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Spatial and temporal analysis of natural hazard mortality in Nepal

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ABSTRACT

The impacts of natural hazards are typically measured in terms of loss of human lives and economic damage, and recent studies demonstrate that deaths attributed to natural hazards have increased. Using the publicly available DesInventar database, we examined spatial and temporal patterns of natural hazard mortality from 1971 to 2011 at the district and village levels of Nepal and identified natural hazards that contributed most to mortality. Spatial clusters of mortality at the district and village levels were detected using local and global spatial autocorrelation measures (Moran's I). Landslides (41.91%) and floods (32.52%) accounted for approximately three quarters of natural hazard mortalities over the study period. A Global Moran's I test positively confirmed clustering at both the district (0.199, $p < .001$) and village (0.256, $p < .001$) levels, whereas a Local Moran's I test further detected clustering in the central and terai regions, where dynamic geologic and geomorphic processes combined with human-environment interaction constitute major risk factors. A better understanding of multihazard mortality patterns across geographic landscapes and time has the potential to aid policy makers, planners, and local officers to more efficiently allocate scarce capital and human resources to reduce mortality.

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Mortality; natural hazard; disaster; Nepal; vulnerability; spatial analysis

1. Introduction

A common approach to understanding the impacts of natural disasters is the linear-temporal approach, in which the impacts of disasters are measured simply in terms of loss of human lives or economic damages over specified periods of time. Recent studies adopting this method have demonstrated that loss of both life and property from natural disasters are increasing (CRED, 2015; Huggel et al., 2015; Paul, 2011). For example, globally, the human toll from natural disasters averaged more than 99,700 deaths per year from 2004 to 2013 compared to only 68,000 per annum over the full 20-year period (1994–2013) (CRED, 2015). Further, the annual economic cost of natural disasters was estimated at \$67 billion USD between 1994 and 2003 (Guha-Sapir, Hargitt, & Hoyois, 2004), a several fold increase since the 1950s (De Haen & Hemrich, 2007). Though the linear-temporal approach provides insight on disaster losses over

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time, such analyses should be paired with spatially explicit analyses in order to provide information on not only how impacts of disasters have changed over *time*, but also *where* those impacts have occurred and empirical comparisons of such impacts.

Trends in disaster losses are partly a function of spatial processes, including local and regional land use decision-making, population expansion (often in vulnerable locations such as fault lines, floodplains, and coastal areas), and the intensification and shifting of human-environment interactions. Increases in disaster losses cannot be equated solely to a simple increase in natural hazards, per se, but rather they reflect the cumulative consequence of a series of human decisions and actions made over time in a particular place or region (Comfort et al., 1999; Juran & Trivedi, 2015). Thus, incorporating the nuances of place and spatial processes into disaster loss research may aid the process of identifying disaster loss 'inequities' in, for example, underdeveloped countries confronting issues of poverty, government capacity, access to resources and technology, and overstressed infrastructure (Borden & Cutter, 2008; Kahn, 2005).

This research investigates spatial and temporal patterns of natural disaster mortality using Nepal as a case study by posing two specific research questions. First, what are the spatiotemporal patterns of natural hazard mortality in Nepal? Second, which natural hazard contributes most to mortality in Nepal? Our specific objectives are to identify: (1) characteristics of spatial and temporal patterns of natural hazards at the district and villages levels; and (2) those natural hazard types contributing most to mortality, after controlling for population.

A better understanding of spatial characteristics of human losses to natural disasters is crucial for implementing effective, evidence-based policies, and programs for vulnerability reduction. Thus, this study examines place-based vulnerability across time, which we operationalize here as the analysis of a specific geographic location's vulnerability compared to the level of vulnerability of other geographic locations. Analyses that identify vulnerable locations and clusters of vulnerable populations can aid in disaster preparedness and mitigation. While socioeconomic and physical attributes may indicate vulnerability, they jointly coalesce in explicit spatial locations and thus represent a composite of complex interactions among social, natural, and engineered environments in a particular place. Using this lens, spatial analyses can assist local managers to efficiently allocate scarce financial, human, and technical resources to address vulnerability in coupled human-environment systems. The study of mortality has potential to inform all stages of the disaster cycle, and mortality mapping supports the exploration of spatial patterns, tests for statistically significant spatial clusters, and identification of temporal and multi-scalar dynamics (Borden & Cutter, 2008; Combs, Quenemoen, Parrish, & Davis, 1999; Kahn, 2005; Petal, 2011). Thus, mortality mapping represents a valuable tool for refining mitigation efforts and reducing human and economic losses.

Research on natural hazard mortality often focuses on developed countries (where data are typically disaggregated and of higher quality) (Barredo, 2010; Coates, 1999; Jonkman, Maaskant, Boyd, & Levitan, 2009); the global scale (using publicly available national level data) (Guha-Sapir et al., 2004; Jonkman, 2005; Kahn, 2005; Peduzzi, Dao, & Herold, 2005); or the national scale of lesser developed countries (the level of aggregation at which data in underdeveloped countries are typically available) (Huggel et al., 2015; Pradhan et al., 2007). Thus, the biggest hindrance to conducting spatial-analytical research on the geography of hazard deaths – particularly in Nepal and other underdeveloped countries – is the availability of appropriate data. In order to explore disaster mortality in a meaningful way, a large data repository that houses information on a variety of hazard types at a resolution fine enough to detect spatial patterns is required. However, there exists a disproportionately smaller number of high quality repositories with georeferenced data in the lesser developed world (Gall, Borden, & Cutter, 2009; Huggel et al., 2015). An extensive review of the literature was unable to identify a comprehensive accounting of georeferenced natural hazard deaths for Nepal, let alone one that is complemented with temporal analyses. To address this gap, we manually georeferenced and spatially analyzed a mortality dataset for Nepal (i.e. the DesInventar database) that was recently made available in 2003.

2. Study area and methods

2.1. Study area

Nepal is located in the central Himalayan region, stretching over 900 km east to west across some of the highest peaks of the range (Figure 1). Elevation in Nepal ranges from 59 masl to 8848 masl at the summit of Mount Everest, the highest peak in the world. Based on altitudinal variation, Nepal is divided into five major physiographic

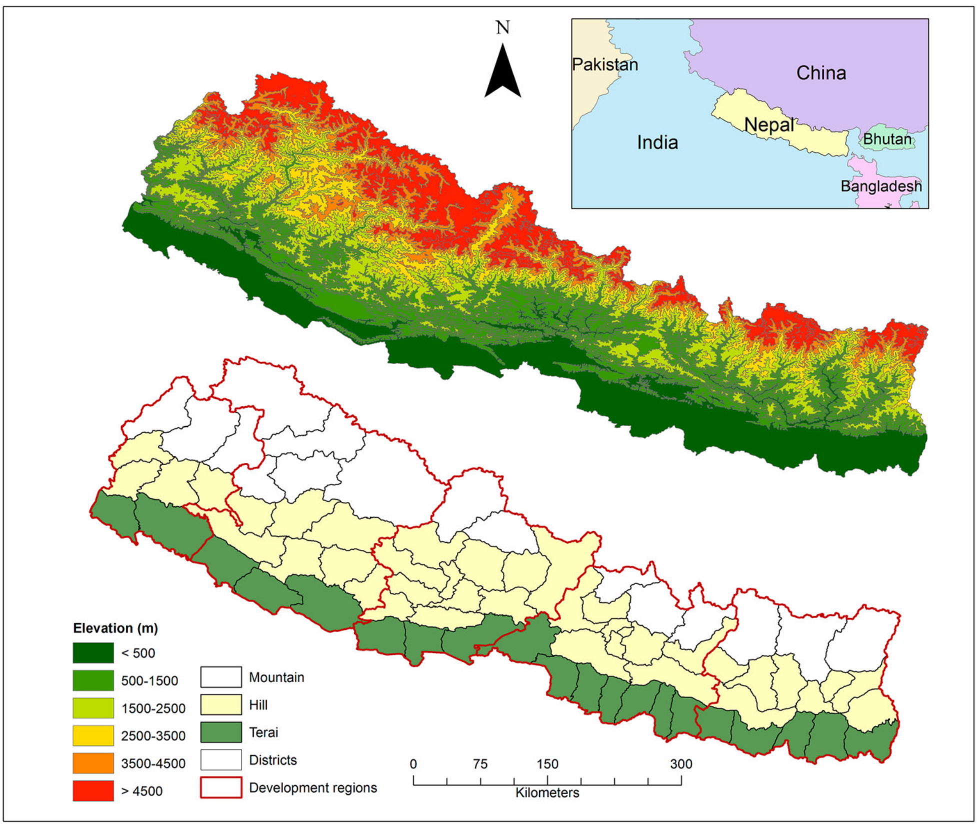

Figure 1. Physical and political map of Nepal.

regions. The terai is located along the northern edge of the Indo-Gangetic plain. The terai extends 30–40 km north to south with elevation ranging from 59 to 300 masl; it is generally flat and predominantly composed of alluvial plains. The Siwalik, commonly known as the Churia hills, ranges 300 to 1000 masl and rises abruptly from the terai. The Siwalik ends with the beginning of the mid-hills and is characterized by low terraces and alluvial fans with steep topography. The mid-hills range 1000–3000 masl and represent the first barrier to monsoon winds that produce heavy precipitation on its southern flanks due to orographic effects. The mid-mountain region, north of the mid-hills, ranges 3000–5000 masl and exhibits river valleys, tectonic basins, and a cool, temperate climate. Finally, the Himalaya region ranges 5000 to over 8000 masl and is mostly occupied by glaciers, rocky slopes, and colluvial deposits. Table 1 provides a snapshot of vulnerable regions of the country by hazard types.

Nepal, a lesser developed country that recently emerged from a decade-long civil war, is currently redrafting its constitution, establishing a new governance structure, and transitioning from a purely centralized to more decentralized state. These disruptions have hindered the state's ability to enact a comprehensive and proactive disaster management plan. For administrative purposes (e.g. governance, taxation, and resource allocation), Nepal is divided into several jurisdictional units: development regions (5); zones (14); districts (75); village development committees (3833); and municipalities (130) (Central Bureau of Statistics, 2014). Some of these political units serve as scales of spatial analysis in this paper.

Nepal is an ideal location for a study addressing spatiotemporal patterns of hazard mortality given its mountainous terrain and exposure to many hazard types. Dynamic geomorphic slope processes underlain by a complex and active geology characterize the country. Furthermore, densely concentrated populations, seasonal monsoon rains, and the steep, unstable slopes of a geologically young mountain range situate Nepal one of the most disaster-prone countries in the world. Thus, owing to topographical variation, active geological processes, and climatic stressors (e.g. monsoons and climate change), Nepal is at risk to a multitude of natural hazards, including earthquakes, landslides, debris flows, and floods (see Table 1). Poor populations residing on marginal urban lands, at the bottom of river valleys, and in remote mountain villages are often the hardest hit and thus suffer disproportionally (Osti, Tanaka, & Tokioka, 2008). While a

Table 1. Natural hazard vulnerability and mortality in Nepal, 1971–2011.

Hazard type	Vulnerable areas	Total mortality*	Percent total mortality*
Landslide	Mid-mountain, mid-hills, Siwalik, and valleys	3302	41.91
Flood	Terai, mid-hills, and valleys	2562	32.52
Thunderstorm	Entire country	913	11.59
Cold wave	Mid-mountain and mid-hills	542	6.88
Strong wind	Mostly Terai regions	143	1.82
Avalanche	Mid-mountain and Himalaya	80	1.01
Snowstorm	Mid-mountain and Himalaya	69	0.88
Forest fire	Mid-hills and terai (forest belt at foot of Siwalik)	61	0.77
Earthquake	Entire country	50	0.63
Rain	Mid-hills	47	0.60
Hailstorm	Mid-hills	40	0.51
Storm	Mid-hills	39	0.50
Heat wave	Terai	30	0.38

*Source: DesInventar Database.

variety of geological, meteorological, and ecological processes coalesce in space and time to generate hazards in Nepal, demographic factors such as population growth and density, land use, poverty and underdevelopment, inadequate disaster planning, and scarce mitigation resources serve to further aggravate the context.

Little research has been conducted to examine deaths across hazard type in Nepal (Aryal, 2012; Petley et al., 2007), and there especially exists a paucity of research on spatiotemporal dimensions of hazard mortality in Nepal. Natural hazards have resulted in massive loss of life and significant impacts on socioeconomic development. The frequency and magnitude of natural disasters, number of fatalities, extent of damage, and spatiotemporal dynamics (i.e. distribution across space and time) are essential for understanding the vulnerability calculus in an underdeveloped, hazard-prone country such as Nepal.

A recent report ranks Nepal seventh worldwide in mortality as a result of floods, landslides, and debris avalanches combined, and eighth in flood-related deaths alone from 1988 to 2007 (Government of Nepal, 2009). In fact, Nepal has a higher average annual death rate per million people than neighboring India, a country that also struggles with issues of vulnerability and multihazard risk (Upreti, 2010). Disaster types, vulnerable regions, and mortality per disaster type in Nepal from 1971 to 2011 are presented in Table 1. Together, landslides and floods contribute close to three-fourths of total human losses, with thunderstorms, cold waves, strong winds, avalanches, snowstorms, forest fires, and earthquakes comprising most of the remaining roughly one-fourth of deaths. While often extreme in terms of mortalities per event, and unlike floods and landslides, these latter disasters are more episodic and do not occur every year. However, their magnitude can propel losses dramatically, especially when analyzing mortality over a short period of time or in only one place or region. For example, Nepal has experienced eight major earthquakes over the past century. In 1934, the Bihar-Nepal earthquake of 8.1 magnitude claimed 8519 lives (more than half were in Kathmandu Valley) and damaged over 200,000 buildings (about 55,000 in Kathmandu Valley). In 1980, the Chainpur earthquake (6.5 magnitude) claimed 103 lives and destroyed over 25,000 buildings, and the 1988 Udayapur earthquake (6.5 magnitude) killed 721 and damaged over 66,000 buildings (Dahal & Bhandary, 2013). More recently, the Gorkha earthquake (7.8 magnitude) of 25 April 2015 claimed approximately 9000 lives, injured approximately 22,000, destroyed approximately one million buildings, and damaged electricity, water, and other public utilities, and caused more than $7 billion USD in economic losses. Nepal is currently in the midst of recovering from this massive disaster.

2.2. Data and methods

Mortality data for Nepal were obtained from the DesInventar Disaster Inventory Management System database, a database developed by The Network for Social Studies on Disaster Prevention in Latin America (LA RED). As suggested by the name, the database originated for Latin America in the mid-1990s due to a lack of standardized data on the occurrence of small- and medium-scale disasters. Thus, a group of researchers from different institutions linked to LA RED developed a conceptual typology for inventorying disaster events across nine Latin American countries based on existing newspaper articles, government data, and reports. In collaboration with United Nations agencies and several national governments, the database was expanded to more than 35 countries in Africa and Asia, Nepal being one.

At the global level, there exist only a few disaster databases that are publicly available and consistently updated. Of these, DesInventar and EM-DAT represent two databases that have been used extensively; however, they differ markedly as a function of resolution, criteria used to denote a disaster, and number of variables stored for each disaster (Velasquez, Cardona, Mora, et al., 2014). EM-DAT has stricter criteria to be classified as a disaster. For example, an event must satisfy at least one of the following criteria in order to qualify as a disaster: 10 or more people reported killed; 100 or more people affected; declaration of a state of emergency; or an official call for international assistance (Huggel et al., 2015). The DesInventar database, on the other hand, includes these relatively large disasters as well as smaller disasters that kill or injure fewer people, and such events are also recorded at the local level (e.g. municipality and village) (Marulanda, Cardona, & Barbat, 2010). Thus, DesInventar is suitable for this study in that it is more comprehensive and that the events can be geocoded at a finer spatial scale.

DesInventar is a computer-based information management system that houses an inventory of large and small disaster occurrences. The database has been improved both methodologically and data-wise since its establishment in 1993. Several studies have used the database to study disaster losses, for example, in Colombia (Marulanda et al., 2010), Pacific Island countries (Noy, 2016), and Peru (Huggel et al., 2015). Moreover, Velasquez, Cardona, Carreno, and Barbat (2014) performed a retrospective assessment of risk to natural hazards in 23 countries and contend that DesInventar is more robust compared to EM-DAT because it includes a greater number of variables.

The DesInventar database was expanded to Nepal in 2003 and currently includes natural disaster and mortality data from 1971 to 2011 for a total of 30 hazard classifications. It was constructed by systematically reviewing data published in two leading newspapers of the country, *Gorkhapatra* and *Kantipur*. DesInventar also incorporates data from the disaster review series published by the Ministry of Home Affairs as well as annual reports published by the Department of Water Induced Disaster Prevention, both from the Government of Nepal. For each disaster, DesInventar records the type, location (at local, regional, and national level), number of fatalities, and damage to infrastructure (United Nations International Strategy for Disaster Risk Reduction, 2009). The National Society for Earthquake Technology-Nepal (NSET), a well-known nongovernmental organization based in Kathmandu, consistently updates the database. In addition to disaggregation across 30 hazard types, the spatial-analytical objective of this paper is made possible by hazard events and mortalities having been recorded by village name. Thus, the DesInventar database was ultimately selected to undertake this study given its reliable and robust recording of disaster events, high resolution of events at the local level (which facilitate geocoding), and based on the literature (see Velasquez, Cardona, Carreno, et al., 2014).

From the DesInventar database, we extracted all data for Nepal and segregated into a list only those natural hazard events that caused mortality during the study period (1971–2011). The resulting list contains 13 natural hazard types: avalanche, cold wave, earthquake, flood, forest fire, hailstorm, heat wave, landslide, rain, snowstorm, storm, strong wind, and thunderstorm. In total, 2839 individual events resulted in at least one death, and these close to 3000 events across 13 hazard types became the basis for this study. To analyze events spatially, each event was manually provided a district and village code to join them to an ArcGIS environment. The statistical software package JMP Pro Version 11 was used to pool and summarize data into the following categories: Event, Year, District, Village, and Mortality.

The most common measure used to characterize mortality is crude death rate, which calculates a generalized death rate for a population by dividing number of fatalities by the corresponding midyear population (McGehee, 2004). Crude rates indicate where number of deaths are highest. However, a major limitation is that crude death rates do not account for population concentrations and differences in population structure among spatial units (Wilson & Buescher, 2002), which means that visualizations and analyses based on crude rates alone may indicate 'false' clusters of mortality. Therefore, beyond the basic measure of crude death rates, we also control for population concentrations and use measures of spatial autocorrelation to identify 'true' clusters of mortality.

Spatial autocorrelation techniques can be employed to analyze spatial patterns of mortality. In simple terms, spatial autocorrelation explores relationships among nearby spatial units whereby nearby areas have stronger relationships and similarities than relatively distant areas, resulting in spatial patterns of attributes. This concept has been applied in a wide range of fields to assess spatial diffusion of technologies and contagious diseases, to test and calibrate models, and of course to identify spatial clusters, outliers, and relationships (Getis, 2010). Spatial autocorrelation includes two families: global and local. Global measures of spatial autocorrelation summarize the extent to which neighboring areas (e.g. districts and villages) are similar in terms of a variable (e.g. mortality), while local measures detect pockets of spatial association (e.g. clusters of mortality) (Grubesic, Wei, & Murray, 2014).

Moran's I, a well-known test for spatial autocorrelation, assumes that the measure of similarity between values at two locations is a product of the deviation between the value at each location and the estimate of the global mean (Aldstadt, 2010). As a method of global statistics, Moran's I values fall between −1.0 and +1.0, and they indicate both the existence (positive or negative) and degree (p value) of spatial autocorrelation. Positive spatial autocorrelation occurs when values of neighboring features are either larger or smaller than the mean. Similarly, when values are both smaller and larger than the mean, the cross-product is negative – that is, negative spatial autocorrelation occurs. Positive spatial autocorrelation in a dataset means that like values tend to cluster spatially, whereas negative spatial autocorrelation means that high values repel high values and tend to gather near low values, which means that like values do not cluster in space. The Global Moran's I tool in ArcGIS 10.3 was used to compute a single summary value, p-value, and z-score to evaluate the significance of spatial patterns of mortality and to assess whether patterns had an average tendency to cluster in space. Neighbors were designated based on the 'contiguity edges only' function, which analyzes neighboring polygon features that share a boundary or overlap that influence computations for the target polygon feature. A limitation of global tests is that they cannot identify the specific location of detected autocorrelation (Aldstadt, 2010; Anselin, 1995). Hence, we also deployed Local Moran's I to examine sub-regions within the data structure.

Local Moran's I deconstructs global statistics into their local components for the purpose of identifying influential observations and outliers. It detects spatial clusters of both high and low values as well as spatial outliers, which renders the test useful for analyzing spatial variations of clusters that are not apparent in the global measure. The Cluster and Outlier Analysis, or Anselin Local Moran's I, tool in ArcGIS 10.3 was used to calculate a Local Moran's I value, z-score, pseudo *p*-value, and code representing the cluster type for each statistically significant feature. The output distinguishes statistically significant clusters of high values (i.e. disproportionately high mortalities); low values (i.e. disproportionately low mortalities); outliers in which a high value is surrounded primarily by low values (high-low); and outliers in which a low value is surrounded primarily by high values (low-high). High-high clusters denote that high numbers of fatalities occurred in nearby spatial units, while low-low clusters denote that low numbers of fatalities occurred in nearby spatial units.

3. Results

3.1. Spatial distribution of natural hazard mortality

Natural hazard mortality was mapped to illustrate its geographic distribution. First, crude death rates were mapped at the village level (Figure 2). The crude rates show higher mortality in the mid-mountain and Himalaya regions where landslides, thunderstorms, cold waves, snowstorms, and avalanches are common. However, these areas are inhabited by smaller populations compared to the southern part of the country, or the terai. Crude rates report deaths per unit population across the country, but they fail to control for population and do not necessarily (let alone statistically) report true clusters. Thus, mortality data were adjusted to control for population at both the district and village scales and a Global Moran's I test was performed to determine whether any statistically significant spatial clustering or dispersion exist. The test confirmed positive

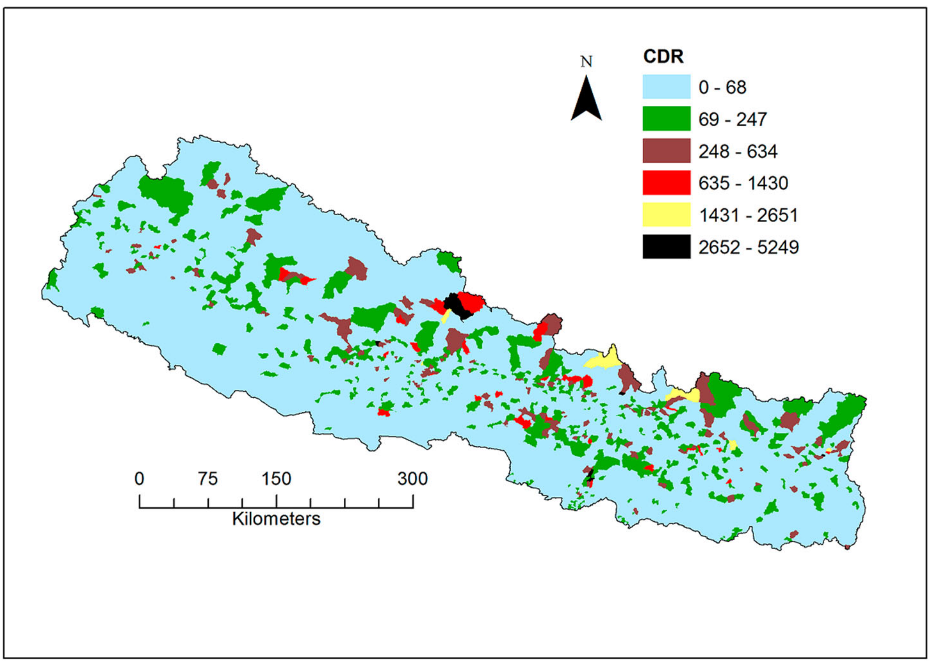

Figure 2. Crude death rate (CDR) from natural hazards at the village level, 1971–2011.

spatial autocorrelation at both the district (0.199, $p < .001$) and village level (0.256, $p < .001$). While the Global Moran's I test confirmed that natural hazard mortalities are clustered in Nepal, it does not identify the specific locations of the clusters.

3.2. Cluster analyses

The geographic identification of clusters must be calculated through local spatial statistics (as opposed to simple visual interpretation), because sizes, shapes, and patterns harbor the potential for spurious rate variations and because polygons can create the illusion of clusters that may not be statistically significant (Borden & Cutter, 2008). Thus, a Local Moran's I test was employed to identify significant spatial clusters (95% confidence interval) of natural hazard mortality at the district (Figure 3(A)) and village level (Figure 3(B)). District level results indicate that natural hazard fatalities are significantly clustered in the central terai, central mid-hills, and central mid-mountain regions of the country. Village level results indicate significant clusters in the same regions as well as the eastern terai, eastern mid-mountains, western mid-hills, and western mid-mountains. The predominance of high-high clustering denotes that areas with relatively high numbers of fatalities are located near areas that also exhibit relatively high numbers of fatalities. These spatial units are 'mortality hotspots' in that there is a higher risk of dying from natural hazards for populations in those spatial units compared to the rest of the country.

At first glance, the district and village level maps (Figures 3(A) and 3(B)) appear similar because clustering patterns are primarily in the same regions – the terai, mid-hills, and mid-mountains. However, the village level map provides alternative insight because it analyzes a greater number of data points. For example, while the central region exhibits high-high clustering in both maps, village level analyses are at a finer resolution and thus portions of many districts identified as high-high are not identified as mortality hotspots at the village scale. Furthermore, the village map detected that low-high clustering is not significant in one of the more populated districts of the central terai, while additional low-high clusters were identified as well as a high-low cluster in the eastern terai.

3.3. Temporal distribution of natural hazard mortality

Total natural hazard mortality over the study period (1971–2011) is portrayed by month in Figure 4. July, August, and September contribute most to mortality, accounting for 68.4% of deaths across the calendar year. These months encompass the monsoon season in Nepal, which ushers in copious amounts of precipitation and associated landslides and floods. Similarly, Figure 5 depicts the distribution of mortality across the entire 41-year study period by natural hazard type, and Figure 6 portrays the same by decade. While the annual reporting in Figure 5 serves to visually conceal increases in mortality over time, the decadal snapshots presented in Figure 6 make it apparent that mortality has increased over the study period. It is important to reiterate that this increase is not necessarily due to a real increase in hazard events, but instead increases and/or perturbations in human-environment interaction coupled with issues of governance, poverty, land use, and population growth.

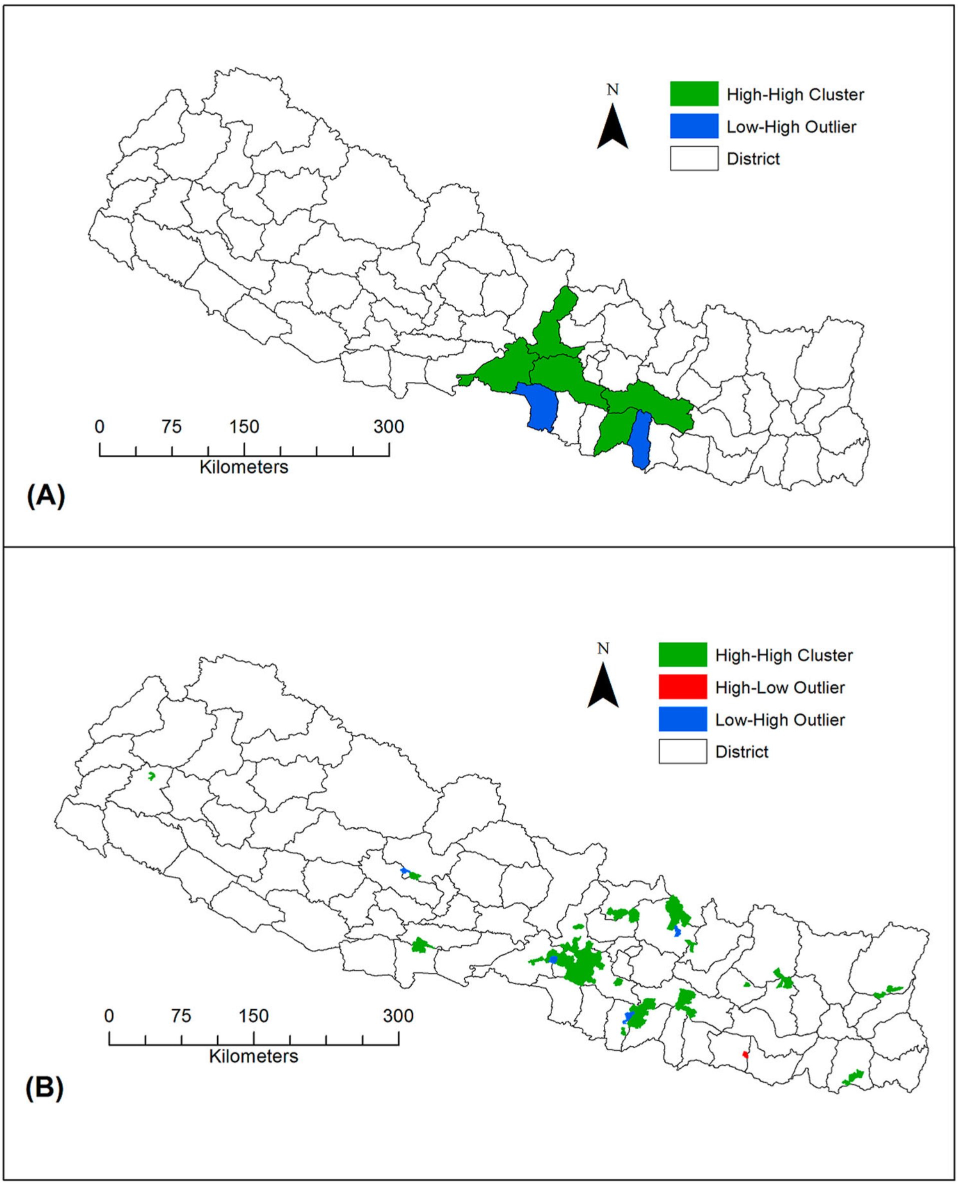

Figure 3. Cluster analysis of natural hazard mortality at the district (3A) and village (3B) level, 1971–2011.

3.4. Deadliest natural hazards

Data from 1971 to 2011 established that landslides are the greatest single contributor to natural hazard mortality in Nepal (Table 1). Landslides rank highest among the 13 natural hazards that caused mortality over the study period, accounting for nearly 42% of all deaths. Landslides are followed by floods (32.52%), thunderstorms (11.59%), and cold waves (6.88%). The remaining nine hazards, earthquakes included, account for the remaining 7.1% of deaths.

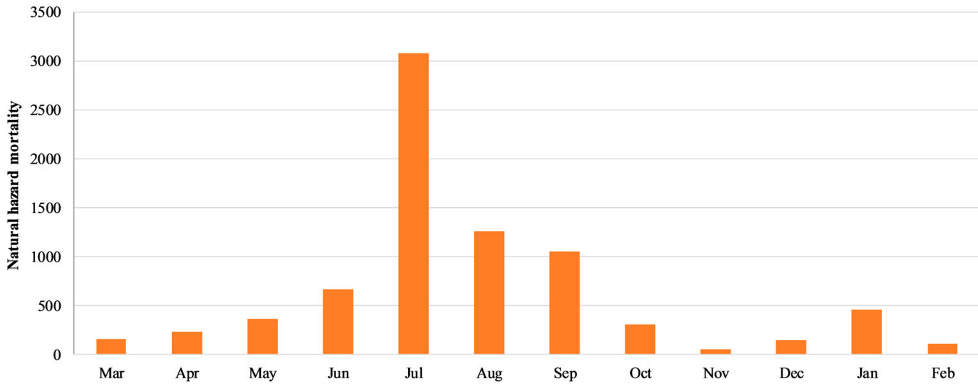

Figure 4. Total natural hazard mortality by month, 1971–2011.

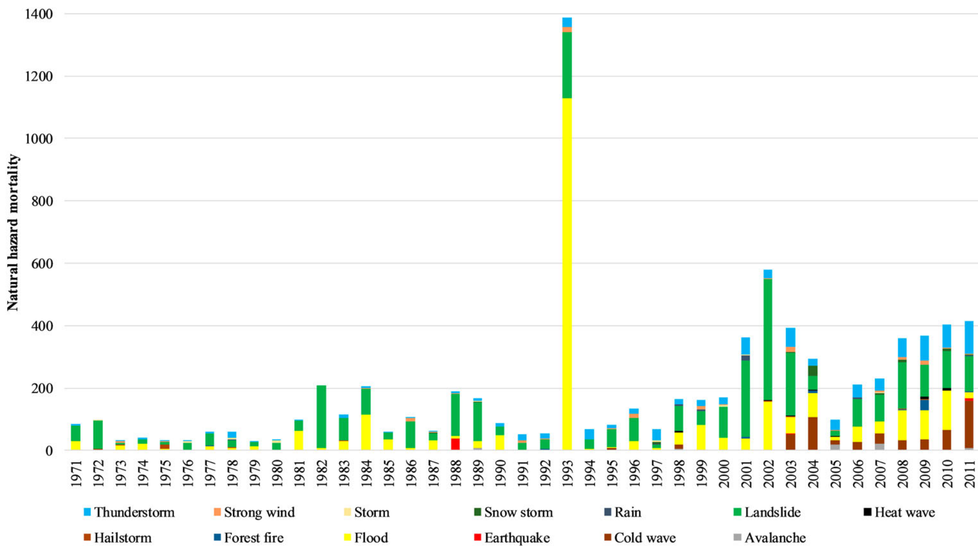

Figure 5. Annual mortality by natural hazard type, 1971–2011.

What is particularly noteworthy is that although landslides constitute the deadliest natural hazard in Nepal, they do not garner a proportional amount of attention from the government, nonprofits, and media. Conversely, while earthquakes and glacial lake outburst floods (GLOFs) are often publicized by the media as catastrophic disasters, they are responsible for fewer deaths compared to more frequent and (often) less catastrophic events such as landslides, floods, thunderstorms, cold waves, and even forest fires. Although the entirety of Nepal is situated in a seismically active region, only two major earthquakes occurred during the study period, the Chainpur (1980) and Udaypur (1988) earthquakes. DesInventar mortality data for both earthquakes are conservative compared to other reports (e.g. EM-DAT and major media outlets), and the dataset does not currently include the 2015 Gorkha earthquake. It is important to note that the Gorkha mega-quake lies outside the scope of this study because the event is not included in the current DesIventar database. Database managers are currently updating the

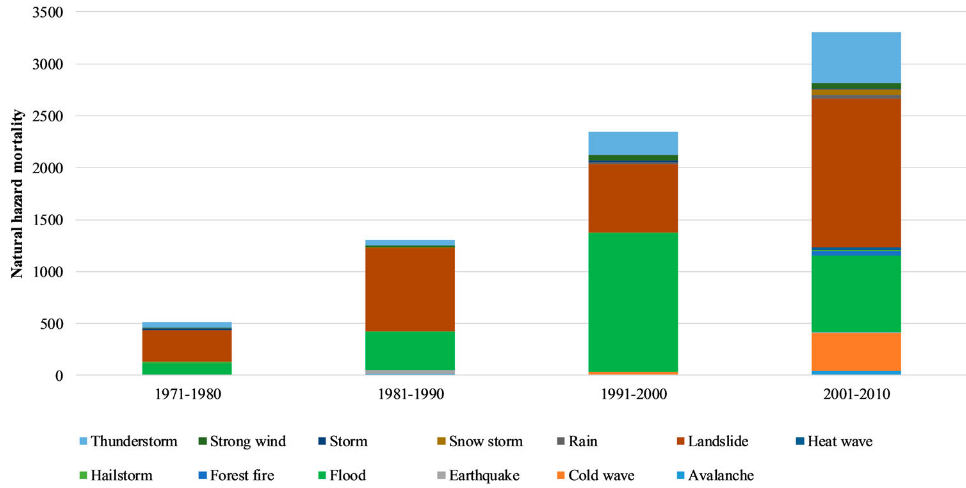

Figure 6. Decadal mortality by natural hazard type, 1971–2010.

database, but a release date is not yet available. Given this background, not only did earthquakes contribute very little to mortality over the study period (only 0.63%), but we argue that mortalities caused by earthquakes may be underrepresented in the dataset given conservative estimates and the current absence of the Gorkha mega-quake. However, just as earthquakes may be underrepresented, Figure 5 shows that a single flood in 1993 may have led to floods being overrepresented. These deaths, which total greater than 1000, are the result of an extreme cloudburst event that occurred 19–20 July. Furthermore, the DesInventar database does not disaggregate GLOF-related fatalities within their typology for floods, which receive much attention due to their sudden force, acute impacts, and links to climate change. A report from the International Centre for Integrated Mountain Development (ICIMOD, 2011) documents 24 GLOF events in Nepal, with 10 occurring over the study period of 1971–2011. The creation of a GLOF category in the DesInventar database, whether as an individual category or a subset of floods, would assist researchers to more accurately identify where particular hazards occur and their attributable fatalities.

4. Discussion

This research investigated spatial and temporal patterns of natural hazard mortality Nepal, a country that exhibits multihazard vulnerability while simultaneously confronting issues of underdevelopment, poor governance, and increased human-environment interaction. Specifically, we uncovered spatiotemporal patterns of natural hazard mortality in Nepal and determined which natural hazard contributes most to mortality.

The results of our study revealed first that spatial concentrations of mortality (based on crude death rates) are concentrated in the mid-mountain and Himalaya regions of Nepal, which is where relatively few people reside. However, more refined spatial analyses that control for population were employed. A Global Moran's I test confirmed positive spatial autocorrelation with a coefficient of 0.199 ($p < .001$) at the district level and 0.256 ($p < .001$) at the village level, which determined that natural hazard mortalities do in fact cluster in Nepal. Further, a Local Moran's I test at the district and village level established that mortality clusters are not in the areas indicated by crude death rates, but are instead significantly clustered in the central terai, central mid-hills, and central mid-mountain regions. The Local Moran's I test also determined the nature of the clusters (e.g. high-high, high-low, and low-high), while village level permutation went on to detect additional pockets of fatalities (i.e. in the eastern terai, eastern mid-mountains, western mid-hills, and western mid-mountains) and did so at a much finer resolution. These findings are important because (1) the district and village analyses concur that the central portion of Nepal is highly vulnerable relative to the rest of Nepal (making the findings more robust); (2) knowledge on the nature or 'direction' of spatial clusters provides insight on specific locations that are both relatively vulnerable and relatively less vulnerable (the former being mortality hotspots and the latter being zones of relatively low mortality); and (3) the finer scale village analyses identify smaller, more explicit jurisdictions that can be more effectively targeted with financial and human resources to reduce vulnerability.

The clustering of high-high fatality zones, or spatial locations with significantly high moralities surrounded by other locations with significantly high mortalities, also provides insights. The clustering of such zones is associated with neither the terai region (i.e. where half of the population resides and multihazard occurrence is great) nor with indicators of socioeconomic development (i.e. the lowest scoring districts in the Human Development Index (HDI) are in the far west and central terai regions (Sharma, Guha-Khasnobis, & Khanal, 2014), which were not identified as high-high clustered regions). This clustering pattern is somewhat counterintuitive and thus calls for a more focused, ground-level investigation of high-high spatial clusters in order to discern how and which social, economic, and environmental factors are coalescing to govern vulnerability. At any rate, this finding reinforces that natural disaster mortality and the related concepts of vulnerability and risk are inherently complex and difficult to understand. Further, it reveals that the vulnerability of these populations may be historically overlooked or overshadowed by regions where more people live, measurements of development are less, or disasters that strike are larger or strike more frequently.

Next, analyses revealed that landslides constitute the most deadly hazard in Nepal from 1971 to 2011, accounting for nearly 42% of all mortalities. Landslides are followed by floods, which account for close to 36% of mortalities. In terms of conventional wisdom, earthquakes – which cause large numbers of mortalities per event – are often perceived as the deadliest natural hazard in Nepal. However, this study demonstrates that it may be wise to afford greater attention and resources to landslides and floods, which cause fewer mortalities per event but are more frequent. Often, communities affected by small and moderate size natural hazards are underestimated and not considered to the extent they should be in disaster planning processes (Marulanda et al., 2010; Price, Byers, Friend, Kohler, & Price, 2013). This only serves to problematize the vulnerability calculus of such populations. We caution that this finding may not hold depending on the data source, how hazards within a dataset are classified, and the study period. For example, a longer study period and/or a study period that includes the 2015 Gorkha earthquake would alter the findings. Moreover, even if researchers could unequivocally identify the 'deadliest hazard,' it may be more practically and academically productive to determine where the most cumulatively vulnerable populations reside and to then address place-based vulnerability from a multihazard perspective. This finding dovetails with the argument above that areas with high-high clusters of mortality warrant closer examination. While data and statistical analyses are able to reveal patterns across space and time, such patterns must be scrutinized more closely to arrive at nuanced, place-based rationale as to why they manifest and what should be done.

Finally, temporal analyses evidenced that natural hazard mortality has increased over time, and this was especially visible in the decadal snapshots. Temporal analyses also distinguished the months of July, August, and September (i.e. the monsoon season) as the deadliest months, accounting for 68.4% of natural hazard mortalities across the calendar year. These findings indicate that (1) the population of Nepal is increasingly vulnerable to natural hazards (the product of a possible increase in events, amplified human-environment interactions, social variables, or a complex combination of these and other factors); (2) outreach, education, and capacity building should emphasize the existence of enhanced vulnerability during the monsoon season; and (3) regarding structural mitigation strategies, it may be wise to deploy structural measures that reduce risk to natural hazards that have a tendency to manifest during the monsoon season.

This study represents an innovative use of the DesInventar database. DesInventar is currently the most robust, long term database for Nepal that is publicly available. However, a limitation of the dataset is that some hazard events appear inconsistent in reporting major flood and earthquake events. For example, the 2008 Koshi flood, 1988 Udaypur earthquake, and 1980 Chainpur earthquake are specific events that appear underreported in terms of mortality. Furthermore, GLOF events are not included in the database although other reports (see ICIMOD, 2011; Shrestha & Aryal, 2011) indicate that GLOFs and GLOF fatalities occurred during the study period. That being said, all databases exhibit limitations and the DesInventar dataset was certainly valuable in advancing understandings of spatiotemporal hazard mortality in Nepal. Further, it represents the best and most comprehensive dataset available at this time.

5. Conclusions

A greater understanding of natural hazard fatalities across the geographic domain is crucial for developing effective disaster management programs and policies. Knowing where natural hazards are fatal across space and time can assist in the allocation of scarce resources, selection of mitigation techniques, and delivery of capacity building and information dissemination campaigns. In this context, we attempted to answer following questions: (1) what are the spatiotemporal patterns of natural hazard mortality in Nepal?; and (2) which natural hazard contributes most to mortality? We used the publicly available DesInventar database to examine these questions, which first required the manual georeferencing of all natural hazard events that resulted in mortality from 1971 to 2011. Spatial analyses identified clusters of fatalities across the country, and temporal analyses revealed that the months that encompass the monsoon season have the highest impact on mortalities (i.e. more than two-thirds of total fatalities throughout the calendar year). Furthermore, landslides emerged as the single most deadly hazard over the study period.

This study is a starting point to better understand the distribution of natural hazard mortality in Nepal. Spatial-analytical research on mortality in Nepal is nascent. However, this paper demonstrates that datasets such as DesInventar can be manipulated to address this gap by enabling the analysis and visualization of natural hazard mortality across the dimensions of space and time. These capabilities can in turn be used to identify clusters of high and low mortality, determine the deadliest hazard in a discrete location or across a period of time, and ultimately for policymaking and resource allocation. Thus, as the DesInventar dataset is expanded and spatiotemporal research continues, such approaches have the potential to refine understandings of mortality in Nepal and foster the formulation of more effective and geographically targeted disaster policies. In Nepal, there is a dearth of research on how disaster mortality is distributed across the country. As a consequence, planners, decision makers, emergency managers, local officers, and nonprofits are constantly facing challenges to adequately plan and prioritize limited resources to reduce the risk of individual communities. To that end, this study can be taken as a starting point to discern and anticipate the spatial clustering and temporal patterning of natural hazard risk. While this study does not necessarily reach the point of evidence-based decision-making, strides have been made towards a more informed avenue for natural hazards management in Nepal.

Researchers engaging in similar future studies may wish to consider the following potential limitations. First, a longitudinal and comprehensive database that simultaneously geolocates natural hazard events is currently nonexistent for Nepal. The database used for the study (i.e. DesInventar) fulfills this gap to some extent. However, some events appear underreported; the issue of hazards that subsequently trigger additional hazards is difficult to disentangle (e.g. an earthquake that triggers a landslide); and significant time was expended to manually geolocate 2839 natural hazard events. The issue of researcher discretion in terms of geographic and temporal bounds of analysis also exists. Furthermore, analytical products are highly dependent on the spatial unit of analysis (e.g. regional vs. district vs. village vs. point based), and the same goes for temporal slices (e.g. study period vs. decadal vs. seasonal vs. monthly). In this study, we were careful to disclose these spatial and temporal limitations as results were presented. Finally, this paper is a beginning foundation and should thus be considered as a starting point towards understanding spatiotemporal patterns of mortality in Nepal. Thus, we call for the collection and sharing of more data that have the ability to advance spatiotemporal natural hazards research as well as future studies that can advance or refute analyses and conclusions presented in this study.

Disclosure statement

No potential conflict of interest was reported by the authors.

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