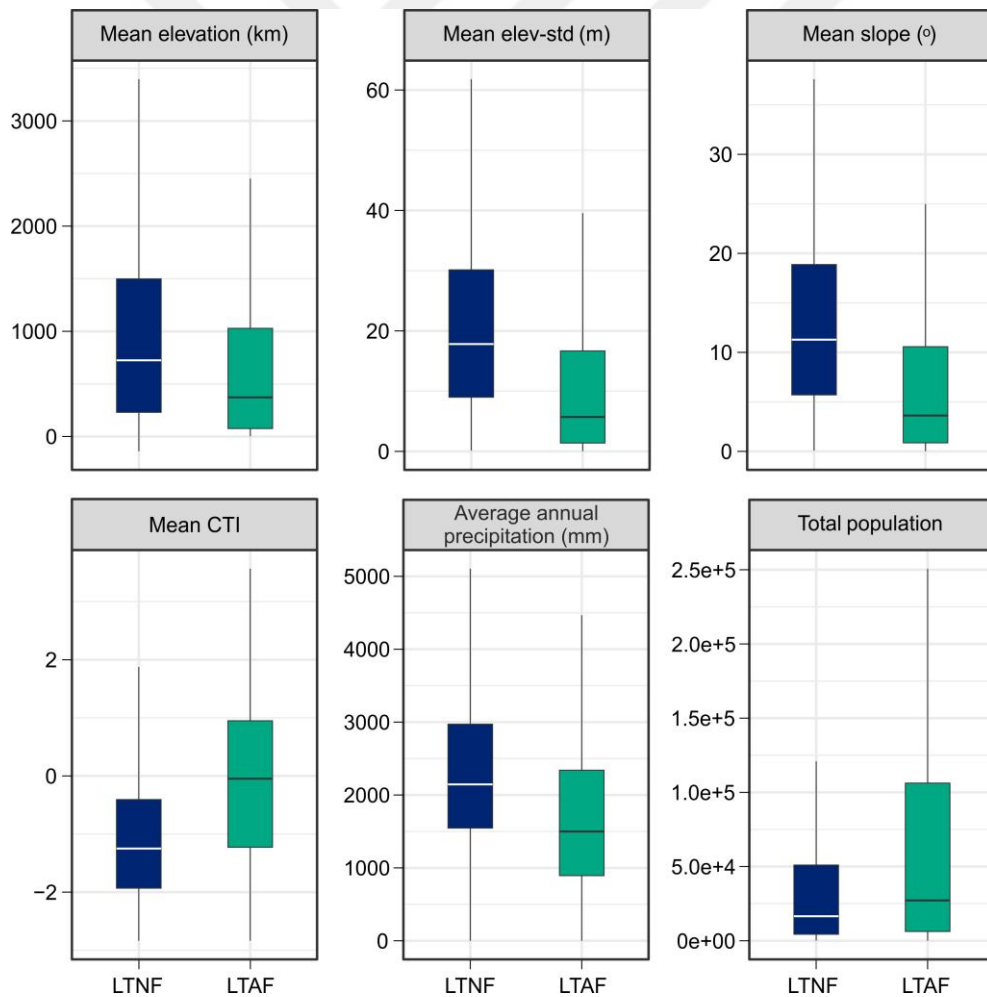


Figure 3. 5: Graphs showing the distribution of different controlling factors of fatal landslides are presented separately for both LTNF (blue boxplots) and LTAF (green boxplots).

3.2 Discussion

Our results show that LTNF is associated with higher average fatality rates than LTAF, specifically in arid, polar, and continental climatic regions when we consider the average number of fatalities per climate-landform region (see Figure 3.2). This indicates that LTNF are much rarer in these environments, although the rate of mortality per single landslide is also much higher. Conversely, LTNF are much more common in tropical and temperate climatic regions (94% of the total) but their mortality rate is comparably lower than in other regions. However, when we examine fatalities at the sub-basic level, results show that high fatalities are mostly associated with rare landslides (see Figure 3.4).

We computed spatial densities to complement the information presented above (Figure 3.6). The fatal landslides across the Himalayan Range are shown separately because they would saturate the signal due to the large number of samples from this rough terrain.

Based on landslide densities, we identified ten hotspots distributed in Central American Ranges and Hispaniola, Northern Andes, Brazilian Highlands, Great Rift Valley, Western Ghats and Sri Lanka, Himalayan Range, North East India and Bangladesh, Vietnam, Philippines and Taiwan, and Indonesia (Figure 3.6). These regions also refer to areas where landslide rates are expected to increase due to climate change. By the end of this century, as global mean surface temperature increases, extreme precipitation events over most of the mid-latitude land masses and over wet tropical regions will very likely become more intense and more frequent (IPCC, 2014). As a result, for instance, shallow landslides and debris flows are expected to increase because of extreme weather events in South and Southeast Asia, Central America and South America, and the Great Rift Valley (Gariano and Guzzetti, 2016) and Himalayan range (D. Kirschbaum et al., 2020). Also, La Nina conditions, which lead to greater landslide exposure, are projected to show the most significant increases in northern South America, Central America and the Caribbean, Indonesia, and the Philippines (Embersson et al., 2021). When land degradation caused by increased human disturbance is added to this, a worse picture may emerge.

The LTNF and LTAF densities demonstrate a positive correlation with elevation, elevation standard deviation, and steepness and a negative correlation with CTI, as expected (Figure 3.6). No

discernible pattern arises in the average annual precipitation, which is somewhat counter-intuitive, but may reflect the adaptation of the landscape to the prevailing climatic conditions. Aside from a few exceptions, LTNF generates more fatalities, these being mostly localized up in the topographic profile at 1019.3 m a.s.l., whereas the same occurs for LTAF at 666 m a.s.l.

Interestingly, the fatal landslides occur at higher elevations on steeper hillslopes in the Himalayan range as compared to the rest of the dataset (Figure 3.6). This is mainly because of the population in the Himalayan range at high elevations. Landslides triggered by natural factors may of course have been influenced by anthropogenic factors because human activities can lead to reduced hillslope stability, which may not be directly seen in this dataset.

Our results also indicate that fatal landslides triggered by natural and anthropogenic factors differ in terms of topography, precipitation, and population density characteristics. LTNF occurs at a much higher elevation, elev-std, slope, and rainfall conditions. These correspond to regions where the population is relatively low compared to its anthropogenic counterpart (see Figure 3.5). Considering that 74.2% of LTNF occur in mountainous areas (Table 3.2), these landslides result in more fatalities and higher impacts despite the lower population density because these landslides are predominantly triggered by prolonged or extreme rainfall that typically affects larger areas. In contrast, LTAF are extremely localized over densely populated areas due to human intervention. Since these landslides usually occur in urban areas and mining sites (Froude and Petley, 2018), their topographic characteristics differ from those of LTNF.

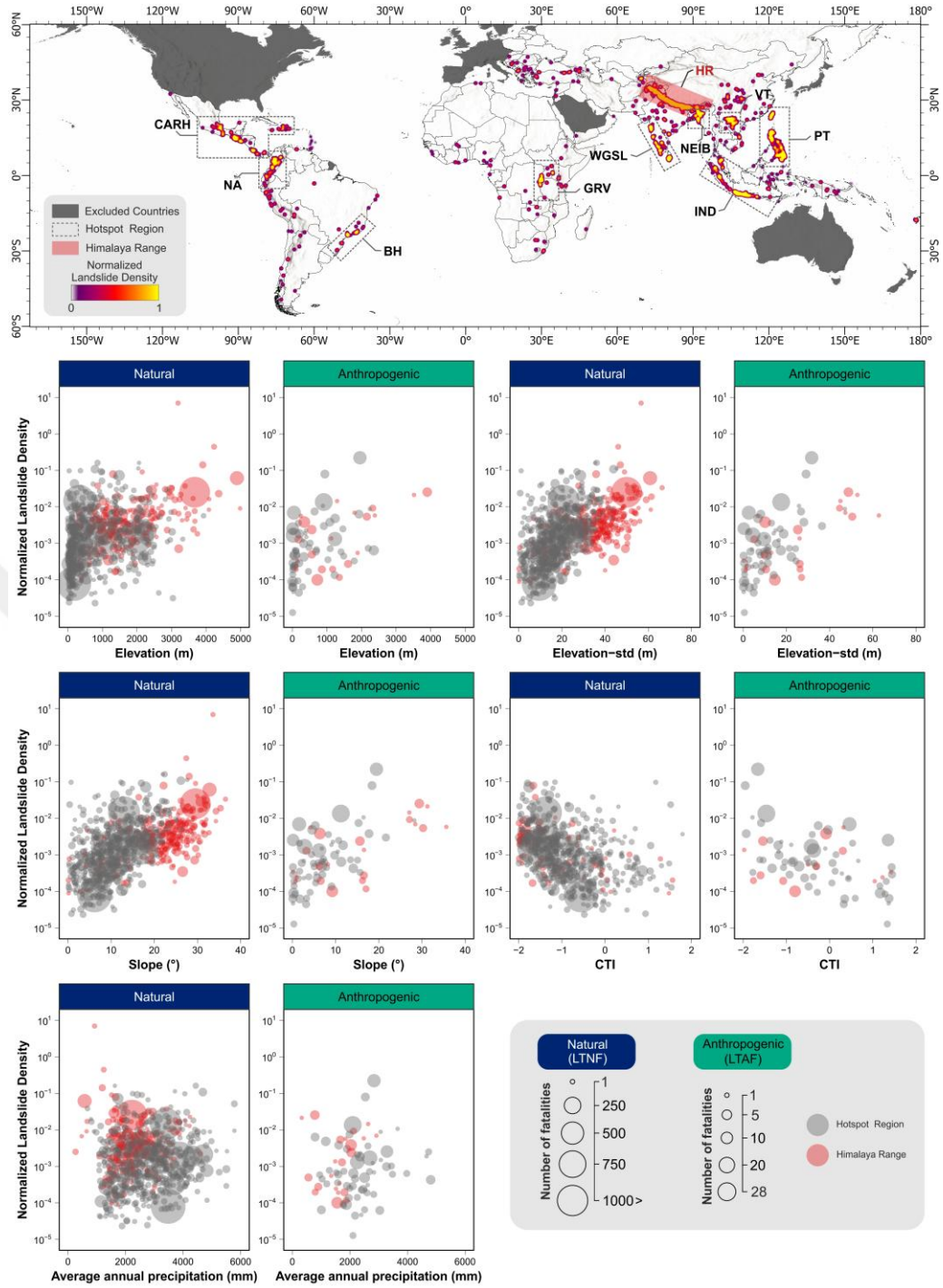


Figure 3. 6: The map shows sub-basin hotspots representing fatal landslides triggered by natural and anthropogenic factors. In the map, the grey dashed line section represents hot spot areas: Central American Ranges and Hispaniola (CARH), Northern Andes (N.A.), Brazilian Highlands (B.H.), Great Rift Valley (GRV), Western Ghats and Sri Lanka (WGS), Himalayan Range (H.R.), North East India and Bangladesh (NEIB), Vietnam (V.T.), Philippines and Taiwan (P.T.), Indonesia (IND). See Figure 3.7 for a zoomed-in representation of the hot spot areas. The graphs plot the distributional characteristics of normalized landslide density (NLD) and fatalities according to the factors controlling landslides. NLD represents the landslide density ($KDE_{sub-basin}$) in each sub-basin divided by the number of people ($Pop_{sub-basin}$).

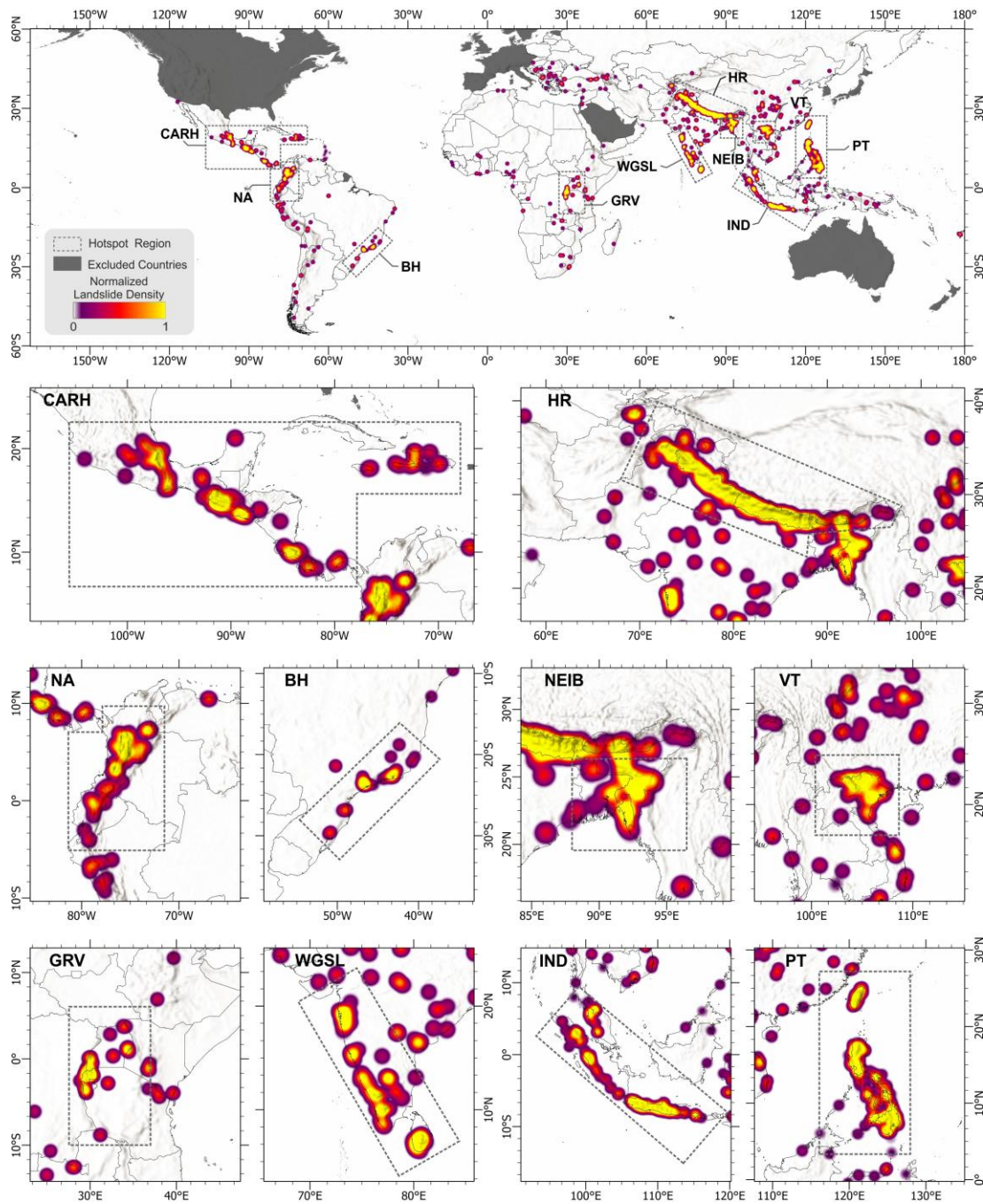


Figure 3. 7: The map shows zoomed-in sub-basin hotspots, representing fatal landslides triggered by natural and anthropogenic factors. In the map, the grey dashed line section represents hot spot areas: Central American Ranges and Hispaniola (CARH), Northern Andes (N.A.), Brazilian Highlands (B.H.), Great Rift Valley (GRV), Western Ghats and Sri Lanka (WGS), Himalayan Range (H.R.), North East India and Bangladesh (NEIB), Vietnam (V.T.), Philippines and Taiwan (P.T.), Indonesia (IND).

Capturing the possible role of anthropogenic factors in the occurrence of naturally triggered landslides is a challenge because human impact may occur over long time periods, which are hard to unfold (Depicker et al., 2021; Glade, 2003; Guns and Vanacker, 2014). Rather than focusing on different environmental conditions

characterizing naturally and anthropogenically induced landslides, identifying similarities between these two could be another way to approach this discussion. We do so by examining the role of land cover change and increasing human pressure in connection to both LTNF and LTAF locations. Figure 3.7 shows that in both cases, we observe quite similar trends in changes in forest cover and proxies of human impact. This implies that human impact disturbing hillslope stabilities in the case of anthropogenically triggered landslides may also exist for naturally occurring ones. Further research on this issue with higher resolution and reliable data is needed. Based on these results, we suggest that anthropogenic factors may also have a partial role in naturally occurring landslides.

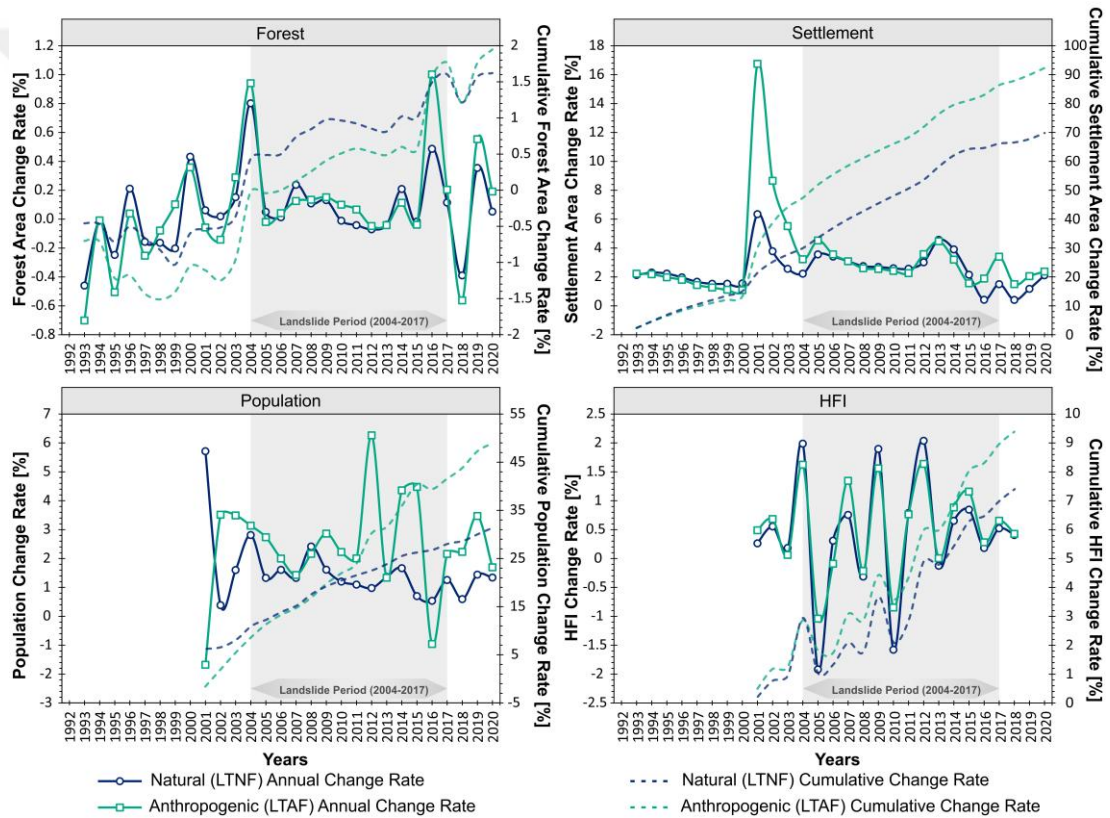


Figure 3. 8: Temporal variations in forest area, settlement area, population and human footprint changes in sub-basins associated with LTNF (blue) and LTAF (green). The solid lines indicate the annual change rate, whereas the dashed lines represent the cumulative change rate.



4. LAND COVER CHANGE CAUSES MORE LANDSLIDE FATALITIES AS ECONOMIC INCOME LEVEL DECREASES

4.1 Results

4.1.1 Global mountain patterns of fatal landslides and land cover dynamics

Our study area consists of 46 countries with six (median value: 5.5) or more fatal landslides, including 2,825 landslide events resulting in 35,593 deaths across K1 mountainous areas globally (Figure 4.1a). A comparative analysis of global land cover from 1960 (Figure 4.1b) and 2019 (Figure 4.1c) shows the trend of changing dynamics in mountainous areas. In 1960, the greater proportion of land cover types in mountainous areas consisted of forests (39%), pastures (27.2%), and sparse and non-vegetated areas (19.5%). 8.5% of the mountainous areas were covered by grass and shrubland and 5.4% by cropland. Urban areas constituted 0.4% (Figure 4.1b). By 2019, the proportion of forest cover had decreased by 4%, and the proportion of grass and shrubland had increased by 2.4%. The proportion of croplands increased by nearly 39%, pastures by 11.8%, whereas sparse and non-vegetated areas decreased by 21.5%. Urban areas doubled, indicating a substantial urbanization trend in mountain areas worldwide (Figure 4.1c).

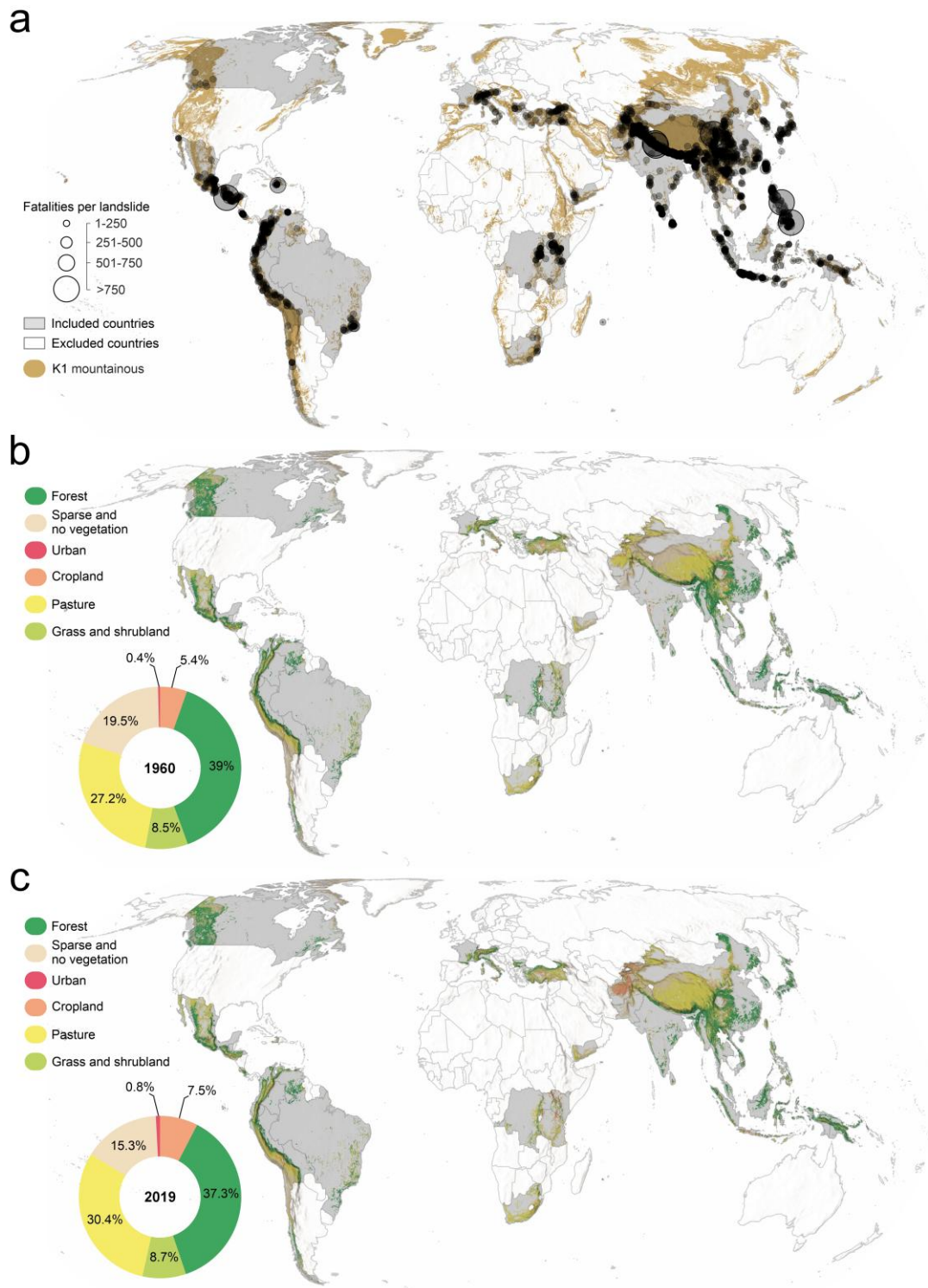


Figure 4. 1: Global distribution of fatal landslides and land cover types in K1 mountainous areas. Panel **a**) illustrates the distribution of fatal landslides in the K1 mountainous areas of countries with a median landslide value of six and above calculated worldwide (gray shading indicates these countries). The size of the landslide point represents the number of fatalities for each event. Panels **b**) and **c**) show the global distribution of land cover types in the K1 mountains for 1960 and 2019, respectively.

4.1.2 LULCC by income levels

To understand the dynamics of LULCC in more detail, we created a Sankey diagram of LULCC in mountainous areas between 1960 and 2019 according to income groups. Our findings highlighted the varying rates and potential impact of LULCC for mountain areas across income levels, and on a global scale (Figure 4.2).

Land cover in high-income countries was mainly unchanged, with minimal exchange between different land cover types (Figure 4.2a). Forest cover increased by 1.7%, sparse and non-vegetated areas by 2.5%, grass and shrublands by 5.4%, and the urban areas nearly doubled (80%). In contrast, the proportions of croplands and pastures decreased by 34.8% and 31.7%, respectively. For upper-middle-income countries, changes between land cover types were also small, with the transition from grass and shrubland areas into pastures explaining most of the expansion in the latter (by 6.9%) and the contraction in the former (by 17.5%, Figure 4.2b). A slight increase was observed in forest cover (0.3%), while a decrease was observed both in sparse and non-vegetated areas (4.4%) and croplands (1.4%). Urban expansion (133%) was supported by a transition from all other land cover types.

In the case of lower-middle-income countries, the transitions among land cover types were somewhat more pronounced than the previous two income levels (Figure 4.2c): pastures increased by 27.8%, grass and shrublands expanded by 25.5%, and urban areas doubled. The amount of land turned into pasture from sparse and non-vegetated areas accounted for 9.2 %. Croplands decreased by 8.7% and forest cover by 4%.

In the low-income countries, LULCC showed higher rates than in all other income groups (Figure 4.2d). Although 7.3% of grass and shrubland areas were converted to forest, the proportion of forest cover was down by almost 20%. 10.9% of the forests transitioned into pasture, and 4% into grass and shrublands. The proportion of croplands almost tripled, and this increase was mainly supported by the 17% of the transition from pastures. In return, the pastures decreased by more than 28% despite receiving a large portion of forest loss. Although part of the forest cover and cropland losses were from transitions into grass and shrubland (by 4% and 4.6%, respectively), the latter still recorded a little over 3% decrease. Sparse and non-vegetated areas also showed a near 3% increase, while urban areas increased by more than ten times,

showing the highest rate of urban expansion in mountainous areas compared to other income groups (Figure 4.2d).

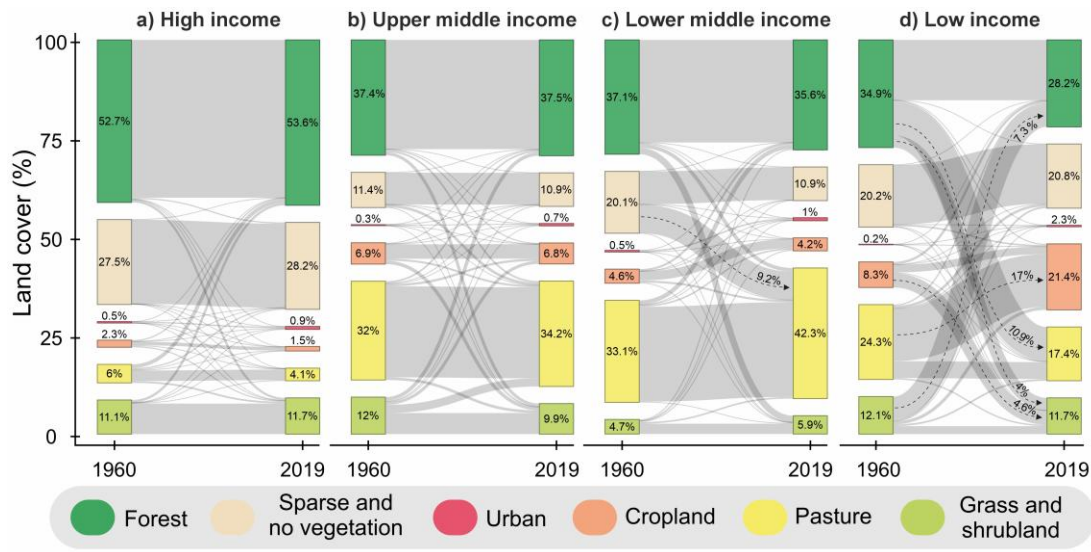


Figure 4. 2: Land cover type transitions in mountainous areas by income classification. Sankey diagrams showing land cover type transitions in mountainous areas of countries by income classification between 1960 and 2019. Each bar illustrates the proportion (%) of the land cover type, and the gray color of the transitions indicates whether the land cover type changes to the same or another type. The dashed arrow indicates major transitions.

4.1.3 Cross-country variation of LULCC

To further explore the variations in LULCC in mountain areas of countries based on income level, we analyzed the transition of land cover types across 46 countries where fatal landslides occurred. Figures 4.3–4.6. illustrate the Sankey diagrams for high-income, upper-middle-income, lower-middle-income, and low-income countries, respectively. Median (Mdn) and mean (M) $LULCCR_{score}$ (showing the score assigned to the rate of change, see Methods section 2.2.4 and Table 4.1-4.2) results are as follows: high-income (Mdn:11.27%, M:10.10%), upper-middle-income (Mdn:6.72%, M:10.81%), lower-middle-income (Mdn:19.83%, M:20.05%), and low-income (Mdn:46.22%, M:46.85%). Additionally, we normalized the $LULCCR_{score}$ to assess the potential impact of LULCC with respect to each country's mountainous area (see Methods section). This allowed us to obtain a comparative measure ($LULCCR_{scoreN}$) across countries. Higher $LULCCR_{scoreN}$ indicates higher LULCC per unit area and can help compare the potential impact of LULCC across different regions. For example, Rwanda, Haiti, El Salvador, Sri Lanka, and Uganda have the highest $LULCCR_{scoreN}$, at

the 90th percentile, indicating high levels of LULCC and significant changes in their mountainous areas (Table 4.2).

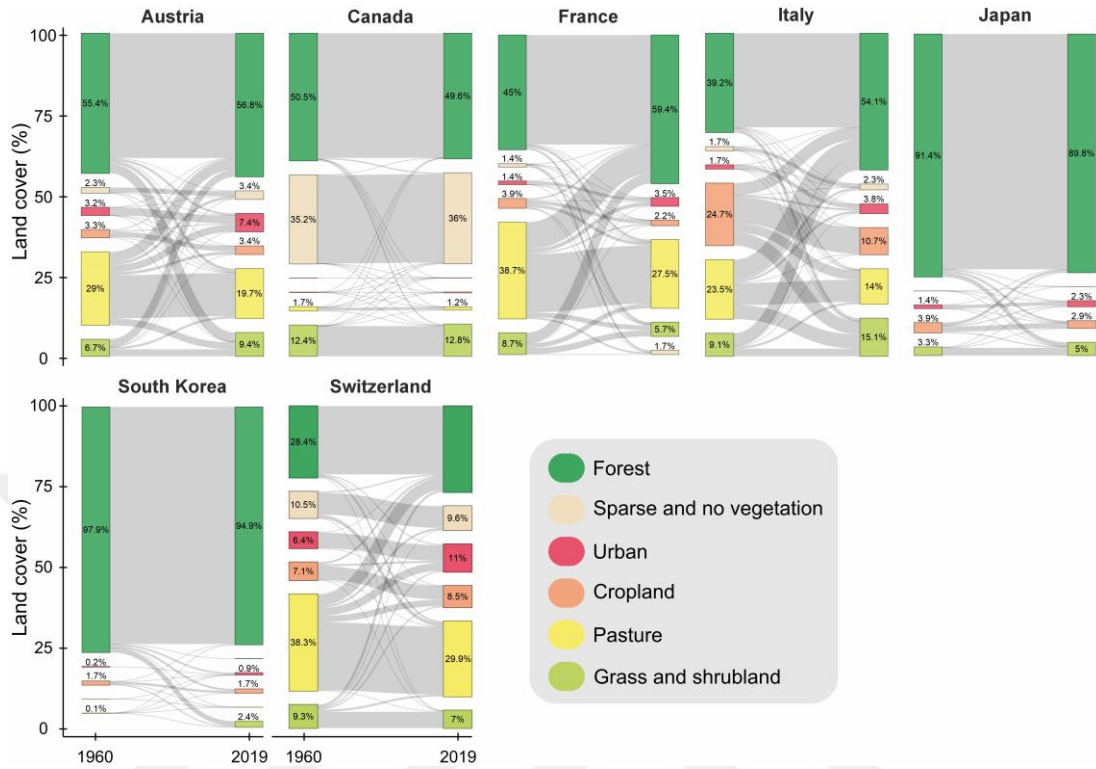


Figure 4.3: Land cover type trajectories in high-income countries. Sankey diagrams showing land cover type transitions in mountainous areas between 1960 and 2019. Each bar illustrates the proportion (%) of the land cover type, and the gray color of the transitions indicates whether the land cover type changes to the same or another type.

In the high-income group with both their $LULCCR_{score}$ and $LULCCR_{scoreNs}$ low (Table 4.1), Canada, South Korea, and Japan show weak transitions among their land cover types. Although Italy, Austria, Switzerland, and France have $LULCCR_{score}$ higher than the group mean, they maintain lower $LULCCR_{scoreNs}$ (Figure 4.3 and Table 4.1). Of these four countries, in Italy, the major transition is both from pastures, grass and shrublands, and croplands to forests in mountainous areas, with the latter showing a 38% increase. Croplands and pastures lose more or less half of their land cover proportion, while their transition into grass and shrublands helps increase this land cover type by 65.9%. Similarly, the main transition in France is between pastures, grass and shrublands, and forests, with forest cover increasing by 32%. In Austria, the fact that the $LULCCR_{score}$ and $LULCCR_{scoreNs}$ are both higher than the group mean is supported by both the dynamic transitions between its grass and shrubland and forest cover. In turn, the 32% decline in its pastures is mainly due to transitions into all other

land cover types. Furthermore, in the Swiss Alps, with both $LULCCR_{score}$ and $LULCCR_{scoreN}$ higher than the group mean, the major transition in land cover is from pastures to forests, croplands, and urban areas. Here, pastures show a 21.9% decline, forests increased by 20%, croplands increased by 19.7%, and urban expansion in Swiss highlands almost doubled, suggesting higher rates of impact of LULCC in this region.

Table 4. 1: Summary statistics of land cover change and population change rates in sample high and upper-middle-income countries.

	Country	Area (km ²)	$LULCCR_{score}$ (%)	$LULCCR_{scoreN}$	PCR	PCR_N
High-income countries	Austria	61111	16.27	0.05679	0.123	0.078
	Canada	1930067	2.06	0.00001	0.514	0.065
	France	127430	11.27	0.01872	0.292	0.080
	Italy	147950	21.01	0.03020	-0.026	0.061
	Japan	168578	3.86	0.00469	-0.037	0.061
	South Korea	28814	3.93	0.02900	-0.233	-0.001
	Switzerland	37586	12.30	0.06985	0.348	0.135
	Median	127430	11.27	0.02900	0.122	0.064
	Mean	357362	10.10	0.02989	0.140	0.068
Upper-middle-income countries	Brazil	516727	11.83	0.00469	0.711	0.073
	Chile	470812	4.31	0.00175	1.205	0.082
	Costa Rica	23285	17.82	0.16370	1.426	0.541
	Malaysia	90151	1.79	0.00404	1.831	0.221
	Mexico	961723	5.20	0.00094	1.179	0.072
	South Africa	446514	5.83	0.00258	0.894	0.078
	Türkiye	552550	32.07	0.01222	0.638	0.072
	Venezuela	240511	7.62	0.00657	0.711	0.086
	Median	458663	6.72	0.00437	1.036	0.080
	Mean	412784	10.81	0.02456	1.074	0.153

Note: Area (km²): the mountainous area of each country. $LULCCR_{score}$: the total land cover change rate. $LULCCR_{scoreN}$: normalized total land cover change rate between 0-1 by mountainous areas. PCR: population change rate. PCR_N : normalized population change rate between 0-1 by mountainous areas.

Upper-middle-income countries, except Türkiye ($LULCCR_{score}$: 32.07%, $LULCCR_{scoreN}$: 0.01222), generally have weak transitions between land cover types, and both their $LULCCR_{score}$ and $LULCCR_{scoreN}$ ranges (except for Costa Rica) are also similar to those observed in high-income countries (Figure 4.4 and Table 4.1). In Türkiye, where the normalized impact score is lower, the exchanges are mainly between grass and shrublands and all other categories, with a fivefold urban expansion between 1960-2019. In Costa Rica, due to the smaller area of the country and its mountain regions, although the $LULCCR_{score}$ is nearly half of Türkiye, the normalized score is much higher (0.16370). The main transitions are from forests into pastures and

grass and shrublands into all other land cover types. The forest cover decreases by 6.4%, pastures and cropland increase by 66.7% and 45.8%, respectively. Urban areas in Costa Rica nearly quadrupled, a pattern that can be observed in the highlands of all upper-middle-income countries except for Chile and Malaysia, where they stay the same.

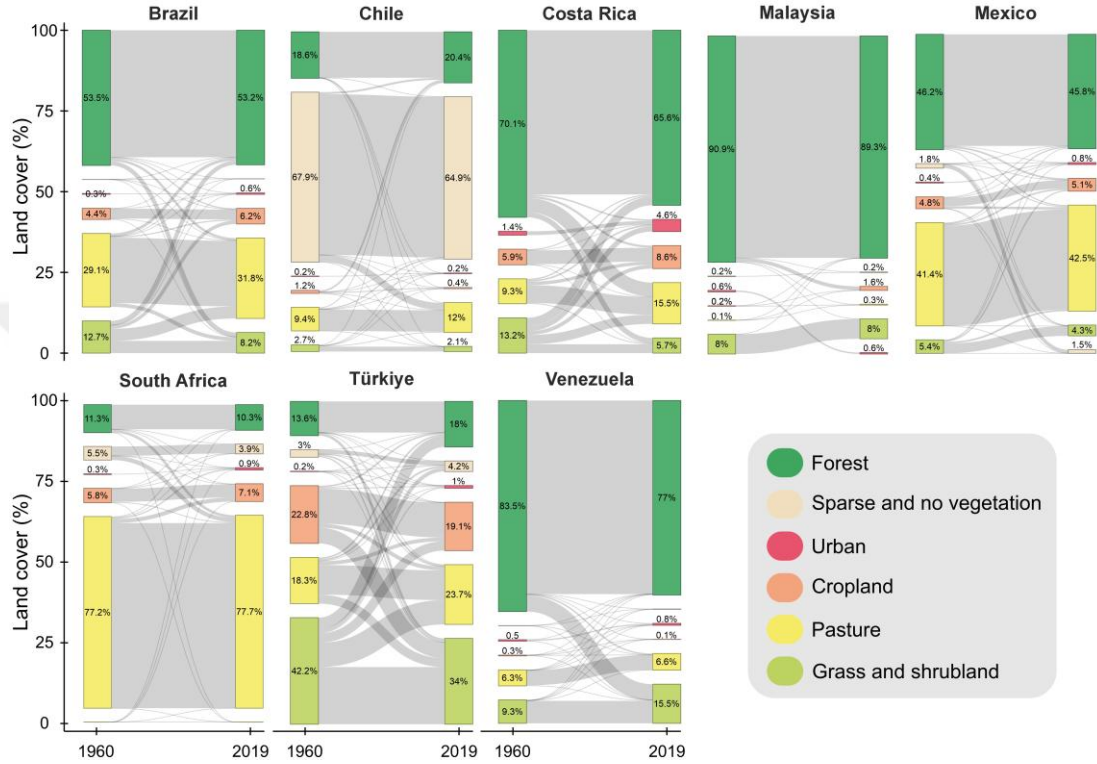


Figure 4. 4: Land cover type trajectories in upper-middle-income countries. Sankey diagrams showing land cover type transitions in mountainous areas between 1960 and 2019. Each bar illustrates the proportion (%) of the land cover type, and the gray color of the transitions indicates whether the land cover type changes to the same or another type.

Although lower-middle-income countries show relatively higher land cover transformations in the Sankey diagrams, some countries in this group have $LULCCR_{score}$ comparable to those in high-income and upper-middle-income countries, and most of their $LULCCR_{scoreN}$ is also relatively low. For example, the scores for Papua New Guinea ($LULCCR_{score}$: 2.87%; $LULCCR_{scoreN}$: 0.00288), the Philippines ($LULCCR_{score}$: 4.29%; $LULCCR_{scoreN}$: 0.00881), Peru ($LULCCR_{score}$: 10.26%; $LULCCR_{scoreN}$: 0.00328), Thailand ($LULCCR_{score}$: 11.59%; $LULCCR_{scoreN}$: 0.01712), and Bolivia ($LULCCR_{score}$: 11.62%; $LULCCR_{scoreN}$: 0.00594) indicate lower rates of transitions and potential areal impact. In contrast, in Guatemala ($LULCCR_{score}$: 38.84%, $LULCCR_{scoreN}$: 0.16575), El Salvador ($LULCCR_{score}$: 33.10%; $LULCCR_{scoreN}$:

0.61086), and Sri Lanka ($LULCCR_{score}$: 24.37%; $LULCCR_{scoreN}$: 0.55823) higher rates of LULCC also bring along higher potential areal impact (Figure 4.5 and Table 4.2). Colombia ($LULCCR_{score}$: 33.85%; $LULCCR_{scoreN}$: 0.02438) and Ecuador ($LULCCR_{score}$: 33.85%; $LULCCR_{scoreN}$: 0.06467) both have high transitions, with lesser areal impact than the previous three countries. In Colombia, Ecuador, Honduras, Indonesia, Guatemala, Sri Lanka, and Thailand, the largest transition is from forests into grass and shrublands (and back, in the case of Thailand) and between grass and shrublands into croplands and pastures. In China and Bolivia, a conversion from sparse and non-vegetated areas (with this land cover type showing a decrease of 53.5% and 11.8%, respectively), making up a large part of these countries' land cover, into cropland is observed. Urban expansion is also high in the mountainous areas in most of these countries, with the highest rate of increase observed in Sri Lanka (442%). Urban areas in the Philippines, Georgia, China, and Bolivia remain unchanged.

Countries in the low-income group are represented by a wide range of $LULCCR_{score}$ (3.75%-99.67%). Yemen ($LULCCR_{score}$: 3.75%; $LULCCR_{scoreN}$: 0.00430), Pakistan ($LULCCR_{score}$: 5.29%; $LULCCR_{scoreN}$: 0.00305), and Bhutan ($LULCCR_{score}$: 6.86%; $LULCCR_{scoreN}$: 0.03689) have weaker transitions among land cover types similar to higher-income countries, indicating higher rates of land cover permanence. Alternately, Haiti ($LULCCR_{score}$: 47.74%; $LULCCR_{scoreN}$: 0.76917), Rwanda ($LULCCR_{score}$: 93.81%; $LULCCR_{scoreN}$: 0.99989), and Uganda ($LULCCR_{score}$: 75.75%; $LULCCR_{scoreN}$: 0.31126) stand out with high rates of change, which also highlights the dynamic and often unstable land cover transitions in these regions (Figure 4.6 and Table 4.2). In Haiti, the transition from grass and shrublands into forests increases the proportion of the latter by more than ten times. Also, major shifts between forests and pastures, pastures and cropland, cropland and forests, and grass and shrublands explain the high rate of change in this country. In Rwanda, major transitions are from forests into pastures and grass and shrublands, leaving near complete deforestation in their wake. Also, pastures transform into cropland, and cropland into grass and shrubland, while in neighboring Uganda, both countries sharing the Virunga Mountain Range, similar dynamic shifts can be seen with forests transitioning into pastures, which in turn transition into cropland and grass and shrublands.

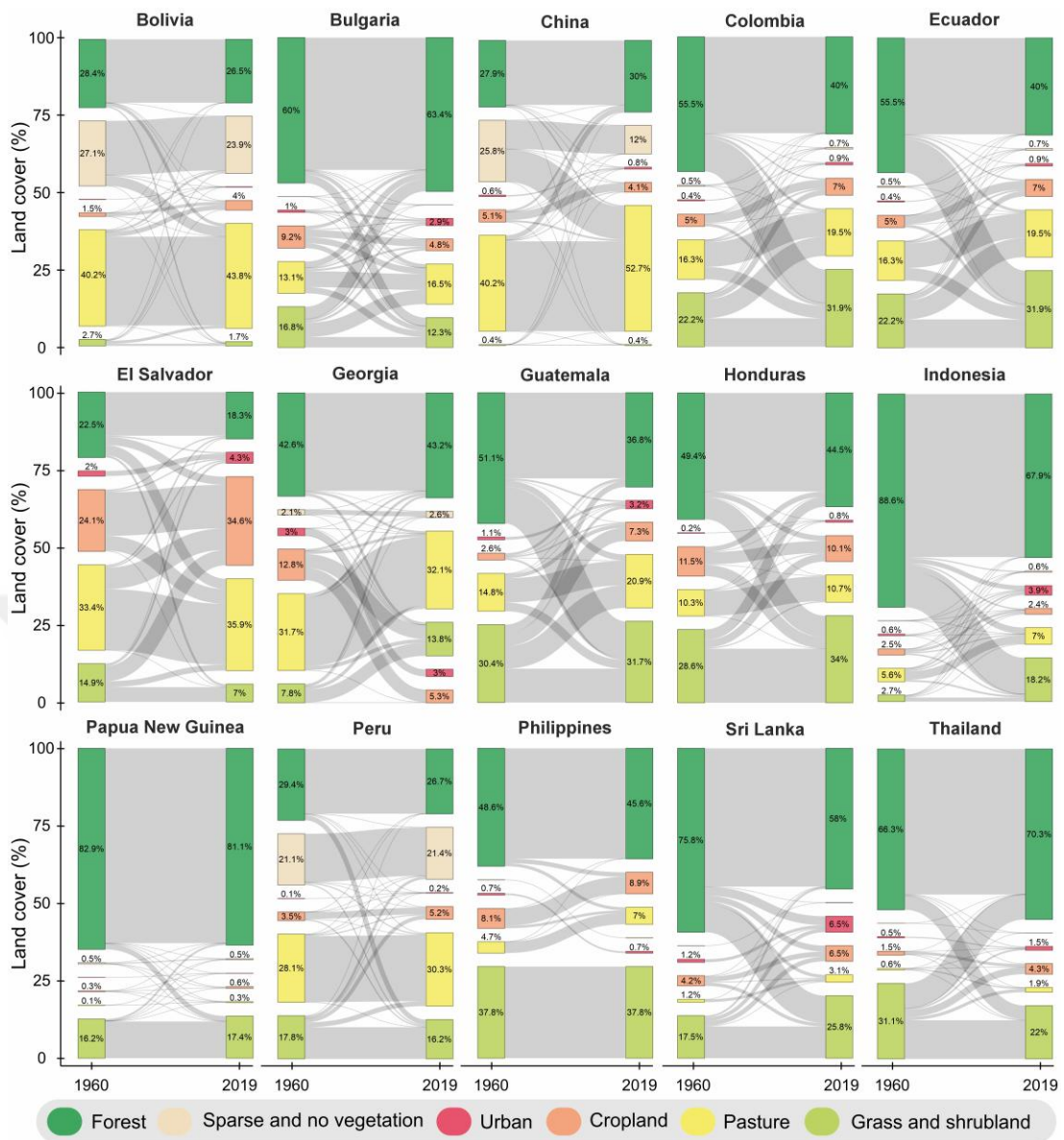


Figure 4. 5: Land cover type trajectories in lower-middle-income countries. Sankey diagrams showing land cover type transitions in mountainous areas between 1960 and 2019. Each bar illustrates the proportion (%) of the land cover type, and the gray color of the transitions indicates whether the land cover type changes to the same or another type.

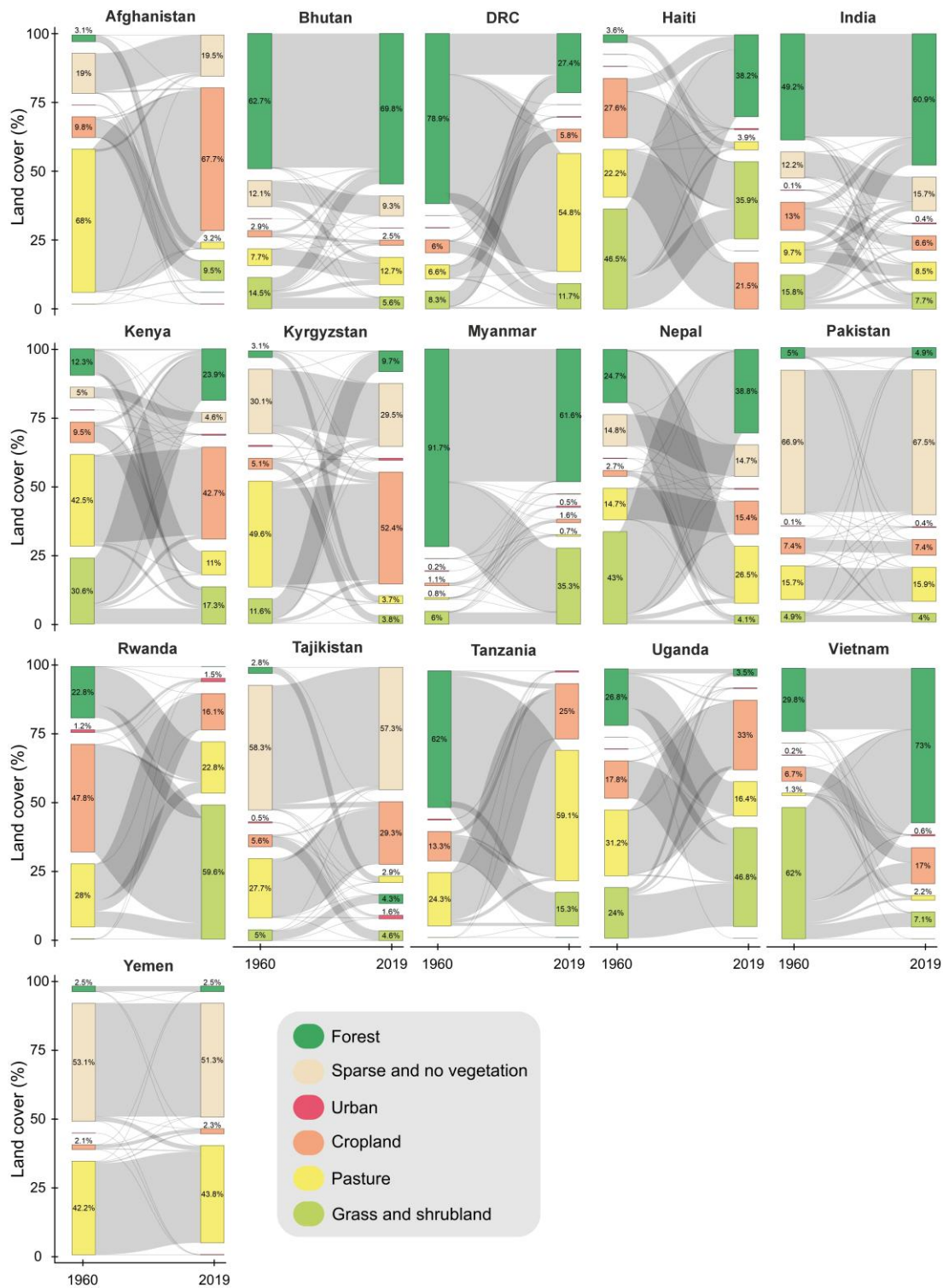


Figure 4. 6: Land cover type trajectories in low-income countries. Sankey diagrams showing land cover type transitions in mountainous areas between 1960 and 2019. Each bar illustrates the proportion (%) of the land cover type, and the gray color of the transitions indicates whether the land cover type changes to the same or another type.

Table 4. 2: Summary statistics of land cover change and population change rates in sample lower-middle and low-income countries.

	Country	Area (km ²)	$LULCCR_{score}$ (%)	$LULCCR_{scoreN}$	PCR	PCR_N
Lower-middle-income countries	Bolivia	404225	11.62	0.00594	0.997	0.082
	Bulgaria	48836	21.84	0.09553	-0.142	0.040
	China	5159174	16.05	0.00045	0.210	0.063
	Colombia	294776	33.85	0.02438	0.977	0.088
	Ecuador	111706	33.85	0.06467	1.277	0.152
	El Salvador	11598	33.10	0.61086	0.598	0.465
	Georgia	55616	13.00	0.04985	-0.222	0.031
	Guatemala	50114	38.84	0.16575	1.774	0.339
	Honduras	74966	19.83	0.05644	2.108	0.282
	Indonesia	554474	25.38	0.00959	1.097	0.078
	Papua New Guinea	198177	2.87	0.00288	3.151	0.187
	Peru	628789	10.26	0.00328	0.955	0.074
	Philippines	101905	4.29	0.00881	1.340	0.165
	Sri Lanka	9344	24.37	0.55823	0.622	0.582
	Thailand	143247	11.59	0.01712	0.601	0.095
	Median	111706	19.83	0.02438	0.977	0.095
	Mean	523130	20.05	0.11158	1.022	0.181
Low-income countries	Afghanistan	391827	81.43	0.04429	2.455	0.111
	Bhutan	39603	6.86	0.03689	1.181	0.296
	DRC	248655	71.50	0.06136	2.750	0.149
	Haiti	13287	47.74	0.76917	1.071	0.692
	India	599440	14.26	0.00488	1.069	0.076
	Kenya	145930	63.77	0.09336	2.234	0.182
	Kyrgyzstan	180879	61.61	0.07272	1.044	0.108
	Myanmar	319788	30.94	0.02050	10.020	0.307
	Nepal	117880	44.71	0.08100	0.271	0.080
	Pakistan	347420	5.29	0.00305	2.169	0.111
	Rwanda	20085	93.81	0.99989	1.826	0.773
	Tajikistan	135248	38.97	0.06149	1.758	0.164
	Tanzania	235149	96.67	0.08781	2.335	0.140
	Uganda	52073	75.75	0.31126	2.327	0.412
	Vietnam	136309	12.47	0.01938	1.204	0.132
	Yemen	177863	3.75	0.00430	2.806	0.186
	Median	161897	46.22	0.06143	1.997	0.156
	Mean	197590	46.85	0.16696	2.282	0.181

Note: Area (km²): the mountainous area of each country. $LULCCR_{score}$: the total land cover change rate. $LULCCR_{scoreN}$: normalized total land cover change rate between 0-1 by mountainous areas. PCR: population change rate. PCR_N : normalized population change rate between 0-1 by mountainous areas.

Although Afghanistan ($LULCCR_{score}$: 81.43%; $LULCCR_{scoreN}$: 0.04429), Tanzania ($LULCCR_{score}$: 96.67%; $LULCCR_{scoreN}$: 0.08781), and the Democratic Republic of the Congo ($LULCCR_{score}$: 71.50%; $LULCCR_{scoreN}$: 0.06136) all have high change rates,

their normalized rates are in fact similar to the high-income groups. In DRC and neighboring Rwanda and Uganda, a major transition from forests into croplands is observed, with the proportion of forests decreasing by 65.3%. In Afghanistan, a near complete deforestation can be seen with almost all being converted to pastures. Pastures, in turn, transition into cropland, and former croplands transition into grass and shrubland. Also, in Tanzania, deforestation is nearly complete, with almost all forest cover in mountain areas being converted to pastures and croplands into grass and shrubland. In India, the 51.3% decrease in grass and shrublands explains the 23.8% increase in forest cover, while in Vietnam, this transition is even more significant with an 88.5% decrease in grass and shrublands, which mainly transition into croplands and forests, contributing to the 145% net gain in forest cover. In Nepal, the main source of cropland increase (~80%) is from forests, whereas nearly 90% of grass and shrublands transition into forest cover, which records a 57% increase.

4.1.4 Population changes

We found that the majority of countries affected by fatal landslides in our study area (41 out of 46) experienced population growth between the years 1975 and 2020 (Figure 4.7). All countries except Italy, Japan, South Korea, Bulgaria, and Georgia experienced an increase in population change rates (*PCR*) in mountainous areas between 1975 and 2020 (see Methods section 2.2.5 and Table 4.3-4.4).

Considering the *PCR*, normalized by the extent of the mountainous area in each country (PCR_N , see Methods section 2.2.5), the rate of population change increased as the income level decreased. Countries with lower living standards exhibited considerably higher PCR_N in their mountain regions, with a 2.5-fold higher PCR_N in the low-income group compared to the high-income group (Figure 4.8).

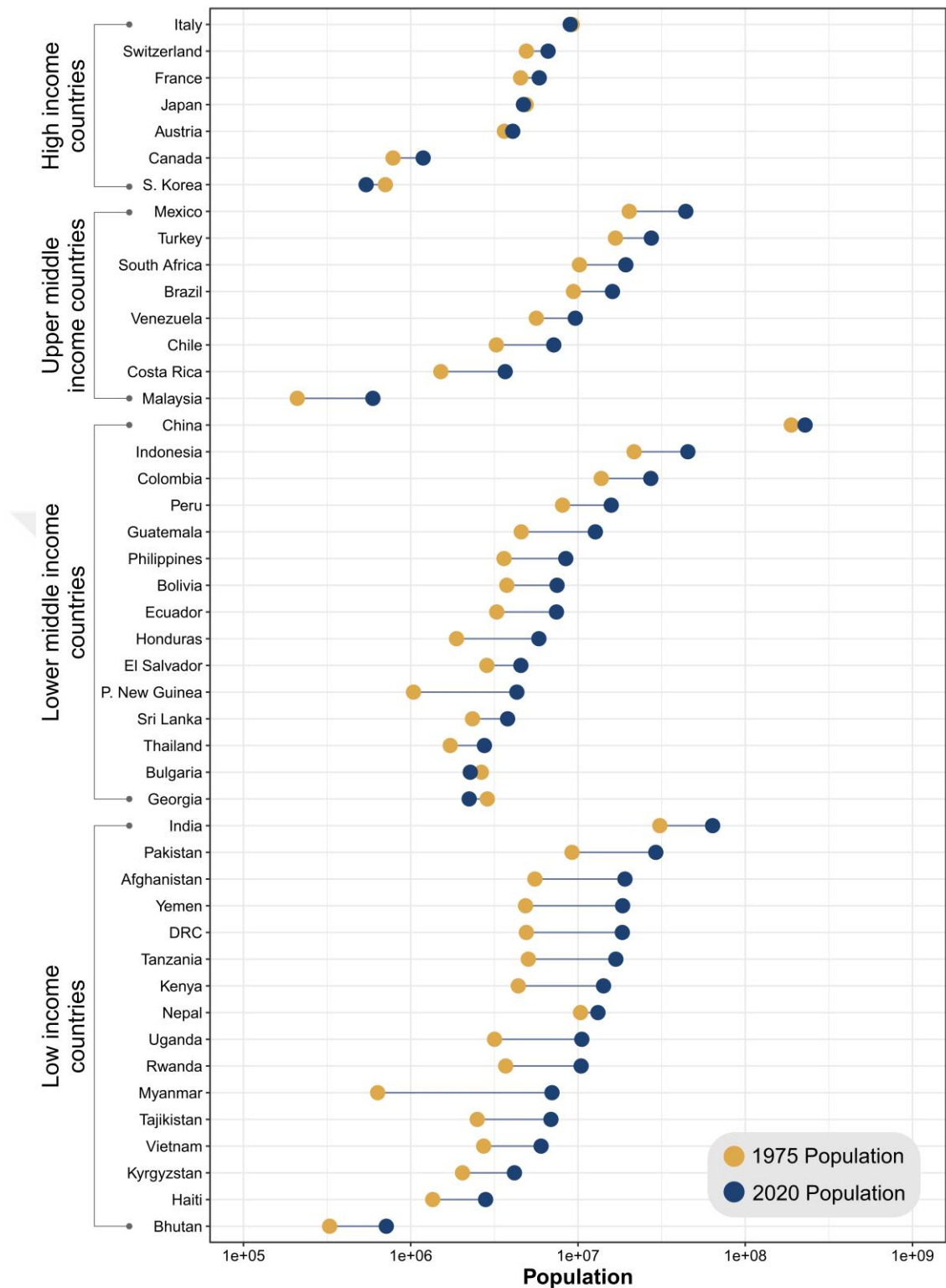


Figure 4. 7: Population change in mountainous areas affected by fatal landslides. The dumbbell plot shows the population change from 1975 to 2020 in mountainous areas of countries affected by fatal landslides. The yellow dots show the population in 1975, and the blue dots show the population in 2020. The lines illustrate the magnitude of population change between the two dates. Countries are categorized by income group.

Table 4. 3: Summary statistics of sample high and upper-middle-income countries.

	Country	Area (km ²)	<i>L</i>	<i>F</i>	<i>LD</i>	<i>FD</i>	<i>LULCCR</i> _{scoreN}	<i>PCR</i> _N
High-income countries	Austria	61111	8	10	0.03323	0.00261	0.05679	0.078
	Canada	1930067	6	7	0.00003	0.00001	0.00001	0.065
	France	127430	7	10	0.01349	0.00122	0.01872	0.080
	Italy	147950	18	71	0.03083	0.00778	0.03020	0.061
	Japan	168578	39	133	0.05933	0.01283	0.00469	0.061
	South Korea	28814	8	60	0.07135	0.03397	0.02900	-0.001
	Switzerland	37586	8	19	0.05452	0.00820	0.06985	0.135
	Median	127430	8	19	0.033	0.00777	0.02900	0.064
	Mean	357362	13.4	44.2	0.037	0.00951	0.02989	0.068
Upper-middle-income countries	Brazil	516727	36	1069	0.01732	0.03375	0.00469	0.073
	Chile	470812	9	53	0.00419	0.00178	0.00175	0.082
	Costa Rica	23285	13	57	0.14427	0.03995	0.16370	0.541
	Malaysia	90151	13	26	0.03669	0.00465	0.00404	0.221
	Mexico	961723	62	437	0.01597	0.00736	0.00094	0.072
	South Africa	446514	7	9	0.00329	0.00026	0.00258	0.078
	Türkiye	552550	36	114	0.01615	0.00331	0.01222	0.072
	Venezuela	240511	18	44	0.01867	0.00293	0.00657	0.086
	Median	458663	15.5	55	0.016	0.00397	0.00437	0.080
	Mean	412784	24.2	226	0.032	0.01174	0.02456	0.153

Note: Area (km²): the mountainous area of each country. *L*: number of landslides. *F*: number of fatalities. *LD*: landslide density. *FD*: Fatalities density. *LULCCR*_{scoreN}: normalized total land cover change rate between 0-1 by mountainous areas. *PCR*_N: normalized population change rate between 0-1 by mountainous areas.

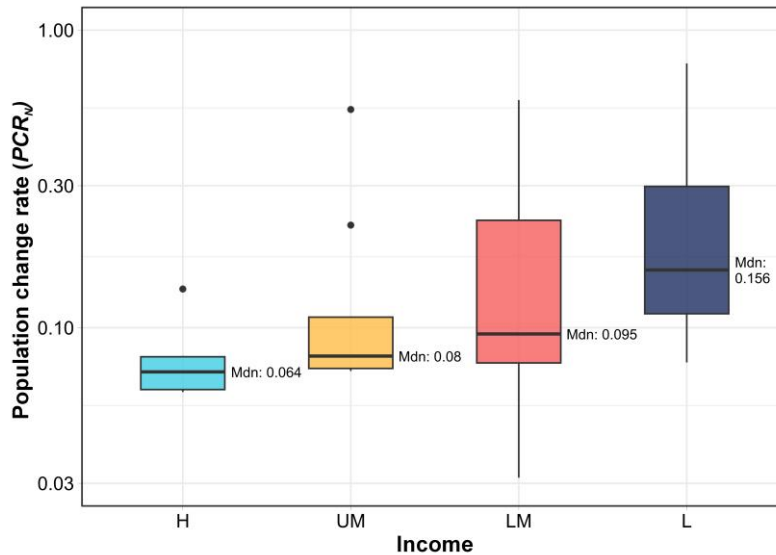


Figure 4. 8: Distribution of population change rates in mountainous areas by income group. The boxplot shows the distribution of population change rates (*PCR*_N) normalized by mountainous areas according to income groups. Income groups are expressed as high-income (H), upper-middle-income (UM), lower-middle-income (LM), and low-income (L) countries. The box hinges show the 25th and 75th percentiles and the middle lines show the median (Mdn).

Table 4. 4: Summary statistics of sample lower-middle and low-income countries.

	Country	Area (km ²)	<i>L</i>	<i>F</i>	<i>LD</i>	<i>FD</i>	<i>LULCCR_{scoreN}</i>	<i>PCR_N</i>
Lower-middle-income countries	Bolivia	404225	8	51	0.00436	0.00200	0.00594	0.082
	Bulgaria	48836	6	11	0.03114	0.00362	0.09553	0.040
	China	5159174	381	6652	0.01841	0.02101	0.00045	0.063
	Colombia	294776	105	1386	0.09177	0.07679	0.02438	0.088
	Ecuador	111706	18	95	0.04109	0.01384	0.06467	0.152
	El Salvador	11598	19	217	0.42482	0.30575	0.61086	0.465
	Georgia	55616	12	51	0.05528	0.01492	0.04985	0.031
	Guatemala	50114	55	2275	0.28435	0.74195	0.16575	0.339
	Honduras	74966	15	67	0.05121	0.01454	0.05644	0.282
	Indonesia	554474	185	1874	0.08591	0.05518	0.00959	0.078
	Papua New Guinea	198177	14	121	0.01757	0.00992	0.00288	0.187
	Peru	628789	44	342	0.01740	0.00883	0.00328	0.074
	Philippines	101905	215	3679	0.54736	0.59004	0.00881	0.165
	Sri Lanka	9344	36	489	1.00010	0.85526	0.55823	0.582
	Thailand	143247	10	36	0.01736	0.00404	0.01712	0.095
	Median	111706	19	217	0.051	0.01492	0.02438	0.095
	Mean	523130	74.8	1156	0.179	0.18117	0.11158	0.181
Low-income countries	Afghanistan	391827	14	603	0.00850	0.02509	0.04429	0.111
	Bhutan	39603	25	57	0.16323	0.02346	0.03689	0.296
	DRC	248655	10	152	0.00967	0.00993	0.06136	0.149
	Haiti	13287	16	813	0.31206	1.00001	0.76917	0.692
	India	599440	541	9373	0.23370	0.25552	0.00488	0.076
	Kenya	145930	35	96	0.06153	0.01069	0.09336	0.182
	Kyrgyzstan	180879	11	66	0.01502	0.00590	0.07272	0.108
	Myanmar	319788	31	884	0.02441	0.04512	0.02050	0.307
	Nepal	117880	417	1665	0.91829	0.23081	0.08100	0.080
	Pakistan	347420	163	1218	0.12112	0.05724	0.00305	0.111
	Rwanda	20085	15	102	0.19325	0.08294	0.99989	0.773
	Tajikistan	135248	20	97	0.03764	0.01166	0.06149	0.164
	Tanzania	235149	6	50	0.00585	0.00341	0.08781	0.140
	Uganda	52073	34	533	0.16885	0.16724	0.31126	0.412
	Vietnam	136309	68	370	0.12883	0.04430	0.01938	0.132
	Yemen	177863	8	49	0.01091	0.00444	0.00430	0.186
	Median	161897	22.5	261	0.091	0.03469	0.06143	0.156
	Mean	197590	88.3	1008	0.150	0.12360	0.16696	0.181

Note: Area (km²): the mountainous area of each country. *L*: number of landslides. *F*: number of fatalities. *LD*: landslide density. *FD*: Fatalities density. *LULCCR_{scoreN}*: normalized total land cover change rate between 0-1 by mountainous areas. *PCR_N*: normalized population change rate between 0-1 by mountainous areas.

4.1.5 Benchmarking between land cover transitions, population change, landslides, and fatalities

As the next step in our analysis, we categorized the $LULCCR_{scoreN}$ and PCR_N by income, compared them with each other, and computed their relationship with landslide and fatality density. Figure 4.9a provides a bivariate map showing the relationship between $LULCCR_{scoreN}$ and PCR_N by country, allowing us to visualize their interaction. Figure 4.9b summarizes this relationship in bivariate plots and reveals the countries with high $LULCCR_{scoreN}$ and PCR_N . Figure 4.9c also presents the same information but is classified by income level to highlight the level of economic development.

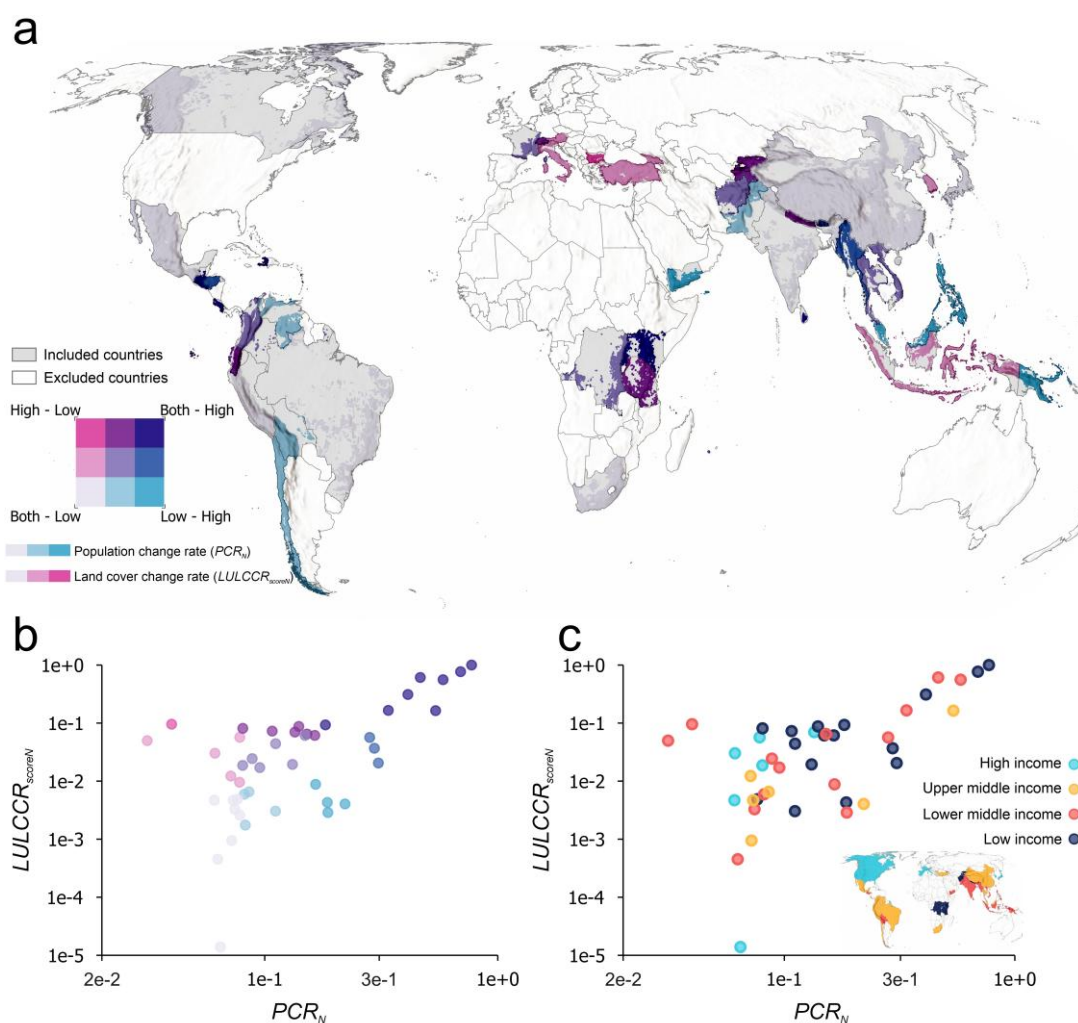


Figure 4. 9: Relationship between LULCC rate and population change rate. Panel a) shows the combined map of $LULCCR_{scoreN}$ and PCR_N based on mountainous areas of countries. Panel b) shows the scatter plot following the same color scheme of the bivariate map presented above, whereas panel c) classifies it by income groups (in log-scale).

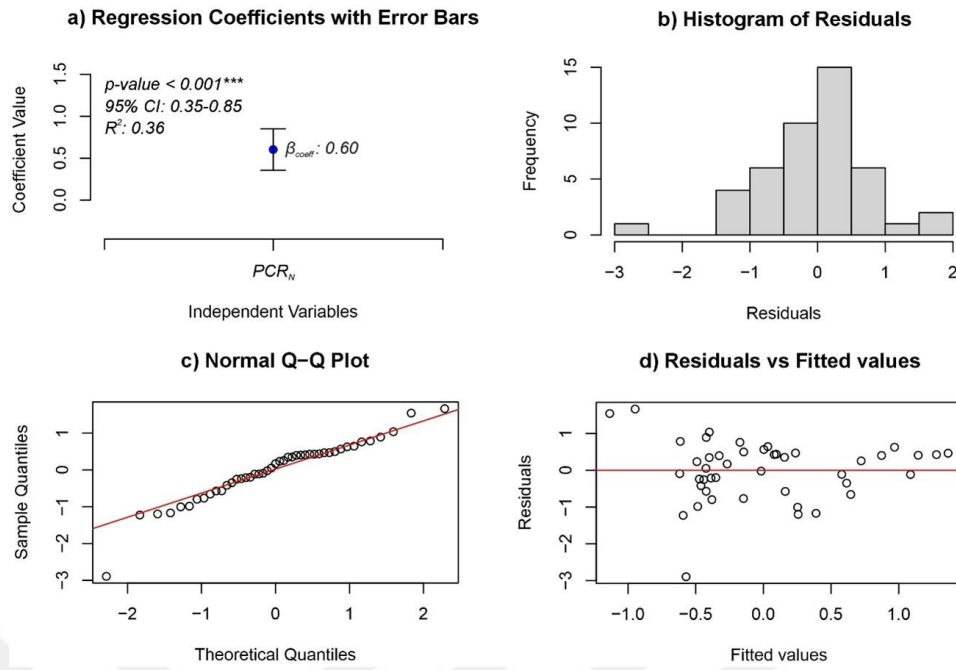


Figure 4. 10: Results from simple linear regression models, using land cover change rate ($LULCCR_{scoreN}$) and the population change rate (PCR_N).

As a result of these bivariate analyses, a positive correlation between $LULCCR_{scoreN}$ and PCR_N emerged, which was higher in low and lower-middle-income countries. To assess the reliability of our results, we also built a Gaussian Generalized Linear Model (GLM) to estimate the association between our change rates. The model also confirmed that the relation between PCR_N and $LULCCR_{scoreN}$ is positive and statistically significant ($\beta_{coeff.} = 0.60$, $p < 0.001$). In the model, a one-unit increase of PCR_N resulted in a 0.60-unit increase in $LULCCR_{scoreN}$, with a 95% confidence interval (CI) of 0.35-0.85 (Figure 4.10). Figures 4.10b-d illustrate that the model assumptions are confirmed; the residuals have a normal distribution (histogram and Q-Q plot), and both the residuals and the fitted values are randomly distributed. These results suggest that in countries with higher population growth, substantial changes in land cover may occur and that these changes are particularly significant in low and lower-middle-income countries.

Next, using a bivariate approach similar to the one described above, we examined the relationship between LULCC, landslide density (LD), and fatality density (FD). The bivariate map in Figure 4.11a portrays the relationship between $LULCCR_{scoreN}$ and LD by country in mountainous areas. The scatterplots show the correlation between these variables (Figure 4.11b) with respect to the income levels of countries (Figure 4.11c). Our results show that LD is positively correlated with $LULCCR_{scoreN}$ and is higher in

low and lower-middle-income countries. Similarly, a positive correlation is observed between PCR_N and LD in low and lower-middle-income countries (Figure 4.12). In addition, the GLM results (Figure 4.13a) support our findings shown in Figure 4.11 and confirm that $LULCCR_{scoreN}$ has a positive and significant correlation with LD ($\beta_{coeff} = 0.61$, $p < 0.001$, 95% CI: 0.33-0.89). As a result, this highlights the fact that countries that are more affected by LULCC have higher landslide densities. However, PCR_N has no significant relationship with LD ($\beta_{coeff} = 0.11$, $p > 0.05$, 95% CI: -0.18-0.40). The residual analysis also shows that the model fits the assumptions (the histogram and the Q-Q plot both suggest a normal distribution, and the residuals and fitted values are randomly distributed, Figure 4.13b-d).

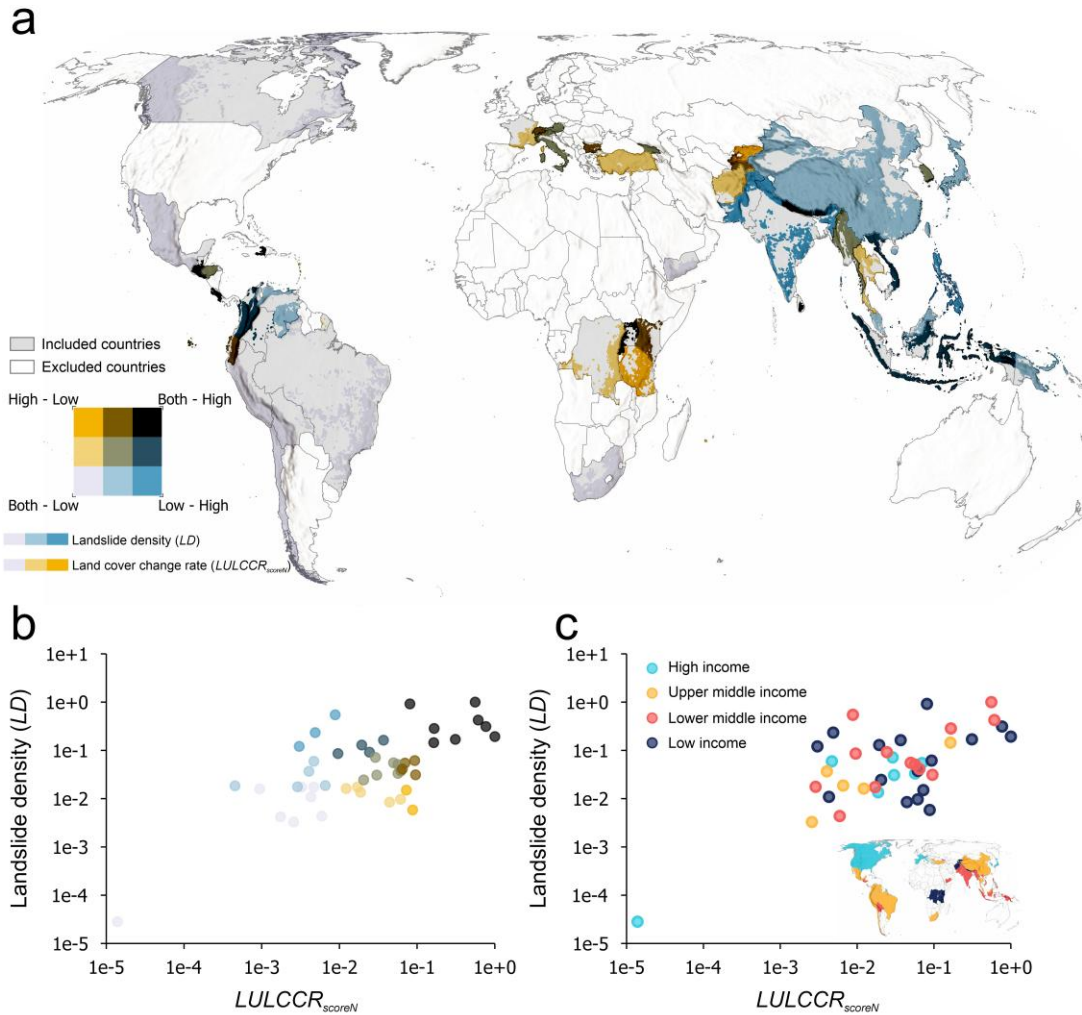


Figure 4. 11: Relationship between LULCC rate and landslide density. Panel a) shows the combined map of $LULCCR_{scoreN}$ and LD based on mountainous areas of countries. Panel b) shows the scatter plot following the same color scheme of the bivariate map presented above, whereas panel c) classifies it by income groups.

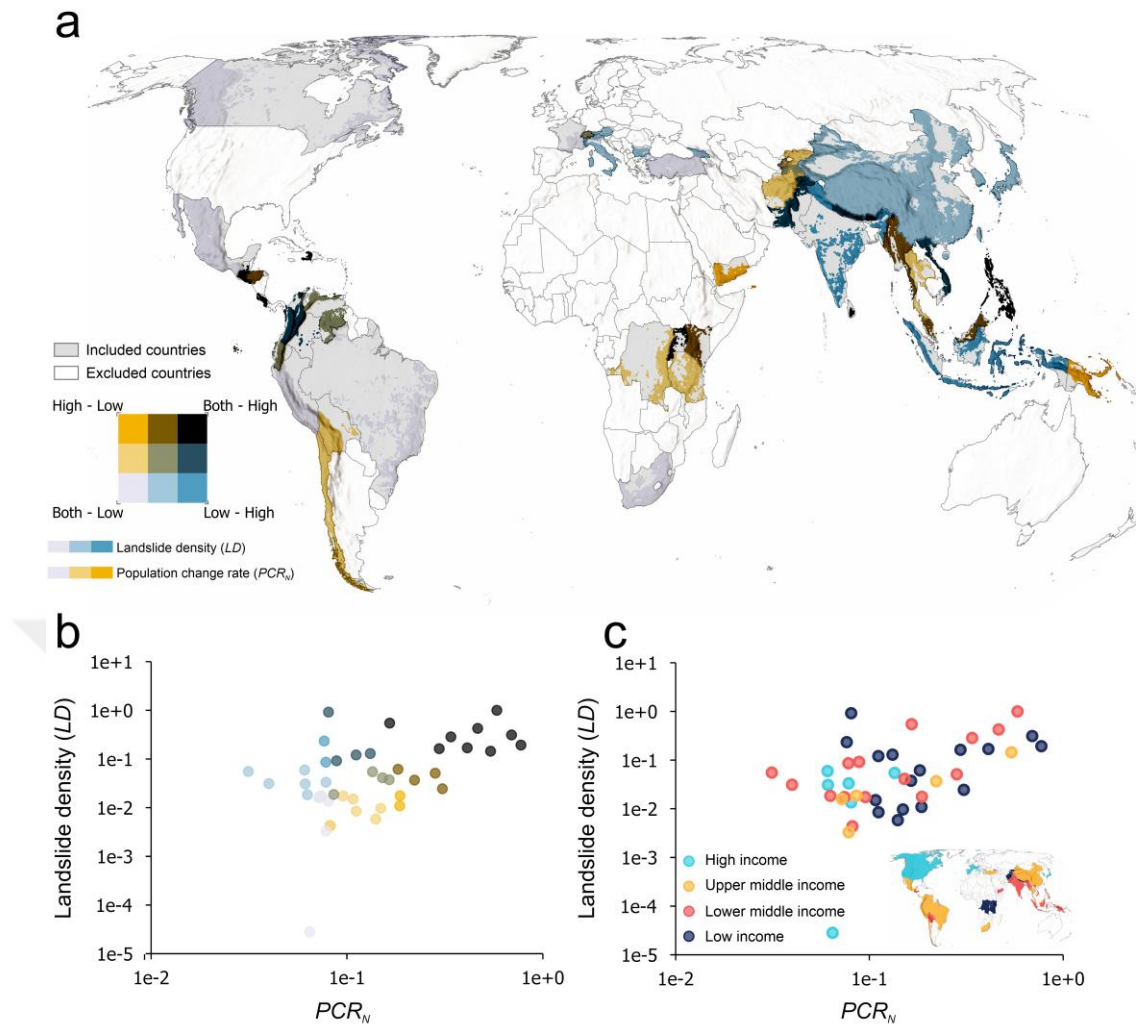


Figure 4. 12: Relationship between population change rate and landslide density. Panel **a)** shows the combined map of PCR_N and LD based on mountainous areas of countries. Panel **b)** shows the scatter plot following the same color scheme of the bivariate map presented above, whereas panel **c)** classifies it by income groups.

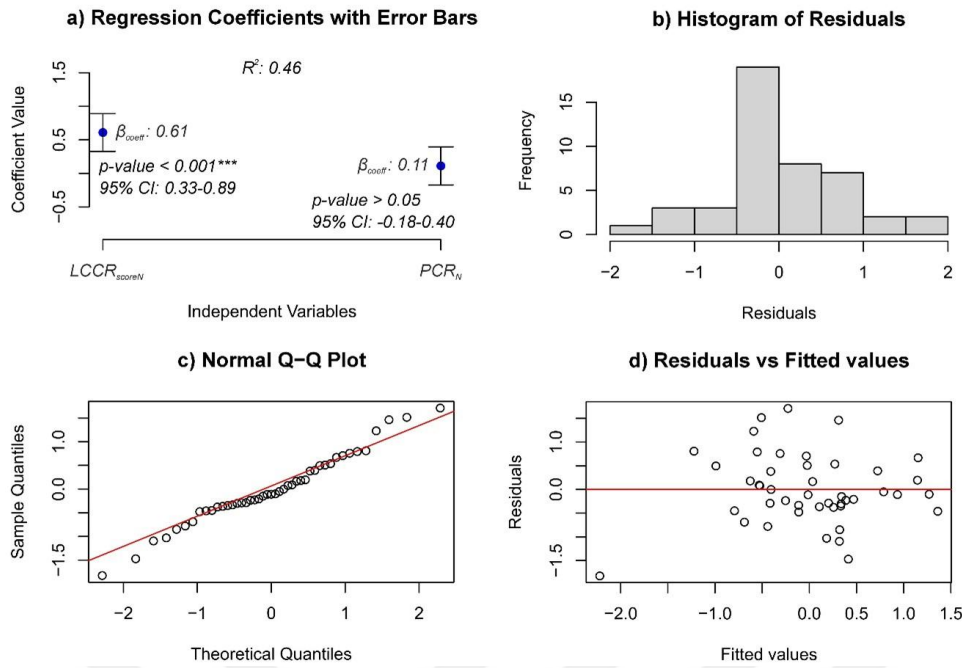


Figure 4. 13: Results from multiple linear regression models, using landslide density (*LD*) with land cover change rate ($LULCCR_{scoreN}$) and population change rate (PCR_N).

To assess the relationship between *FD* and LULCC, we repeated a similar comparative analysis that we conducted for *LD*. Figures 4.14a-b show the spatial relationship between *FD* and LULCC, and the scatter plot in Figure 4.14c shows this relationship classified according to income level. Our results showed that *FD* is positively correlated with $LULCCR_{scoreN}$, which was higher in low and lower-middle-income countries. A similar positive correlation is also followed between PCR_N and *FD*, notably in these same income groups (Figure 4.15). According to the GLM results shown in Figure 4.16a, which also support our findings presented in Figure 4.14, $LULCCR_{scoreN}$ had a positive and statistically significant effect on *LD* ($\beta_{coeff} = 0.46$, $p < 0.01$, 95% CI: 0.16-0.76) in our study area. However, the relationship of PCR_N with *LD* was still not statistically significant ($\beta_{coeff} = 0.25$, $p > 0.05$, 95% CI: -0.04-0.55). A further analysis of the residuals confirmed the validity of the model's assumptions. Similarly, for this model, the histogram of the residuals had a normal distribution (Figure 4.16b), the Q-Q plot followed the theoretical distribution (Figure 4.16c), and the residuals vs. fitted values were randomly distributed (Figure 4.16d).

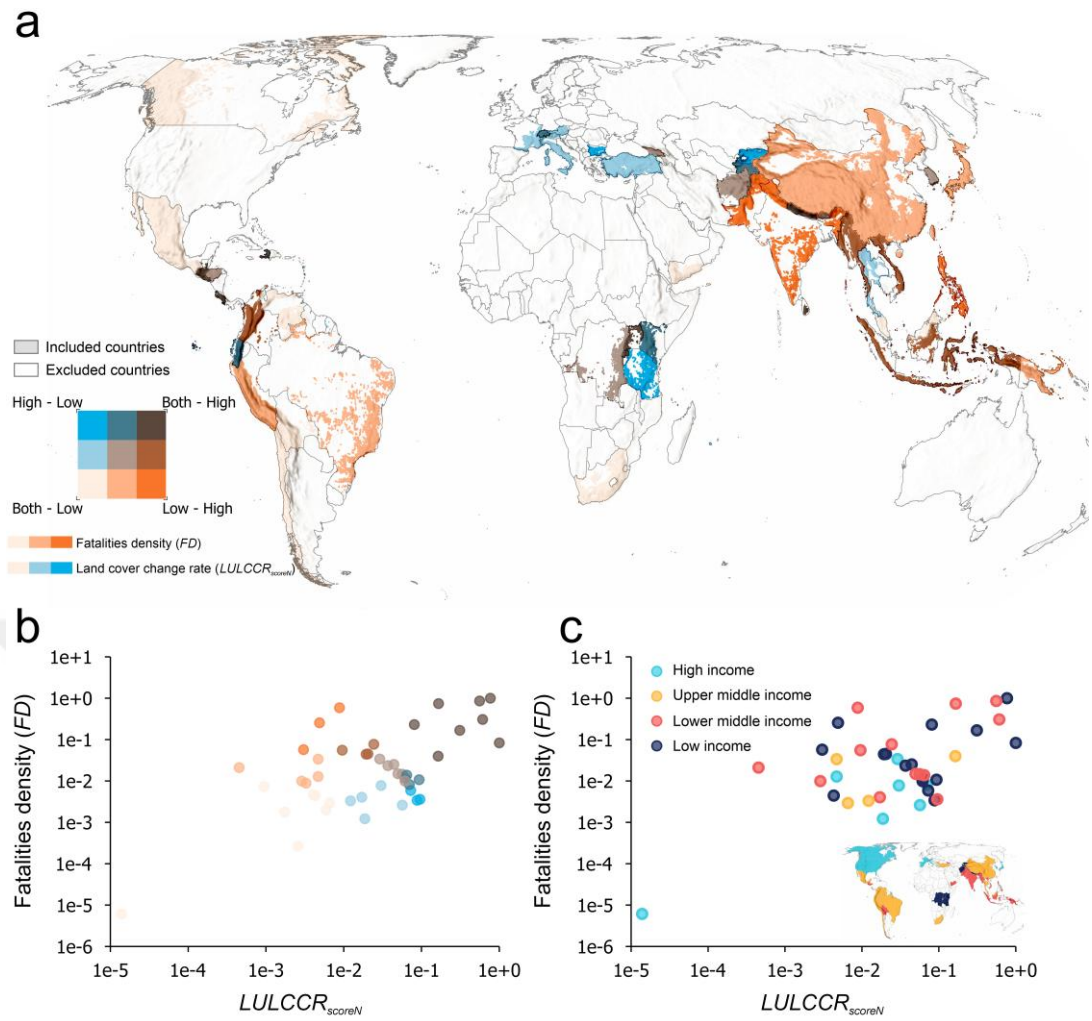


Figure 4. 14: Relationship between LULCC rate and fatality density. Panel **a)** shows the combined map of $LULCCR_{scoreN}$ and FD based on mountainous areas of countries. Panel **b)** shows the scatter plot following the same color scheme of the bivariate map presented above, whereas panel **c)** classifies it by income groups.

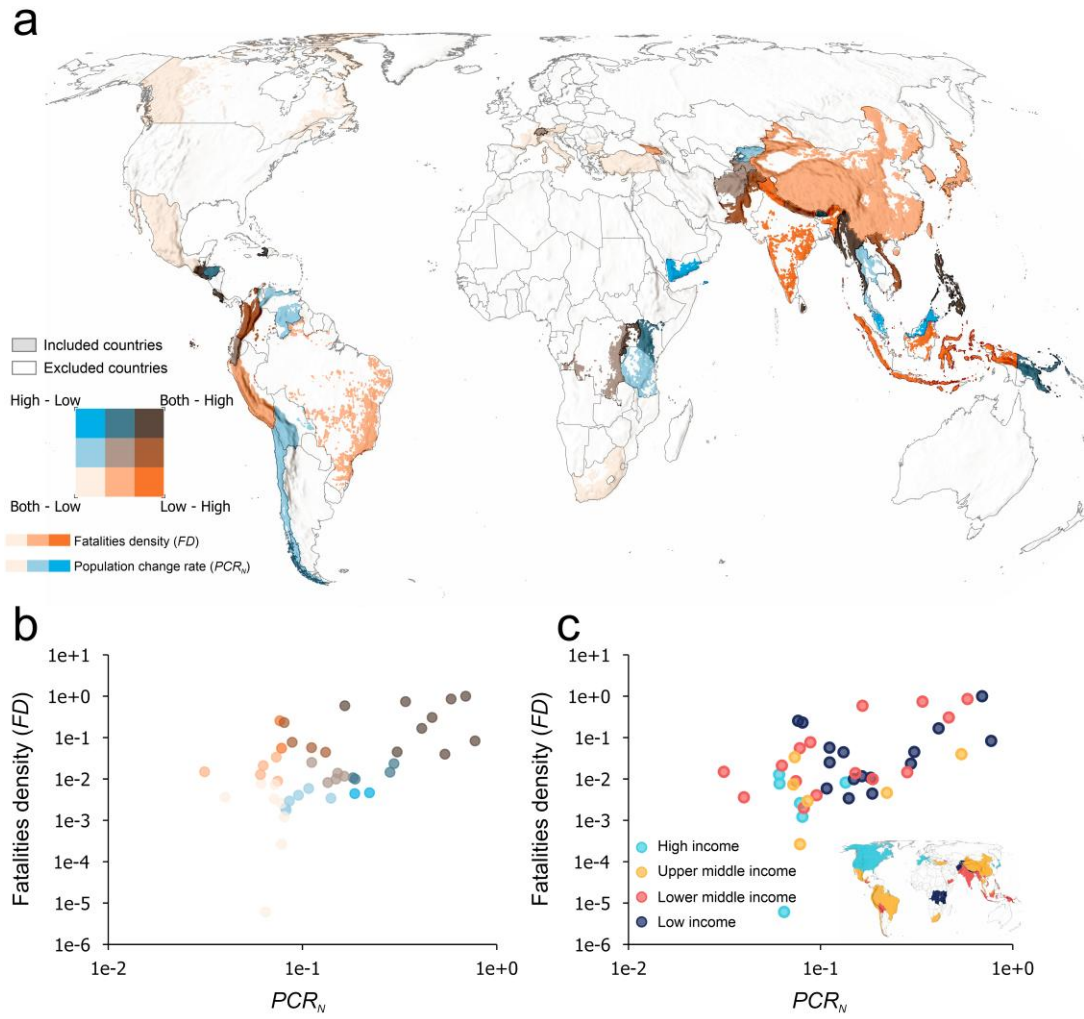


Figure 4. 15: Relationship between population change rate and fatality density. Panel **a**) shows the combined map of PCR_N and FD based on mountainous areas of countries. Panel **b**) shows the scatter plot following the same color scheme of the bivariate map presented above, whereas panel **c**) classifies it by income groups.

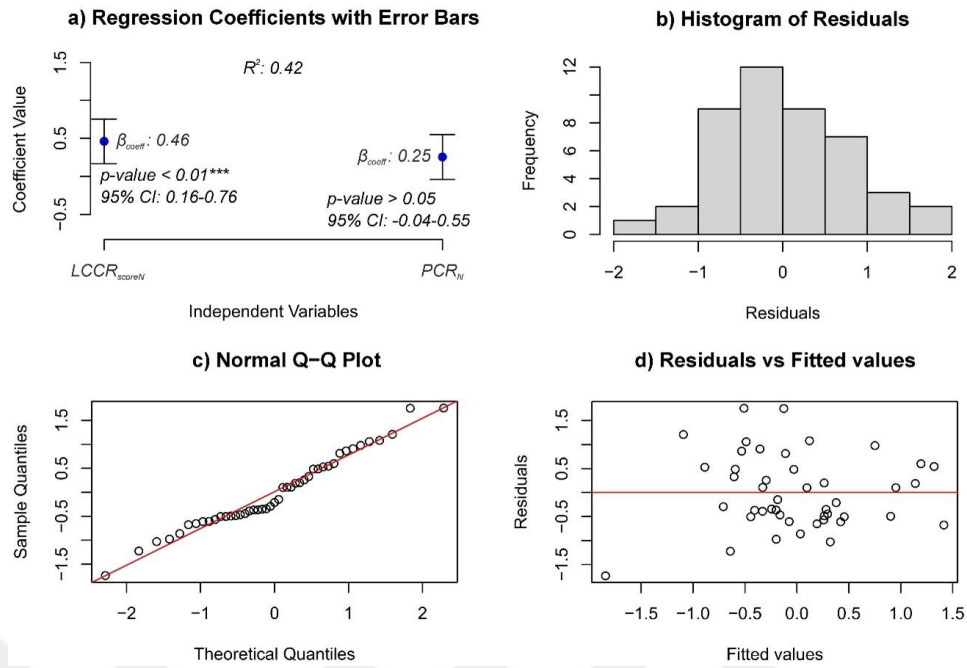


Figure 4. 16: Results from multiple linear regression models, using fatalities density (FD) with land cover change rate ($LULCCR_{scoreN}$) and population change rate (PCR_N).

4.2 Discussion

By examining the impacts of human pressure through LULCC in mountainous areas of 46 countries classified by income levels, we provide a comprehensive assessment of landslide incidence and fatalities. Our results illustrate that LULCC and population growth are more pronounced in low and lower-middle-income countries. We also find that landslides and fatalities tend to be higher in countries with lower income levels and higher LULCC rates. Although our analyses do not render a direct relationship between population growth and FD and LD , the strong relationships between income level and PCR_N , and population change and $LULCCR_{scoreN}$ highlight a possible indirect relationship between the three: at lower income levels, PCR_N tends to increase and so does $LULCCR_{scoreN}$, which is a direct driver behind FD and LD .

Population growth, especially in low-income countries, could affect anthropogenic environmental change in mountainous areas through urban sprawl, the development of road networks, and increased mining activities, leading to transformations that may destabilize slopes (Froude and Petley, 2018). The development of urban areas and infrastructure transforms the landscape and may increase the susceptibility of slopes to potentially fatal landslides (Ozturk et al., 2022; Petley, 2009, 2010; Sepúlveda and Petley, 2015). Also, increases in intricate road networks and mining activities in

mountainous areas further exacerbate slope instability, making these areas more prone to landslides (Kirschbaum et al., 2015; Petley et al., 2007; Tanyaş et al., 2022). Moreover, LULCC in mountainous areas can trigger landslides by disrupting the resisting forces against sliding and the hydrological conditions (i.e., pore pressure above hydrostatic pressure) (Jaboyedoff et al., 2018; Montgomery et al., 2000; Sidle et al., 2006; Vanacker et al., 2003).

These issues are more pronounced in low-income countries, where economic constraints limit the implementation of protection measures, adequate land use/cover management (Hailu et al., 2020; Maja and Ayano, 2021), and other disaster mitigation strategies (Schumacher and Strobl, 2011). High-income countries, on the other hand, can undertake effective disaster prevention and mitigation planning (Kahn et al., 2005; Tselios and Tompkins, 2019), which can help alleviate the potential impacts of LULCC on landslide risks. However, changes in land cover leave low- and lower-middle-income countries more exposed and vulnerable to the impacts of landslides, and LULCC can act as a potential precondition/trigger for landslides and associated fatalities. The additional stress of anthropogenic climate change (Gariano and Guzzetti, 2016), increasing landslide susceptibility (Felsberg et al., 2021; Stanley and Kirschbaum, 2017) of mountainous areas due to abrupt changes in climatic drivers, and the limited adapted capacities of at-risk populations add to the challenges (Fankhauser and McDermott, 2014). In this context, not only are the direct effects of human activities (such as deforestation) decisive, but also their indirect effects through LULCC (such as changes in soil/slope properties as a result of agricultural expansion and urban sprawl), need to be considered as potential precondition/triggers of landslide in mountainous environments.

In addition to the role of $LULCCR_{scoreN}$ in fatal landslides, in Figure 4.17a-d, we also demonstrate how it interacts with other variables for different income levels, such as topographic relief and average annual precipitation. Our analysis shows that LD and FD are not higher in regions with more precipitation and topographic relief; instead, they are more pronounced in low and lower-middle-income countries with high $LULCCR_{scoreN}$. For example, high-income countries with high landslide frequencies, such as Switzerland (Badoux et al., 2016), Japan (Shinohara and Kume, 2022), Italy (Rossi et al., 2019), Austria (Haque et al., 2016), and South Korea (Kim et al., 2021), have higher topographic relief and precipitation conditions similar to those of low-

income countries like Haiti, El Salvador, and Sri Lanka. However, despite similar physical conditions, LD and FD are higher in these low-income countries with high $LULCCR_{scoreN}$ (and high PCR_N), and fewer people die in high-income countries where $LULCCR_{scoreN}$ are much lower (Table 4.1).

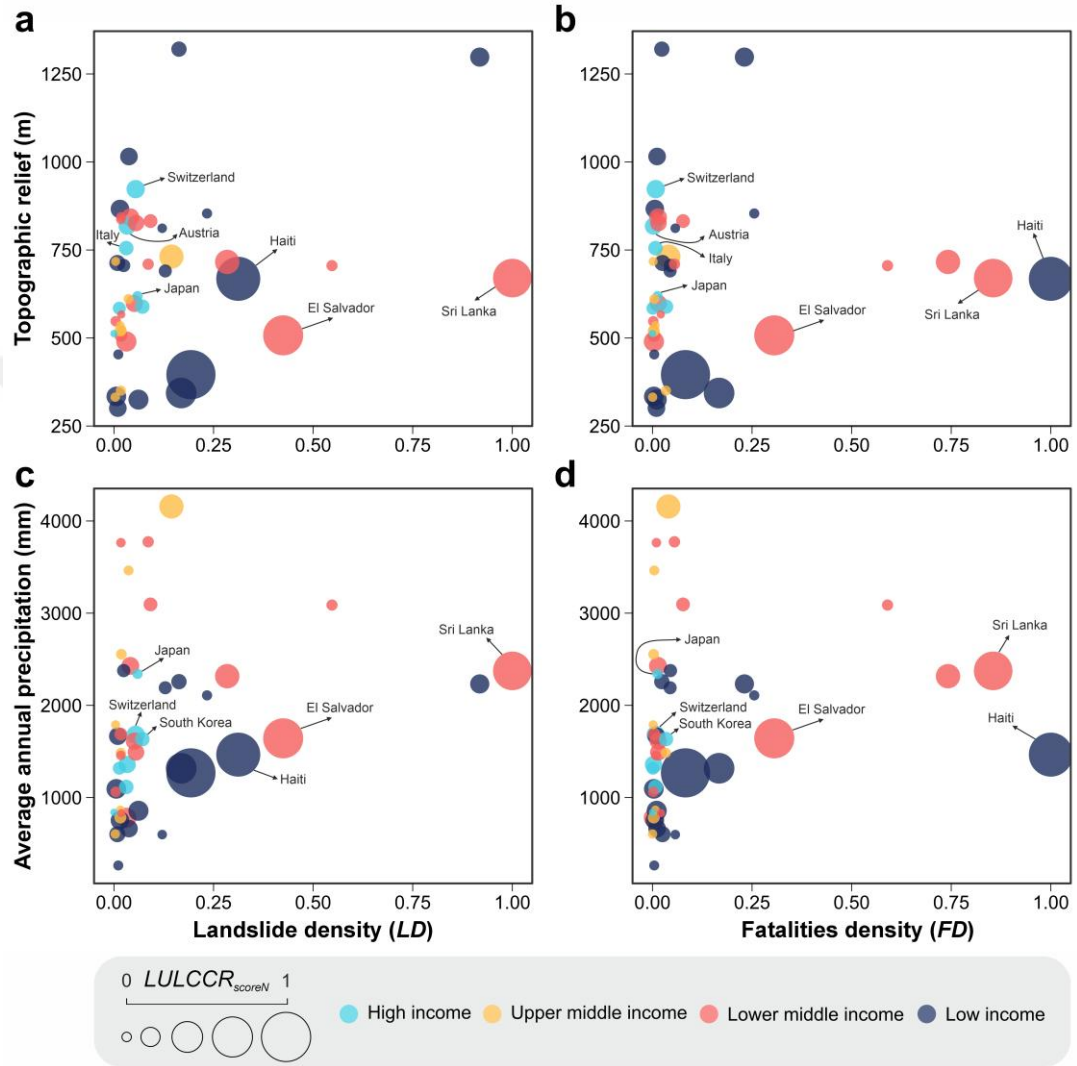


Figure 4. 17: Comparative landslide and fatalities density analysis with topographic relief and precipitation across income groups. Graphs **a)** and **b)** show the relationship between topographic relief and LD and FD , while graphs **c)** and **d)** show the relationship between average annual precipitation and these same variables. Bubble size indicates $LULCCR_{scoreN}$, and colors represent income levels.

Although our study is comprehensive, it has some limitations due to its scale. Firstly, the landslide database has location uncertainties inherent in data derived from global databases. The location accuracy in GFLD is based on administrative units such as villages or states (Froude and Petley, 2018). To bypass this, we aggregated our analyses over mountainous areas that may extend across several of these units, their

parts, or across several countries (see Methods section 2.2.1). This approach provided us with a more reliable framework to better understand the spatial overlap between fatal landslides and LULCC. Secondly, since our study focuses only on fatal landslides and aims to provide crucial information on the direct and indirect causes behind landslide fatalities in mountainous areas per income level, it does not take into account the potentially non-fatal but economically damaging events. Future research that will improve the accuracy of landslide location data and integrate a more comprehensive range of landslide impacts into the datasets would, by and large, contribute to the understanding of the spatial overlap of income disparity, LULCC, and surface processes.



5. LANDSLIDE FATALITIES INCREASE AS ECONOMIC INCOME, HUMAN DEVELOPMENT, AND GOVERNANCE DECLINE

5.1 Results

Our study area consists of 62 countries with 5 (median value: 5) or more landslides with five or more fatalities, including 4026 landslide events resulting in 53,277 deaths worldwide (Figure 5.1). Using both income inequality-based proxy (Figure 5.1a) and proxy for per capita real GDP (Figure 5.1b), we link fatality records caused by landslides to socioeconomic indicators.

Figure 5.2 shows the variation in landslide-related fatalities by income level across countries. Overall, with 4026 landslide records, the median number of fatalities per landslide is three, while the median fatalities per million people potentially exposed is 79.9. Specifically, the median death values are 3, 7, 14.5, and 12 in high-income, upper-middle-income, lower-middle-income, and low-income countries, respectively (Figure 5.2a). In terms of potentially exposure-related deaths, low-income countries (Mdn: 184.9) have the highest median fatalities rates, while upper-middle-income countries have the lowest median at 44.1 (Figure 5.2b). Although the overall dataset showed a downward trend ($p = 0.006$), we found that only high-income countries ($p = 0.016$) and lower-middle-income countries ($p = 0.012$) experienced significant downward trends in the potentially exposed population. We also do not observe significant trends in absolute fatalities per landslide for any income group or the overall data sample (Table 5.1).

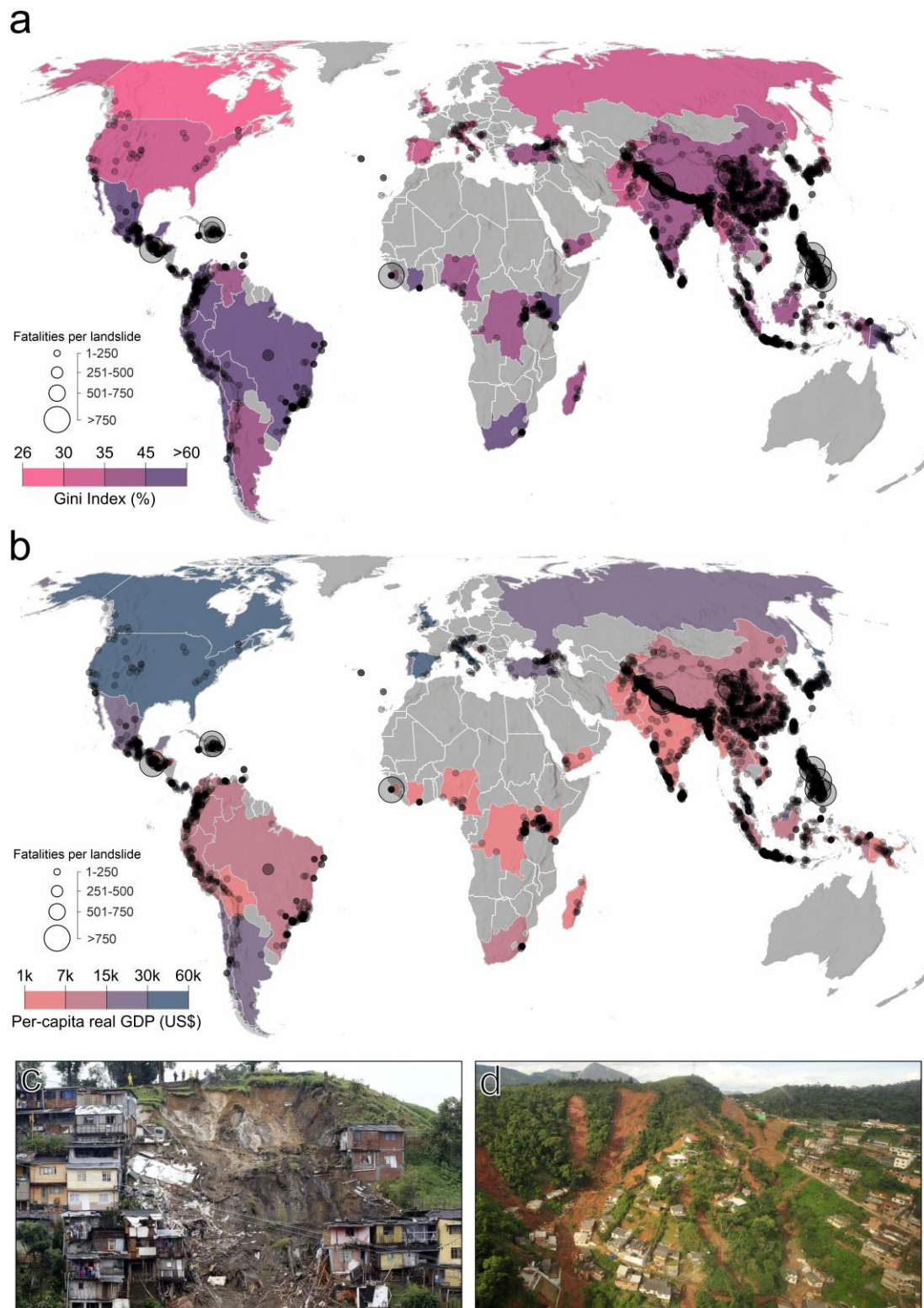


Figure 5. 1: Panels showing **a)** the average level of income inequality across countries and **b)** per capita real GDP. The size of the dots indicates the number of deaths caused by the reported landslide event. Countries with fewer than five landslides, which are not included in the analysis, are represented by grey dots. **c)** Fatal landslide in Manizales of central Colombia in 2017. Photo via BBC News. **d)** Fatal landslides in Brazil's Rio de Janeiro region in 2010. Photo via RTE News.

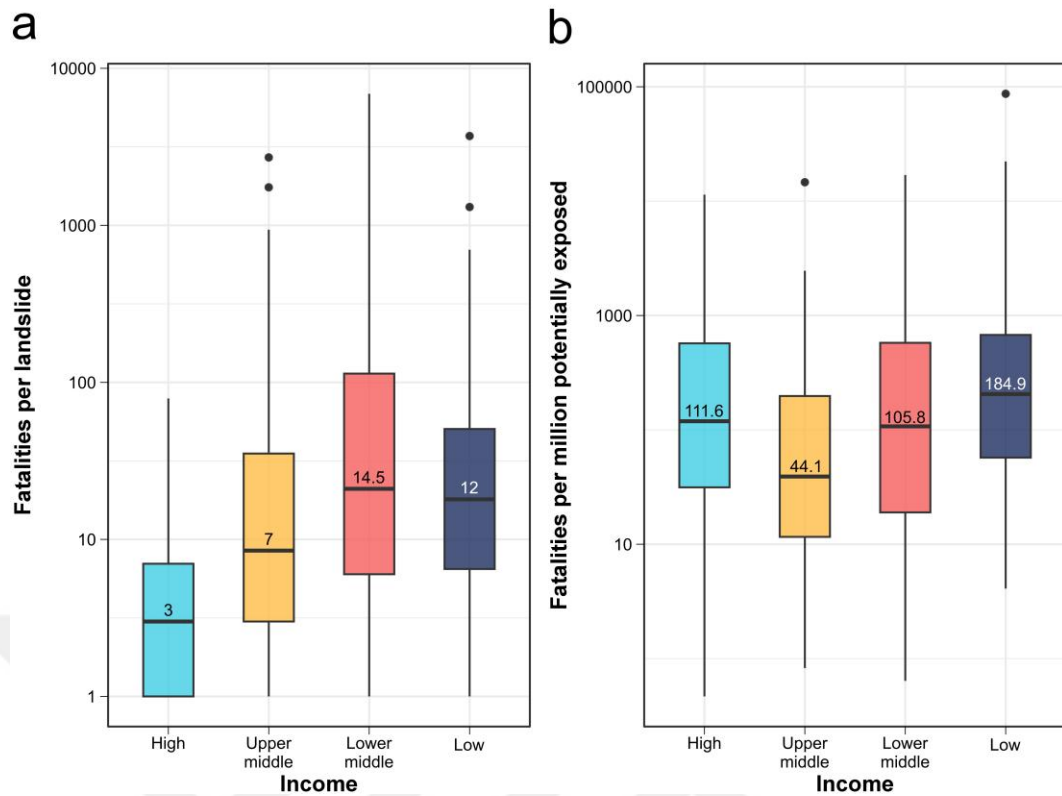


Figure 5. 2: Box plots showing the distribution of **a)** the fatalities per landslide and **b)** fatalities per million people potentially exposed to landslides across income groups at the country level. The box hinges show the 25th and 75th percentiles and the middle lines show the median (Mdn).

Table 5. 1: Resulting p-values controlling temporal trends across income groups in fatalities per landslide and potentially exposed population. The p-values have been calculated using two-sided Mann-Kendall tests.

	Fatalities per landslide		Potentially exposed population	
	<i>t</i>	<i>p-value</i>	<i>t</i>	<i>p-value</i>
All data	-0.363	0.080	-0.560	0.006*
High income	-0.033	0.913	-0.495	0.016*
Upper middle income	0.0769	0.743	-0.121	0.584
Lower middle income	-0.354	0.089	-0.516	0.012*
Low income	-0.275	0.189	-0.143	0.511

Across continents, we found that the absolute number of fatalities is highest in Asia (Mdn: 14), Africa (Mdn: 8), and the Americas (Mdn: 8) (see Figure 5.3a), while exposure-related fatalities are highest in Europe (Mdn: 408.9), Africa (Mdn: 111.2) and Asia (Mdn:105.5) (see Figure 5.3b). We observed a significant increasing trend in fatalities per landslide only in Africa ($p = 0.037$), while significant decreasing trends in the potentially exposed population were observed in Asia ($p = 0.012$) and the Americas ($p = 0.049$) (see Table 5.2).

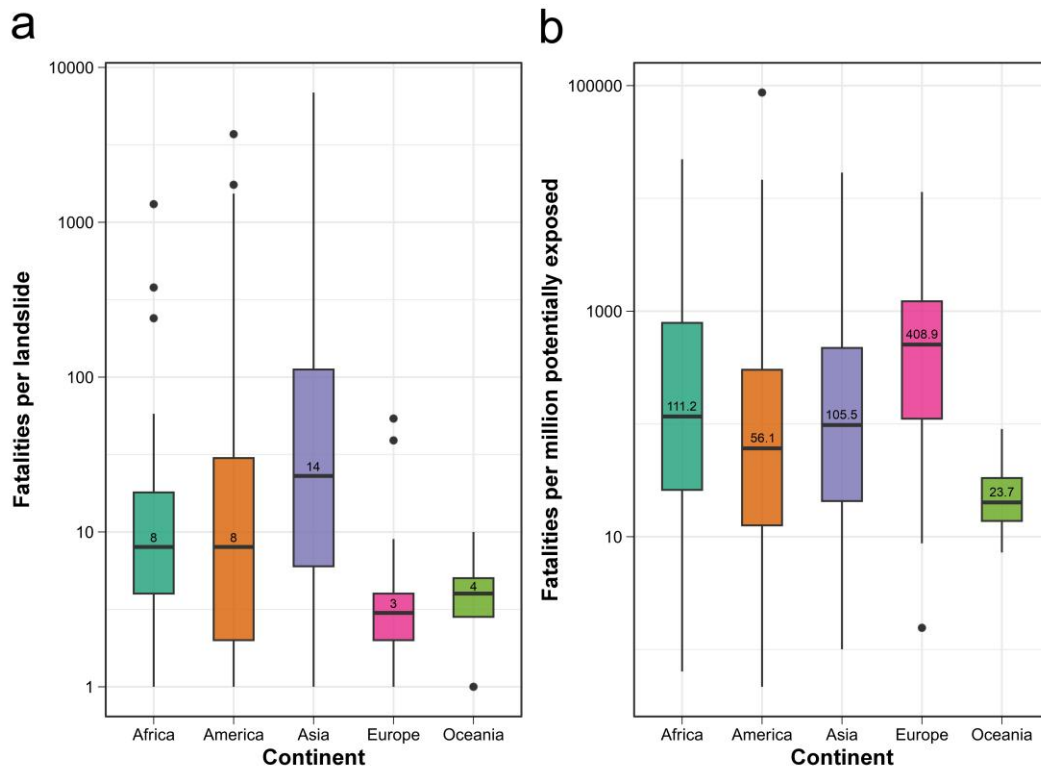


Figure 5. 3: Box plots showing the distribution of **a)** the fatalities per landslide and **b)** fatalities per million people potentially exposed to landslides across continents. The box hinges show the 25th and 75th percentiles and the middle lines show the median (Mdn).

Table 5. 2: Resulting p-values controlling temporal trends across continents in fatalities per landslide and potentially exposed population. The p-values have been calculated using two-sided Mann-Kendall tests.

	Fatalities per landslide		Potentially exposed population	
	<i>t</i>	<i>p-value</i>	<i>t</i>	<i>p-value</i>
Asia	-0.319	0.125	-0.516	0.012*
Africa	0.429	0.037*	0.319	0.125
America	-0.253	0.228	-0.407	0.049*
Europe	-0.011	0.951	-0.165	0.443
Oceania	-0.086	0.747	-0.071	0.797

Figure 5.4 shows the relationship between various socioeconomic factors and fatalities per landslide. Countries with high Gini index values tend to exhibit a wide range of landslide fatalities, and more equal high-income countries generally experience fewer deaths (Figure 5.4a). Low per capita real GDP countries are associated with higher landslide fatalities, while high-income countries (with higher per capita real GDP) tend to have fewer fatalities per landslide (Figure 5.4b). Landslide fatalities are generally higher in countries with a higher potentially exposed population (Figure 5.4c), and similarly, higher HFI values are associated with increased landslide fatalities (Figure

5.4d). As for the Human Development Index (HDI), countries with lower HDI values show a higher number of fatalities per landslide compared to countries with higher HDI values (Figure 5.4e). Finally, a weaker Government Effectiveness Index (GEI) is linked to higher landslide fatalities, with low-income countries generally experiencing the most fatalities (Figure 5.4f).

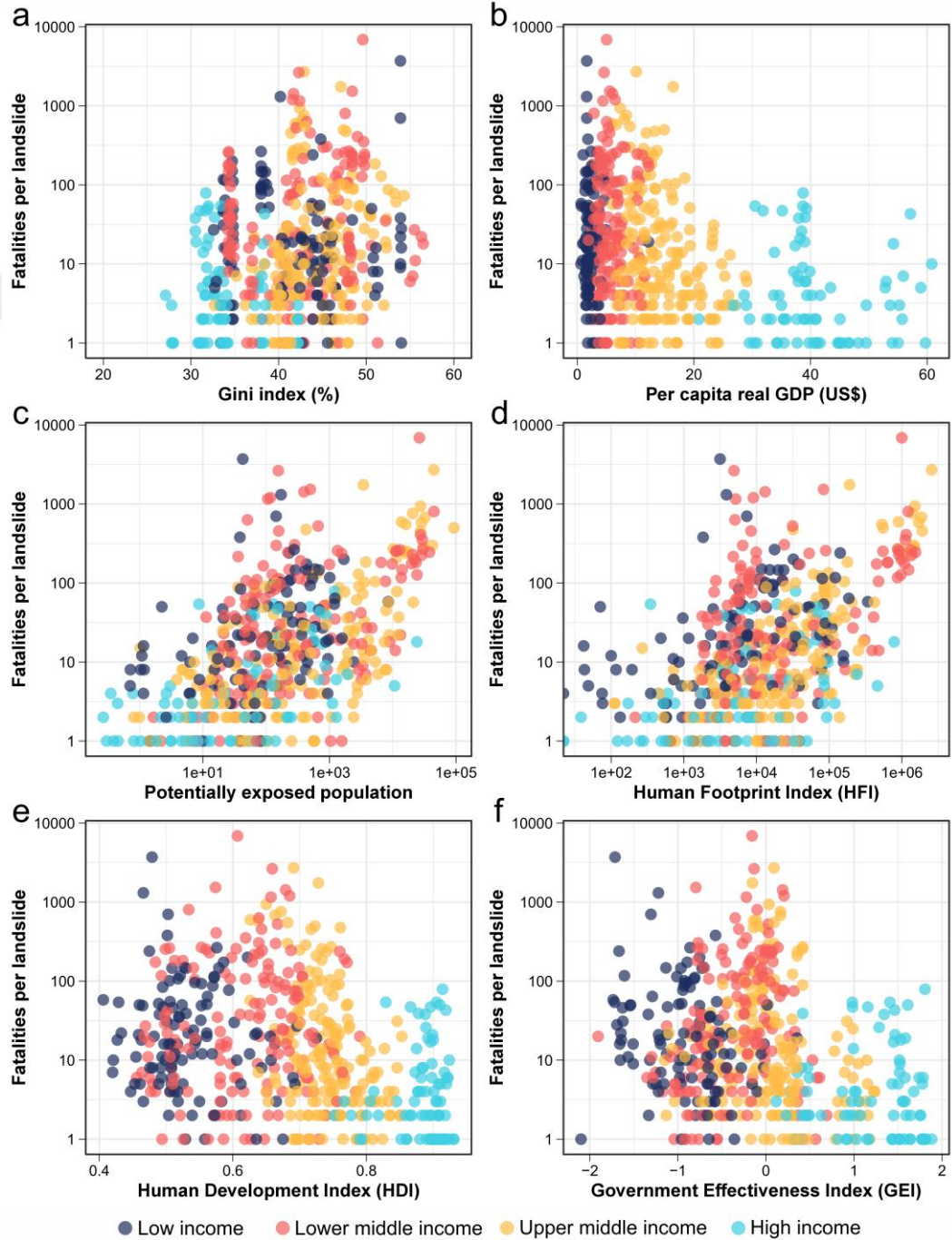


Figure 5. 4: Scatter plots showing the relationship between socioeconomic factors and fatalities per landslide across countries: **a)** Gini index, **b)** per capita real GDP, **c)** exposed population, **d)** Human Footprint Index (HFI), **e)** Human Development Index (HDI), and **f)** Government Effectiveness Index (GEI).

In the negative binomial model of fatalities for all landslides, we found no change in fatalities for a unit increase in the Gini index. However, for a unit increase in the potentially exposed population, we found a 27% increase in fatalities, with a 95% confidence interval of 21-34% ($p < 0.001$). In contrast, for a one-unit increase in the per-capita real GDP, we found a 30% decrease in fatalities, with a 95% confidence interval of 22-37% ($p < 0.001$) (Table 5.3 and Figure 5.5).

Table 5. 3: All countries regression results.

Variables	Incidence Rate Ratios	CI	p-value
Gini index	1.00	0.98 – 1.02	0.86356
Potentially exposed population (log)	1.27 ***	1.21 – 1.34	<0.00001
GDP/cap (log)	0.70 ***	0.63 – 0.78	<0.00001
Observations	446		
<i>R</i> ² Nagelkerke	0.33		
Deviance	491.761		
AIC	3477.778		

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

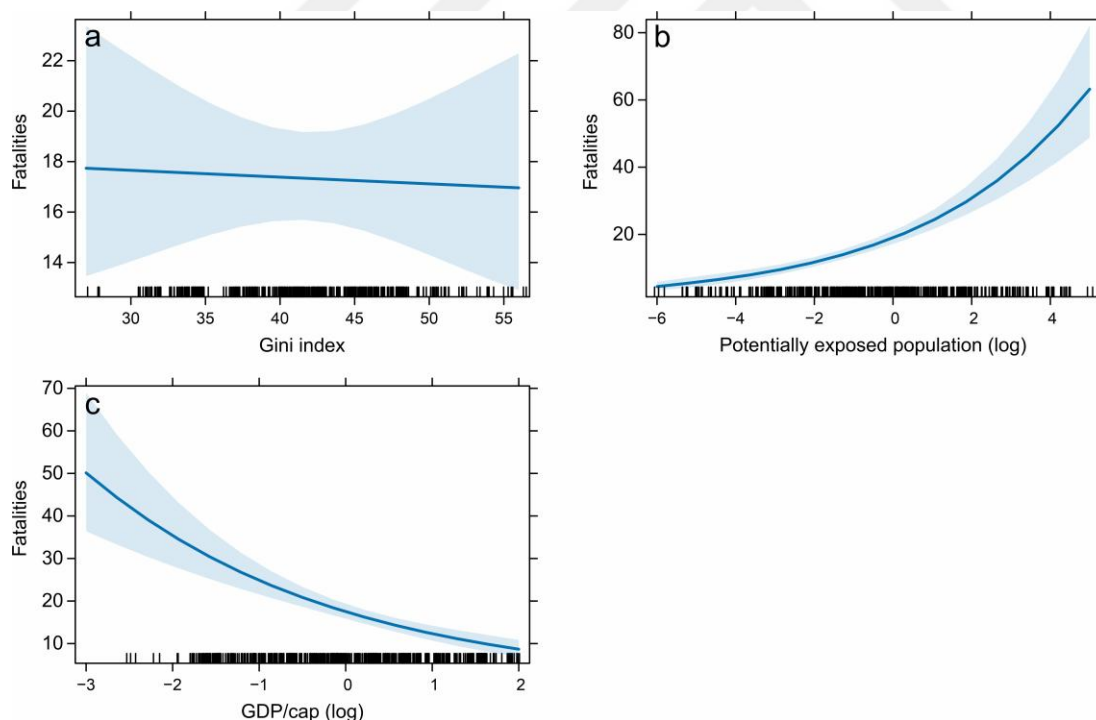


Figure 5. 5: Negative binomial regression model results for fatalities per landslide for all countries, displaying the relationships with **a)** Gini index, **b)** potentially exposed population (log-transformed), and **c)** per capita GDP (log-transformed). Shaded areas represent the 95% confidence intervals.

For high-income countries, we found that a unit increase in the Gini index was associated with a 17% decrease in fatalities (95% CI, 0.5-27%, $p = 0.00085$). A unit increase in the potentially exposed population was associated with a 42% increase in fatalities (95% CI, 27-61%, $p < 0.00001$). Per-capita real GDP and GEI were not statistically significant in determining landslide fatalities (Table 5.4 and Figure 5.6).

Table 5. 4: High-income countries regression results.

Variables	Incidence Rate Ratios	CI	p-value
Gini index	0.83 ***	0.73 – 0.95	0.00085
Potentially exposed population (log)	1.42 ***	1.27 – 1.61	<0.00001
GDP/cap (log)	0.38	0.08 – 1.68	0.22559
Government Effectiveness Index (GEI)	0.86	0.41 – 1.78	0.69180
Observations	71		
R^2 Nagelkerke	0.56		
Deviance	71.475		
AIC	441.068		

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

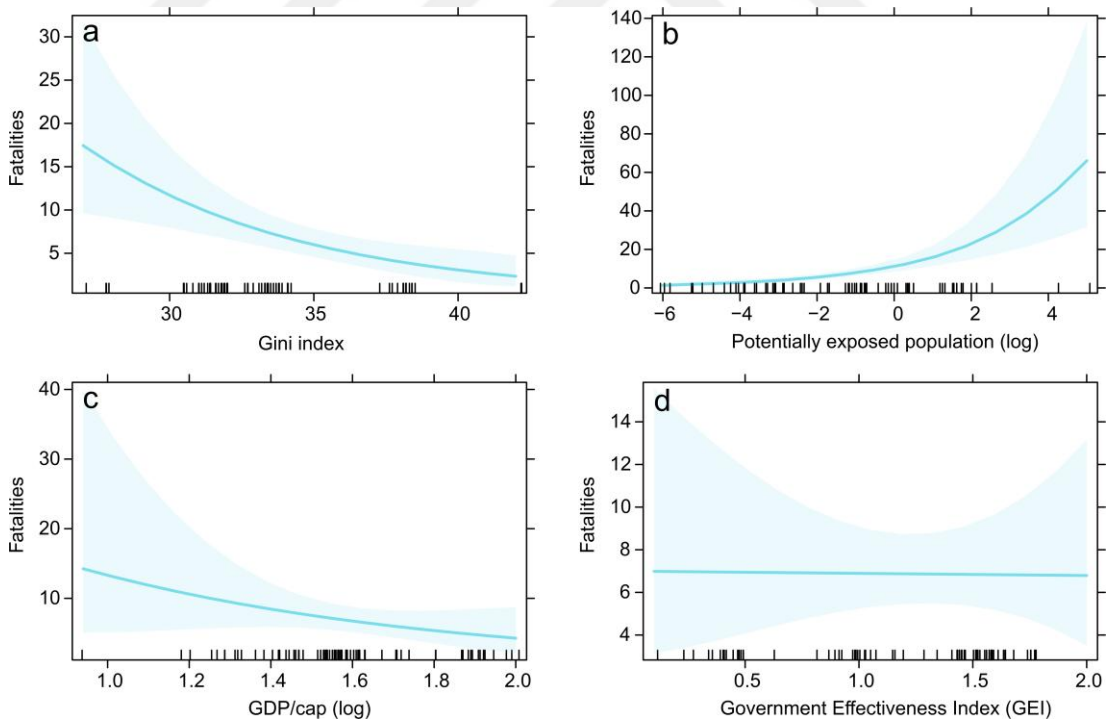


Figure 5. 6: Negative binomial regression model results for fatalities per landslide for high-income countries, displaying the relationships with **a)** Gini index, **b)** potentially exposed population (log-transformed), **c)** per capita GDP (log-transformed), and **d)** Government Effectiveness Index (GEI). Shaded areas represent the 95% confidence intervals.

For upper-middle-income countries, a unit increase in the Gini index was associated with a 16% increase in fatalities (95% CI, 10-22%, $p < 0.00001$), while a unit increase in the potentially exposed population resulted in a 21% increase in fatalities (95% CI, 12-29%, $p < 0.00001$). Per-capita real GDP was not significant in determining landslide fatalities, but a unit increase in the GEI was associated with a 37% decrease in fatalities, with a 95% CI of 7-57% ($p = 0.00603$) (Table 5.5 and Figure 5.7).

Table 5. 5: Upper-middle-income countries regression results.

Variables	Incidence Rate Ratios	CI	p-value
Gini index	1.16 ***	1.10 – 1.22	<0.00001
Potentially exposed population (log)	1.21 ***	1.12 – 1.29	<0.00001
GDP/cap (log)	1.35	0.74 – 2.41	0.26244
Government Effectiveness Index (GEI)	0.63 **	0.43 – 0.93	0.00603
Observations	155		
R^2 Nagelkerke	0.54		
Deviance	166.498		
AIC	1145.825		

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

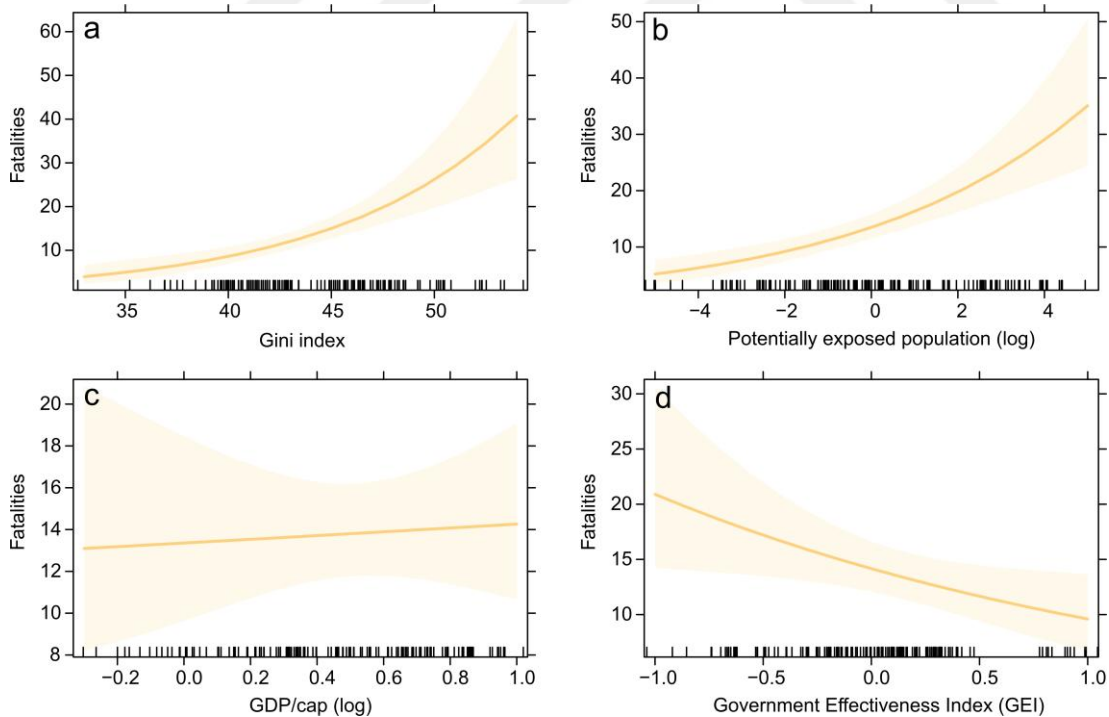


Figure 5. 7: Negative binomial regression model results for fatalities per landslide for upper-middle-income countries, displaying the relationships with **a)** Gini index, **b)** potentially exposed population (log-transformed), **c)** per capita GDP (log-transformed), and **d)** Government Effectiveness Index (GEI). Shaded areas represent the 95% confidence intervals.

In lower-middle-income countries, changes in the Gini index did not significantly influence landslide fatalities. Similarly, neither per-capita real GDP nor the GEI had a significant effect on fatality rates (GDP/cap: 95% CI, 0.74-2.37, $p = 0.33732$; GEI: 95% CI, 0.92-2.19, $p = 0.11823$). However, an increase in the potentially exposed population corresponded to a 33% rise in fatalities (95% CI, 17-51%, $p < 0.00001$) (Table 5.6 and Figure 5.8).

Table 5. 6: Lower-middle-income countries regression results.

Variables	Incidence Rate Ratios	CI	<i>p</i> -value
Gini index	0.98	0.94 – 1.02	0.15579
Potentially exposed population (log)	1.33 ***	1.17 – 1.51	<0.00001
GDP/cap (log)	1.33	0.74 – 2.37	0.33732
Government Effectiveness Index (GEI)	1.41	0.92 – 2.19	0.11823
Observations	130		
R^2 Nagelkerke	0.29		
Deviance	144.613		
AIC	1108.191		

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

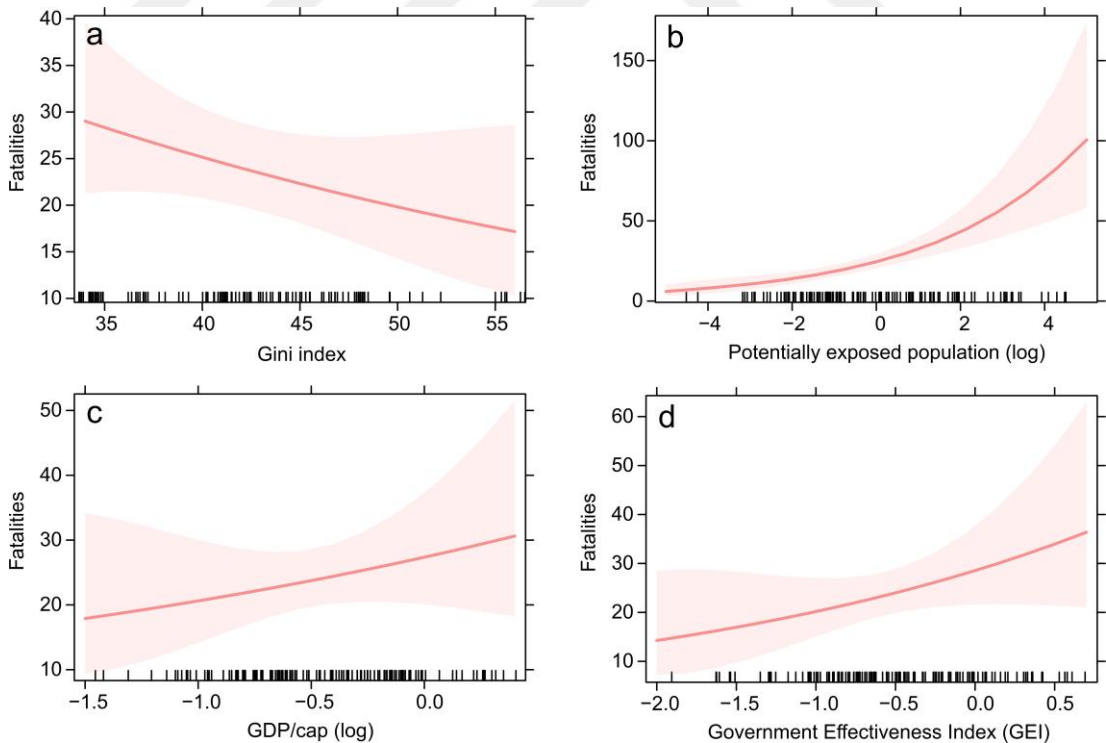


Figure 5. 8: Negative binomial regression model results for fatalities per landslide for lower-middle-income countries, displaying the relationships with **a)** Gini index, **b)** potentially exposed population (log-transformed), **c)** per capita GDP (log-transformed), and **d)** Government Effectiveness Index (GEI). Shaded areas represent the 95% confidence intervals.

In low-income countries, changes in the Gini index did not significantly affect landslide fatalities. However, an increase in the potentially exposed population was linked to a 33% rise in fatalities (95% CI, 13-57%, $p = 0.00003$). A higher HDI was also associated with a 99% reduction in landslide mortality (95% CI, 0-61%, $p = 0.00883$). While the GEI indicated a potential effect, it was not statistically significant (95% CI, 0.95-3.40, $p = 0.05158$) (Table 5.7 and Figure 5.9).

Table 5. 7: Low-income countries regression results.

Variables	Incidence Rate Ratios	CI	<i>p</i> -value
Gini index	0.97	0.93 – 1.01	0.10968
Potentially exposed population (log)	1.33 ***	1.13 – 1.57	0.00003
Human Development Index (HDI)	0.01 **	0.00 – 0.61	0.00883
Government Effectiveness Index (GEI)	1.80	0.95 – 3.40	0.05158
Observations	90		
R^2 Nagelkerke	0.31		
Deviance	98.355		
AIC	741.642		

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

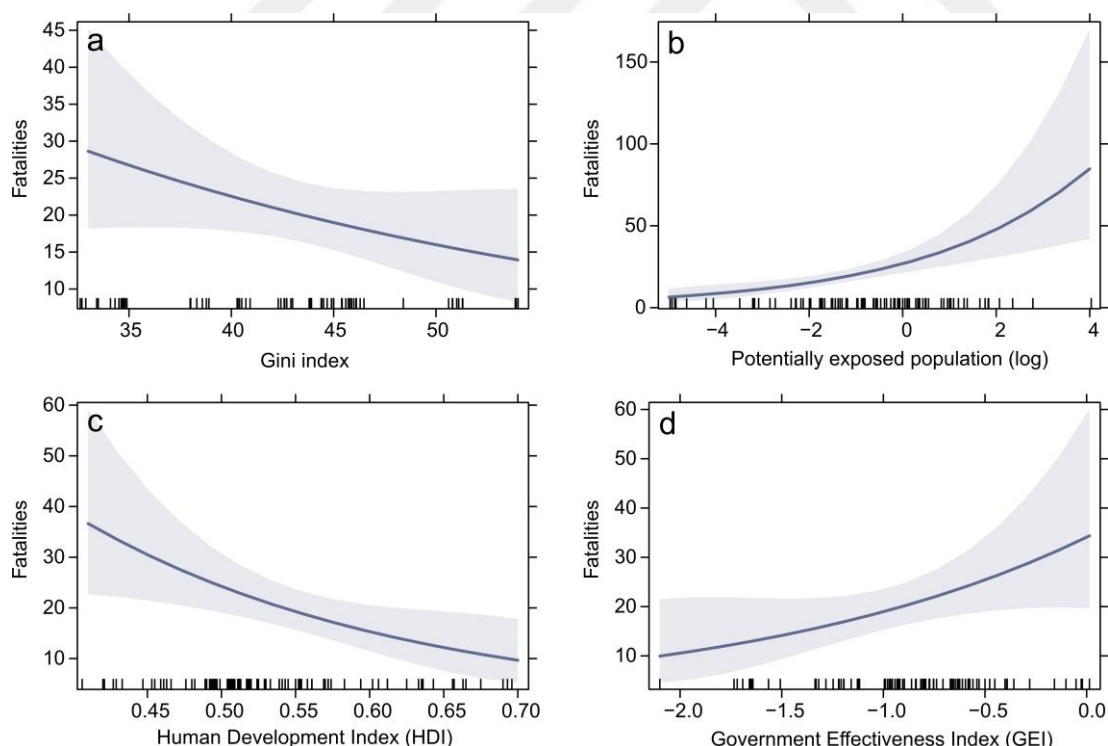


Figure 5. 9: Negative binomial regression model results for fatalities per landslide for low-income countries, displaying the relationships with **a)** Gini index, **b)** potentially exposed population (log-transformed), **c)** per capita GDP (log-transformed), and **d)** Government Effectiveness Index (GEI). Shaded areas represent the 95% confidence intervals.

5.2 Discussion

We present a comprehensive assessment of the role of socio-economic factors on landslide mortality across 62 countries classified by income levels. Our regression results show that countries with lower economic income, human development, and governance quality tend to experience higher landslide fatalities. However, these protective factors lose significance when income inequality and the population exposed to landslides are considered. Notably, landslide fatalities increase across all income groups as the exposed population grows. In upper-middle-income countries, despite high economic and human development, income inequality emerges as a key driver of fatalities, highlighting that economic strength alone is insufficient to reduce mortality without addressing inequality and population vulnerability.

The performance of negative binomial regression models generally fits the data well. The Kolmogorov-Smirnov test indicates a significant deviation from the expected negative binomial distribution in the first model, which uses observations from all countries. However, the corresponding quantile-quantile (Q-Q) plot shows no significant deviation from the straight line (Figure 5.10). In contrast, models using observations from high- (Figure 5.11), upper-middle- (Figure 5.12), lower-middle- (Figure 5.13), and low-income (Figure 5.14) countries demonstrate less problematic residuals. For these models, we did not detect any significant issues in terms of outliers, error overdispersion, deviation from the expected distribution, or changing variance.

Previous studies generally show that disaster-related fatalities are correlated with indicators of economic development and that vulnerability decreases as a country's wealth increases (Noy, 2009). Although wealthier countries are also exposed to natural disasters, poorer countries experience more deaths due to disasters (Kahn et al., 2005). Social well-being in developed countries mitigates the humanitarian impact of disasters (Tselios and Tompkins, 2019). Indeed, there is generally a negative relationship between fatalities and economic development for landslides (Figure 5.4a), as there is for floods (Lindersson et al., 2023). Similar to earlier studies (Kirschbaum et al., 2015; Sepúlveda and Petley, 2015), our results show that GDP and HDI decrease fatalities. Moreover, our regression results (Table 5.5 and Figure 5.7) show that income inequality significantly impacts landslide fatalities, notably in upper-middle-income

countries, which is in line with previous empirical studies (Lindersson et al., 2023; Tselios and Tompkins, 2019). Therefore, these findings suggest that GDP and HDI alone are insufficient indicators to understand landslide fatalities. Especially when income inequality and exposed population are considered, the protective effect of GDP diminishes.

Interestingly, in contrast to upper-middle-income countries, income inequality has a decreasing effect on fatalities in high-income countries (Table 5.4 and Figure 5.6). This may be because the income inequality variables used in the model are insufficient to reflect the disaster effects in high-income countries. In high-income countries, social protection networks, advanced disaster management systems, and the population's pre-disaster preparedness levels are likely to reduce the relationship between income inequality and fatalities (F. Solt, 2020; Tselios and Tompkins, 2019). In this respect, in future research, it would be helpful to develop more comprehensive models that include socioeconomic indicators and various variables related to disaster response capacity to understand better the relationship between income inequality and fatalities in high-income countries.

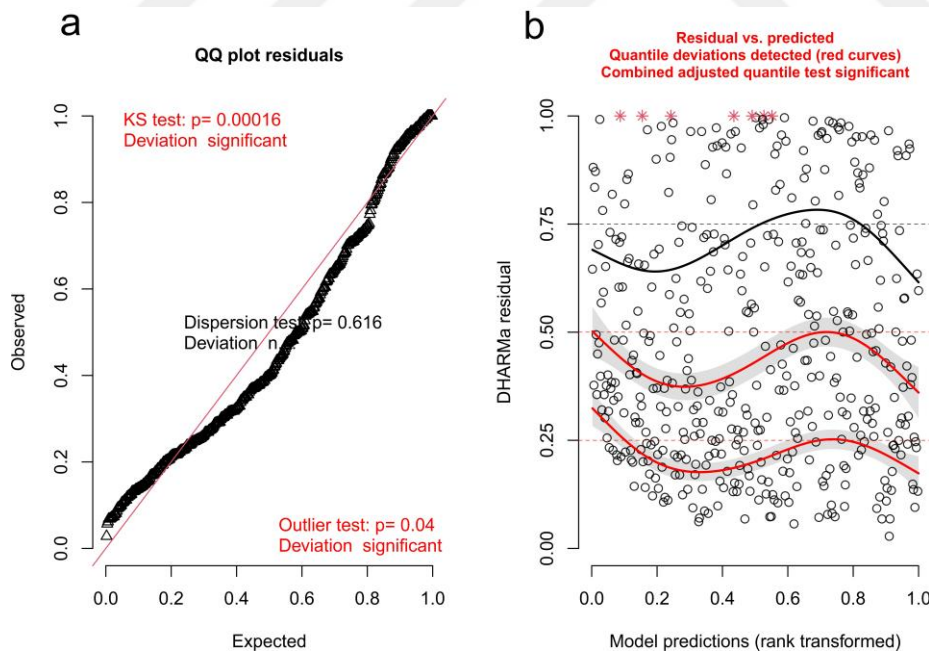


Figure 5. 10: Residual diagnostics for the negative binomial regression model using observations from all countries. Panel **a**) shows the quantile-quantile (Q-Q) plot of residuals, where the Kolmogorov-Smirnov test indicates a significant deviation from the expected negative binomial distribution. Additionally, the dispersion and outlier tests show no significant issues. Panel **b**) illustrates the residuals vs. predicted values, revealing non-constant variance and indicating potential model misfit.

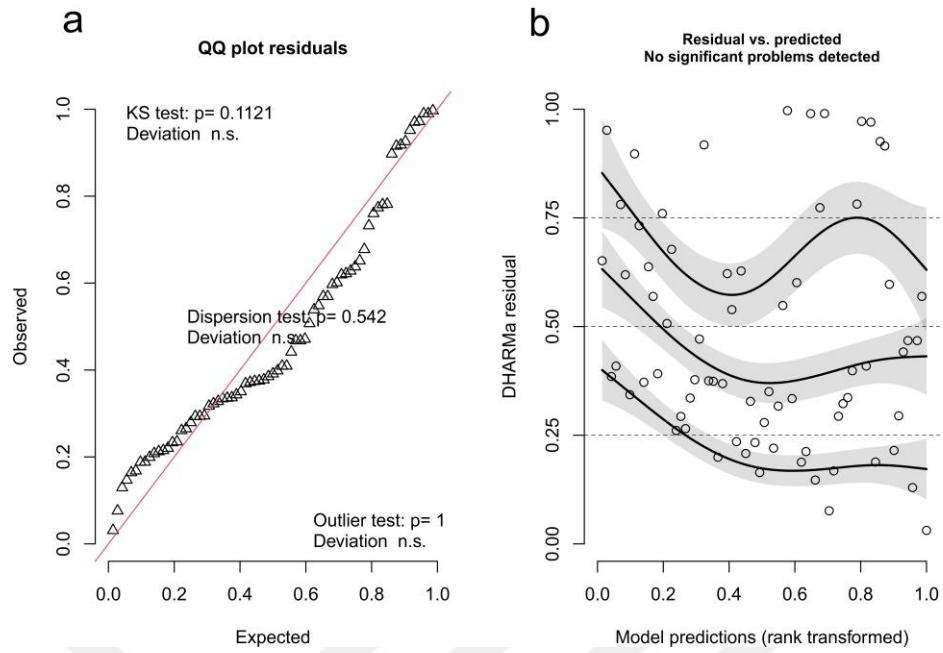


Figure 5.11: Residual diagnostics for the negative binomial regression model using observations from high-income countries. Panel **a)** presents the Q-Q plot of residuals, which shows no significant deviation from the expected negative binomial distribution according to the Kolmogorov-Smirnov test. Both the dispersion and outlier tests indicate no significant problems. Panel **b)** depicts the residuals vs. predicted values, showing no signs of model misfit.

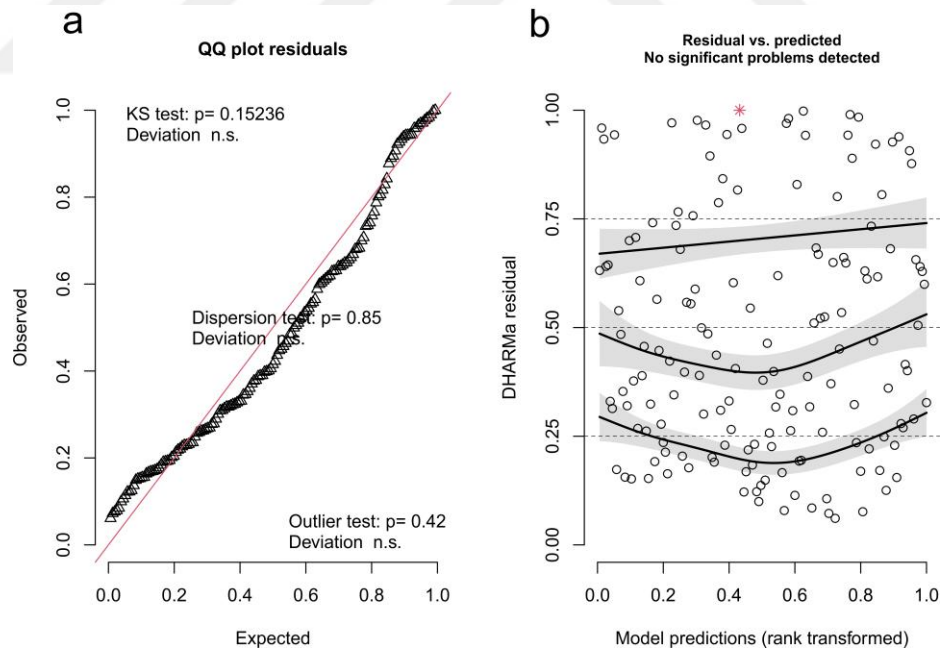


Figure 5.12: Residual diagnostics for the negative binomial regression model using observations from upper-middle-income countries. Panel **a)** displays the Q-Q plot of residuals, indicating no significant deviation from the expected negative binomial distribution. The Kolmogorov-Smirnov dispersion and outlier tests do not detect any significant problems. Panel **b)** shows the residuals vs. predicted values, confirming that the model fits well without notable issues.

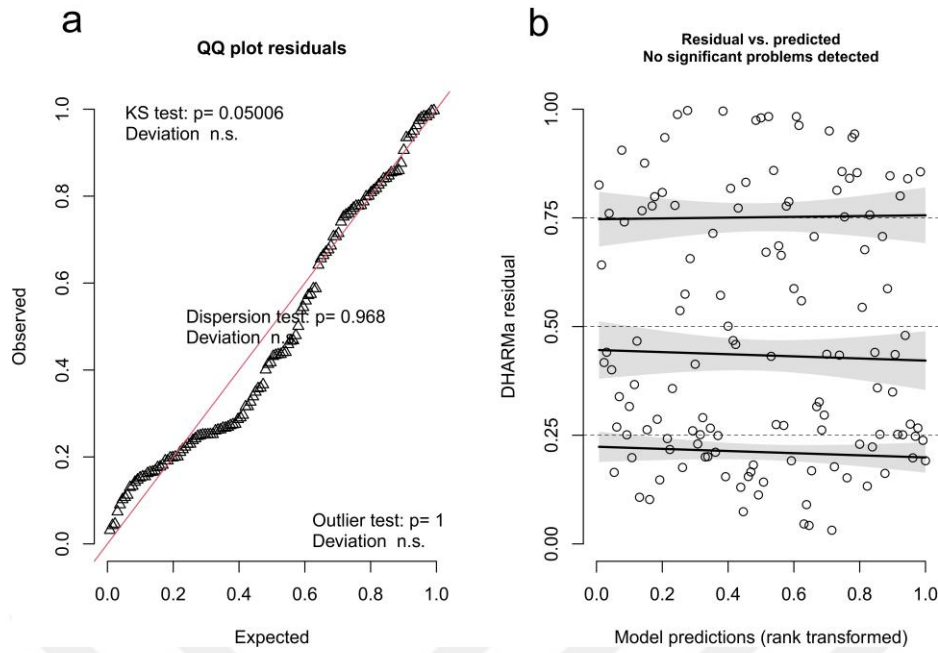


Figure 5. 13: Figure 5.13: Residual diagnostics for the negative binomial regression model using observations from lower-middle-income countries. Panel **a)** illustrates the Q-Q plot of residuals, with no significant deviation detected by the Kolmogorov-Smirnov test. Additionally, the dispersion and outlier tests indicate no significant problems. Panel **b)** displays the residuals vs. predicted values, showing no signs of model misfit.

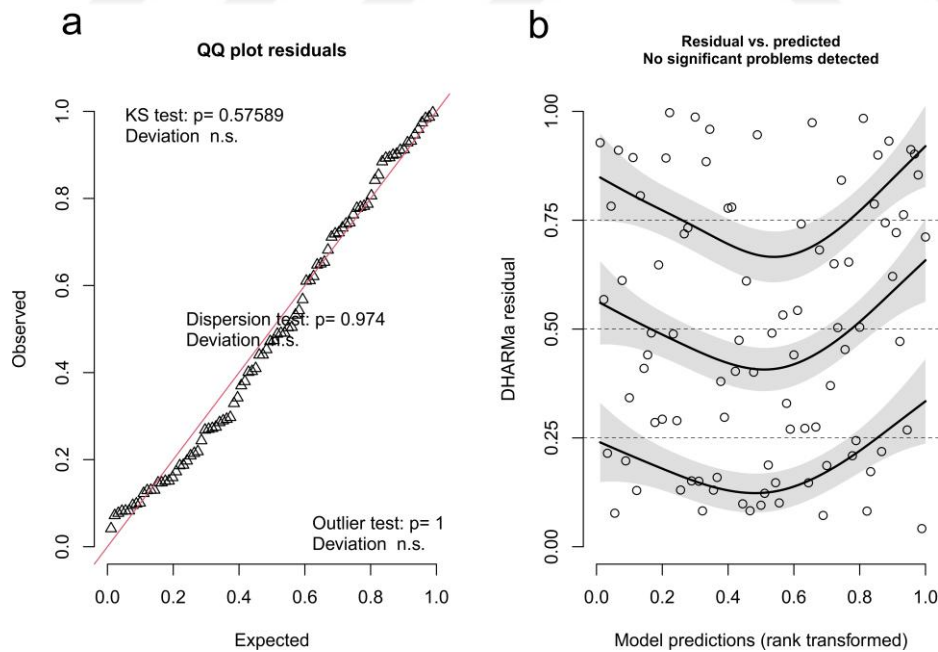


Figure 5. 14: Residual diagnostics for the negative binomial regression model using observations from low-income countries. Panel **a)** shows the Q-Q plot of residuals, with the Kolmogorov-Smirnov test confirming no significant deviation from the expected negative binomial distribution. The dispersion and outlier tests also indicate no significant issues. Panel **b)** depicts the residuals vs. predicted values, with no evidence of variance issues or model misfit.

Our data on fatal landslide events between 2004 and 2017 by income group showed limited temporal variation in the number of deaths per event. We found that Asia, Africa, and the Americas had the highest fatalities, but Europe had much higher potential exposure-related fatalities (Figure 5.3). However, we did not observe significant trends in regions other than Africa (Table 5.2). Here, we also recognize the limitations of data from global databases, as they only include fatal landslides recorded in the GFLD. For example, landslide events are under-reported or not officially recorded in some countries, making the results less accurate (Froude and Petley, 2018). National-scale surveys illustrate this more clearly, showing that fatal landslides are actually higher than recorded in global inventories (Garcia-Delgado et al., 2022; Görüm and Fidan, 2021; Q. Lin and Wang, 2018). A more accurate determination of the number of fatalities, as well as economic damages and the number of affected individuals, would improve the results of such studies and allow for clearer and more meaningful conclusions. In this way, both a better understanding of fatal landslides and a more effective planning of the measures to be taken will be possible.



6. CONCLUSION

The aim of this thesis is to investigate the topographic, climatic, and anthropogenic characteristics of fatal landslides at the global scale and to clarify the role of the factors controlling these landslides using a holistic approach at the regional and national scales. The first stage of the thesis, consisting of three stages, focuses on the complex influence of macro-landforms and morphometric characteristics, anthropogenic pressure, and climatic regimes on fatal landslides from a comprehensive approach. In the second stage, we highlighted how land cover changes vary in mountainous areas of countries at different income levels and the effects of this human influence on fatal landslides. The final stage aimed to identify how socioeconomic factors such as economic and human development, income inequality, and governance affect landslide fatalities. The results of these three stages are detailed below.

6.1 Conclusions on the Role of Topographic, Climatic, and Anthropogenic Factors on Fatal Landslides

The first stage of the thesis provides insight into the spatially persistent pattern of fatal landslides in relation to topographic and climatic factors likely controlling landslide occurrences. Our analyses indicate that landslides triggered by natural factors (69.3%) and fatalities (66.7%), as well as landslides triggered by anthropogenic factors (44.1%) and fatalities (43.0%), occur most frequently in the mountains and tropical/temperate climatic regions.

We also showed that LTNF tends to occur at higher elevations on steeper slopes, while LTAF concentrates at lower elevations and gentler slopes. South and Southeast Asia, Central America and South America, and the Great Rift Valley are global-scale hotspots of fatal landslides. These hotspots correspond to areas vulnerable to climate change and, thus, landscapes with an expected increase in landsliding rates. Therefore, these susceptible areas could be more vulnerable in the future when climatic extremes are coupled with human impact.

Our research also highlights the role of land cover changes and increased human pressure in the occurrence of natural-induced fatal landslides. In this context, we argue that human activities impact not only fatal landslides of anthropogenic origin but also fatal landslides of natural origin. In this respect, we emphasize the importance of understanding the complex interactions between natural and human factors in the occurrence of fatal landslides. Comprehensive and adaptive strategies are needed to reduce landslide risks in mountainous areas of tropical and temperate climatic regions, especially in the face of climate change and increasing human pressure. Finally, future work should continue to monitor and assess fatal landslides and focus on developing more reliable and comprehensive inventories.

6.2 Conclusions on Land Cover Change in Mountainous Areas and Their Impact on Fatal Landslides

The second stage of the thesis examines the effects of human pressure and land use land cover change (LULCC) in mountainous areas of 46 countries classified by income level, providing a comprehensive assessment of fatal landslides. Our results show that high and upper-middle income countries show more stable and limited transitions, while mountainous areas of low and lower-middle income countries are the most affected by population growth and LULCC from 1960 to 2019.

We also found that increased LULCC leads to a corresponding increase in landslide density and associated fatalities. Notably, landslide and fatality densities are significantly higher in low and lower-middle-income countries where LULCC is more pronounced. Our regression analyses provide statistically significant evidence supporting the relationship between LULCC and landslide and fatality density. These findings underscore that LULCC is a critical driver of landscape dynamics and that human pressure is a precondition or trigger for landslides.

Our study also showed that landslide and fatality density is low in high-income countries such as Switzerland, Japan, Italy, Austria, and South Korea, despite favorable conditions for landslide occurrence, when the effects of physical variables such as topographic relief and average annual precipitation are considered. However, we found that these densities are high in low- and lower-middle-income countries such as Haiti, Sri Lanka, and El Salvador. High LULCC in countries with low living standards is the leading cause of landslides that threaten human lives in these countries.

This study highlights that controlling land use/land cover and adopting sustainable management practices can play a vital role in preventing landslide-related fatalities, especially in countries with vulnerable populations and economic conditions.

6.3 Conclusions on the Role of Socioeconomic Factors on Fatal Landslides

In the third stage of the thesis, we present a comprehensive analysis of the impact of socioeconomic factors such as real gross domestic product (GDP), income inequality (Gini index), Human Development Index (HDI), and Government Effectiveness Index (GEI) on landslide mortality in 62 countries classified by income levels. Our findings show that landslide fatalities increase significantly with increasing exposed population, especially in low- and lower-middle-income countries. In these countries, fatalities from landslides increase by 33% as the potentially exposed population increases. Furthermore, landslide fatalities were found to increase in countries with low HDI; however, increasing HDI reduced landslide fatalities by 99%.

The impact of income inequality is especially pronounced in upper-middle-income countries, where a one-unit increase in the Gini index is associated with a 16% increase in fatalities. In high-income countries, an increase in the exposed population increased landslide fatalities by 42%. This suggests that population density can increase vulnerability to landslides even in economically developed countries. Additionally, in countries with a high GEI, fatalities decreased by 37%, suggesting that effective governance plays an important role in reducing the risk of landslides.

Finally, it is understood that landslide fatalities decrease as levels of economic development and human development increase; however, this relationship may be affected by factors such as income inequality and exposed population density. Therefore, reducing landslide risk requires not only economic growth but also to reduce social inequalities and to ensure effective governance mechanisms. Considering socioeconomic factors to prevent landslide-related mortality will contribute to creating more resilient societies against this hazard. It is also clear that future studies should continue to assess the role of socioeconomic factors in fatal landslides with more comprehensive and up-to-date datasets to better understand their impact.



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