Assessing vulnerability and multi-hazard risk in the Nepal Himalaya

Sanam Kumar Aksha

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Luke Juran, Co-Chair

Lynn M. Resler, Co-Chair

Lawrence W. Carstensen Jr.

Yang Zhang

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SCIENTIFIC ABSTRACT

Communities around the world are encountering unprecedented rates of change due to population growth, land use change, development, and increased social vulnerability to natural hazards. Understanding how physical processes and human vulnerability to natural hazards interact is a primary objective of researchers, policy makers, and disaster risk reduction practitioners in order to combat increases in natural hazard frequency and intensity.

Nepal, a landlocked mountainous country spanning the central Himalayan region, has about 28 million inhabitants in 147,181 square kilometers. Nepal is exposed to a multitude of natural hazards, requiring individuals and communities to interact with and make decisions on risk acceptability on a day-to-day basis. In many cases, Nepal’s geographic location, available resources (human, economic, and capital), and limited government capacity coalesce to turn natural hazards into disasters, resulting damaged infrastructure, economic disruptions, and death.

This dissertation evaluates the geographic distribution of natural hazard mortality, quantifies social vulnerability to natural hazards, and models multi-hazard risk in the data deficient environment of Nepal. Chapter 1 conceptualizes relevant terms such as natural hazards, disaster, vulnerability, and risk before discussing the challenges associated with multi-hazard risk assessment in Nepal. Chapter 2 evaluates the spatial and temporal distribution of natural hazard mortalities at the village level using a publicly available disaster database. Results reveal that landslides were the deadliest disasters between 1971-2011. Chapter 3 identifies major social factors and processes that contribute to the vulnerability of individuals and communities using census data. Adapting the Social Vulnerability Index (SoVI) method developed for the US context, this chapter investigates the spatial distribution and clustering of various social vulnerabilities across the country. ‘Renter and Occupation’, ‘Poverty and Poor Infrastructure’, and ‘Favorable Social Conditions’ are three major components that influence social vulnerability in Nepal. Results indicate an interesting regional difference: the eastern and central Tarai are more vulnerable than western Tarai, whereas the eastern Hills and Mountains are less vulnerable than western Hills and Mountains. In Chapter 4, a model of risk from multiple natural hazards in the city of Dharan, Nepal, is presented. Freely available geospatial data in combination with socio-economic data collected from local government and secondary sources are used. Multi-hazard risk assessment is data intensive and requires considerable financial and human resources, which are lacking in Nepal. Results show that geospatial modeling techniques can be used to fill the gap and assist local officers and emergency managers in risk management.

Cumulatively, this work offers new insights on natural hazards, vulnerability, risk, the use of geospatial technologies, and their inter-relationships. Research findings advance scholarly understandings of multi-hazard risk in general and particularly in the Nepali context. Additionally, this work is valuable to disaster practitioners who seek to implement more effective disaster risk reduction programs and policies.
GENERAL AUDIENCE ABSTRACT

Natural hazards are earth system processes that pose threats to people and have the capacity to disrupt social and ecological processes. Thus, a consideration of both physical and social dimensions is required to better understand natural hazards. This research evaluates social factors and processes that have significant roles in enhancing the vulnerability of individuals and communities. First, this dissertation explores spatial and temporal patterns of natural hazard fatalities at the village level in Nepal. Research findings identified that landslides were the highest contributor to natural hazard fatalities from 1971-2011. Second, this dissertation assesses which social factors and processes contribute most to social vulnerability in Nepal. Additionally, the spatial distribution and clustering of social vulnerability is explored. Finally, geospatial modeling was performed to analyze cumulative risk to floods, landslides, and earthquakes in the municipality of Dharan, Nepal.
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Chapter 1. Introduction, literature review, and statement of purpose

1.1 Background

Communities around the world are encountering unprecedented rates of change, due to population growth, urbanization, environmental degradation, and elevated social vulnerability to natural hazards (Gencer 2013). The impact of such changes differs across space, and communities and individuals are increasingly exposed to more risk. As frequency and intensity of natural hazards have been increasing in recent decades, understanding physical processes and human vulnerability have been one of the important priorities in today’s world. Because of ever-increasing human development especially in sensitive locations such as mountains, the potential loss of human lives and/or economic damages are growing (Shaw and Nibanupudi 2015). Communities are constantly exposed to natural hazards, and are vulnerable to disasters. The exploration of fundamental causes of what makes them vulnerable may assist in better preparation, reduce losses during events, and allow quicker recovery after a disaster happens.

Human-environment interaction is a primary focus of research in disaster risk reduction (Alexander 2000, Cutter 1996, Hewitt 1997, Oliver-Smith 1996, Smith and Petley 2009, Wisner et al. 2004). Within this framework, the environment is considered the agent of disaster while development patterns serve to exacerbate risk and vulnerability. Given the intricacies of factors, processes and feedbacks in a coupled human-environment system, a complete vulnerability assessment is a gigantic task. The difficulties of the task are intensified by many factors such as impact of global processes onto the small-scale systems and local communities, the nonsynchronous character of physical and social processes, and/or incongruous goals of the various stakeholders of the system (Turner et al. 2003).
Research indicates that social processes produce disproportionate exposure to risk making some communities and individuals more susceptible to disasters than others (Cutter, Boruff, and Shirley 2003, Wisner et al. 2004). However, vulnerability is not just a characteristic of a particular community but rather a deeply embedded product of complex interaction of social processes. Numerous vulnerability assessments are conducted to understand this complexity mostly based on various sets of indicators. As measuring social vulnerability has capacity to determine populations at risk before, during and after a disaster, it has been widely adopted to inform public policy and allocate scarce resources.

1.2 Literature review

1.2.1 Key definitions

The literature often synonymously uses the terms ‘disaster’ and ‘natural disaster,’ and the terms ‘hazard’ and ‘disaster’ are also used interchangeably. In a broader sense, they can be divided into two categories: natural and man-made. Natural hazards occur naturally as a function of physical processes and can further categorized as geophysical (earthquakes, landslides, tsunamis, and volcanic activity); hydro-meteorological (floods, drought, cyclones, blizzards, windstorms); or biological (epidemics). Man-made hazards, also called technological hazards, occur as a result of human failures and human behavior (conflicts, famine, industrial accidents, transportation accidents). The literature on hazard and disasters spans a wide range of work. This particular study seeks to investigate hazards of natural origin, such as earthquakes, floods, and landslides, in the mountainous and underdeveloped country of Nepal.

In order to understand the dynamic and intricate relationship between society and natural hazards, it is essential to discern some essential concepts: hazard, disaster, vulnerability, risk,
capacity, resilience, and disaster cycle. Each concept has its own place in the literature (e.g. hazard and risk geography, disaster sociology, public health, environmental justice, and emergency medicine), and given the breadth of the literature there is no single perspective or conceptualization that is all encompassing.

**Natural Hazards**

A natural hazard is an agent that has the potential to cause a disaster (Cuny 1994). The term “natural” differentiates such phenomena from social hazards such as terrorist incidents and from technological hazards such as structural collapses, severe contamination, and release of toxic materials. Tobin and Montz (1997, 5) explained that a natural hazard “represents the potential interaction between humans and extreme natural events”. Because of human activities, the hazard exists, and humans are constantly exposed to them.

**Disaster**

Disasters are unusual large-scale events that destroy the capacity of an individual and/or a community to respond and recover from that event. According to Alexander (2000, 21), “in social terms, a disaster is a non-routine event but a routine social problem, because disasters are recurrent and because they can at least be anticipated, even if they cannot be predicted”. As the manifestation of disaster is primarily underlying in society rather than in nature, the theory of vulnerability – “the concept in which aspects of society may either reduce or exacerbate the impact of a hazard” (Oliver-Smith 1996) would be a useful concept to study them.
Vulnerability

The concept of vulnerability is widely used in many diverse research and policy communities. In early days, vulnerability was associated with physical fragility for instance, how a building will perform against an earthquake (Birkmann, 2007). Today, it represents susceptibility of an individual or community to the impacts of hazards. It is defined as “the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impacts of a natural hazards” (Wisner et al. 2004, 11). In this study, the operational definition of vulnerability is conceptualized based on the United Nations International Strategy for Disaster Reduction (UNISDR) as “the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard” (UNISDR 2009).

Risk

Risk is defined as “the combination of the probability of an event and its negative consequences” (UNISDR, 2009). The elements at risk primarily consist of individuals and communities, infrastructures, natural environment, and economic activities and services, which are under the threat of disaster in a given area (Alexander 2000). It can simply be expressed in a “pseudo-equation”: Risk (R) = Hazard (H) x Vulnerability (V) (Wisner et al. 2004).

Capacity

Capacity is “resources, means and strengths that exist in communities, properties, and households and which enable them to cope with, withstand, prepare for, prevent, mitigate or quickly recover from a disaster” (Khan, Vasilescu, and Khan 2008). The term resembles with
other commonly used term such as adaptive capacity, adaptability, coping ability, and resilience (Smit and Wandel 2006).

**Resilience**

Disaster resilience is defined as the “ability of a social system to absorb, respond, and recover from the disaster and re-organize into a fully functioning system” (Cutter et al. 2008, Adger et al. 2005). Often, disaster resilience and vulnerability are understood as opposing concepts. In this case, vulnerability is defined as an exposure to the risk and resilience as resistance to change which could lead to risky interpretation lending to “circular reasoning: a system is vulnerable because it is not resilient; it is not resilient because it is vulnerable” (Klein, Nicholls, and Thomalla 2003).

In hazard research, the concept of resilience is broadly defined in two ways: as a process or as an outcome. In general, the capacity of a community to bounce back to original state is considered an outcome related resilience. While a community learns from the disasters and bounces back to better state making better decisions to increase the capacity to deal hazards, is considered processed to an outcome (Cutter et al. 2008). One of the major pitfalls of considering disaster resilience as an outcome is that resources are invested on the same practices which might have led to that particular event. Hence, defining whether resilience is a process or an outcome is a crucial step in disaster risk reduction.

**Disaster cycle**

Disaster risk reduction comprises of all programs and efforts that can be undertaken before, during, and after a disaster with the purpose to avert a disaster, lessen its impact, and/or
recover from its losses (Khan, Vasilescu, and Khan 2008). The process is often interpreted as an integrated planning cycle consisting of four main phases: Mitigation, Preparedness, Response, and Recovery (Fig. 1). The cycle depicts the continuous process that can be planned to reduce the impacts of disasters and steps to recover when a disaster event happens. Often, disasters are viewed in isolation and treated as a single event. In fact, each society is at different stages of the disaster management cycle. Thus, disasters should be viewed as a continuous process overlaid on social systems that are in perpetual process of recovering from the last disaster and anticipating the next disaster.

*Figure 1: The disaster cycle*
1.2.2 Key concepts in vulnerability research

The concept of vulnerability was evolved as a response to the dominance of hazard-oriented perception of disaster risk in early 1970s (Birkmann 2006). The definition of vulnerability varied across disciplines and thus has no universal definition. In the literature, vulnerability is commonly referred as a characteristic of an individual or a community to respond, recover from, cope with, and to anticipate the impact of a hazard event. It is generally viewed as an innate characteristic of a society or system.

The vulnerability research has been guided by various school of thinking. Researchers have illustrated it based on different categories. Hufschmidt (2011) summarized that the vulnerability research can be divided into two research areas: the “human ecologist school” or “behavioral paradigm”, and “structural paradigm” (Hufschmidt 2011). The author explains that ‘human ecologist school’ is based on seminal work of Gilbert White and viewed as human adjustment to natural hazards whereas structural paradigm focuses on the barriers that restrict access to resources. Fussel (2007) emphasized that three approaches are predominantly used in vulnerability studies: Risk-hazard (Burton, Kates, and White 1978, Downing et al. 1999, Hewitt 1997), political economy (Adger 1999), and integrated approach (Cutter 1996, Cutter, Mitchel, and Scott 2000, Turner et al. 2003). Risk-hazard approach assumes that hazards are rare and stationary while political economy approach focuses the analysis of people, who is vulnerable and why. Integrated approach defines vulnerability as the combination of ‘internal’ factors with its exposure to ‘external’ hazards. The most notable models are the hazard-of-place (Cutter 1996) and coupled vulnerability framework model (Turner et al. 2003).

Based on different disciplinary paradigms assessment of vulnerability is designed and implemented to enhance the understanding of vulnerability in disaster risk. Qualitative
frameworks as well as quantitative indices methods are widely used to measure them. In overall, the concept has been continuously widened and broadened towards a more comprehensive approach encompassing different thematic areas such as physical, social, economic, environmental, and institutional vulnerability as well as various concepts such as susceptibility, exposure, coping capacity, and adaptive capacity are included. However, the challenges remain on how to integrate various components such as exposure, coping capacity, and adaptive as well as the different methods used within different disciplines. Another major challenge is how to represent ever changing interaction between individual and/or groups with physical systems.

1.2.3 Use of geospatial technologies to evaluate natural hazards, risk and vulnerability

The use of geospatial technology such as geographic information system (GIS), remote sensing (RS), and geographic positioning systems (GPS) in disaster risk reduction activities has been very promising for disaster researchers, emergency managers, planners, and decision makers. Geospatial science or Geographic Information Science (GISc) attempts to understand space-time complexities, with a focus on geographic representation, spatial analysis and modeling, and the communication of these complexities (Bishop and Shroder 2004). It emphasizes spatial concepts, knowledge, and empirical research versus the notion of creating software tools for mapping and using GIS to solve environmental problems.

Disaster management constitutes three distinct phases: pre-disaster phase, disaster phase, and post-disaster phase. In the pre-disaster phase, activities are mainly focused on prevention, mitigation, and preparedness, while during disaster phase it is focused on response work. Recovery, reconstruction, and rehabilitation are focused in the post-disaster phase. Geospatial technologies are used in all phases of disaster management cycle in a wide range of applications,
for instance, hazard and risk assessment, vulnerability assessment, damage assessment, resource mobilization and so forth (Herold and Sawada 2012). Geospatial analysis is primarily based on spatial data, hardware and software, and trained personnel. The availability of spatial data, a major component of geospatial analysis, varies from developed to developing countries. Use of geospatial technologies in developing countries is hampered by a lack of financial resources, lack of local human/technical resources, lack of spatial data, and institutional/political instability (Herold and Sawada 2012). However, due to the advancement of internet technologies and capacities, data, such as administrative boundaries, roads, hydrology, cover, and digital elevation models are now freely available and downloadable. The use of these data has empowered decision making within the field of disaster management. In general, the success and effectiveness of disaster management programs largely depend on the availability of spatial data, its effective use, and dissemination. In addition, scale of the data can also limit the usefulness of the spatial data. Nonetheless, together with GPS, remote sensing, and GIS are a proven tool in understanding the processes at varied spatial and temporal scales as well as in execution of disaster risk reduction activities (Campbell and Resler 2015).

A GIS is a key component of any comprehensive and effective disaster risk reduction programs and policies. It is used to collect, map, analyze, integrate, and display the spatial data mostly from earth observation. In the pre-disaster phase, a GIS provides very significant information to assist disaster preparedness activities such as delineation of risk areas, identification of vulnerable populations, analysis of multiple potential scenarios, preparation of inventory of essential supplies, and assessment of critical infrastructure, evacuation routes, and drop off points. For example, by combination of remote sensing and GIS data, Dewan et al. (2007) assessed the flood hazard risk of Dhaka, Bangladesh. Cutter, Mitchell, and Scott (2000)
employed GIS to present a county level ‘hazard-of-place’ map to assess hazard vulnerability in
spatial terms and exhibited how useful a GIS can be to study social and biophysical components
together that influence vulnerability. Prior information and/or knowledge about magnitude,
location, and time related to any disaster event is crucial for emergency managers and disaster
practitioner. Such knowledge will enable them to identify most affected areas and population so
that they can distribute resources efficiently and reduce the impacts of that particular event.

When a disaster strikes, local officers, emergency responders, disaster management
workers, volunteers, and others involved in the search, rescue, and relief activities require near
real-time and updated information. Such information includes: location of potential victims;
nearest hospital and airports; closest evacuation and drop off points; stockpiles of water, food,
blankets, and medical supplies; extent of damages to buildings, roads, and other critical
infrastructures. GIS, in conjunction with satellite images, can provide useful information to assist
response efforts. For example, De La Ville, Diaz, and Ramirez (2002) used GIS and IKONOS
panchromatic images to analyze the contributing factors for various types of mass movements
which included collection and mapping of various factors such as land cover, geology, slope, and
the distribution of deposition zones. However, use of GIS in post-disaster situations is more
challenging than pre-disaster because of crucial time factors (Goodchild 2006).

A broad suite of remotely sensed image products (high-resolution topography data,
passive, and active microwave ranging) is available to aid in disaster management and
mitigation. The use of these data has transformed the disaster risk reduction activities in the last
decade (Tralli et al. 2005) particularly in mountain environments by increasing our ability to
analyze locations that are difficult to access and lack detailed topographic data (Campbell and
Resler 2015). Hundreds of satellites with multiple sensors are revolving in the earth’s orbit to
provide near real time data to emergency managers and decision makers (Gillespie et al. 2007). Such earth observation processes provide details of geology, land use, and morphology including infrastructure and population density to help determine the process of disaster and its impact (CEOS 2003). For example, Enhanced Thematic Mapper (ETM) data of Landsat satellites have been used to prepare landslide inventory, detect changes, extract land use land cover information, and the geomorphology of slopes. Many researchers have used various types of remote sensing data for flood hazard risk assessment (Herold and Sawada 2012).

Despite its many benefits, some limitations and potential obstacles exist in the usage of remotely sensed data for disaster risk reduction and management. The most common challenges are spatial and temporal resolution of these data. The most significant challenge especially in the developing world is absence of high resolution images. In many parts of the world, only 30 m resolution ASTER and Landsat imagery are freely available. Low pixel resolution of satellite data pose constraints while preparing a fundamental spatial database for further analysis. Temporal resolution also known as repeat frequency is very significant in post-disaster situation. Many satellite revisit times are too long to assess the damage extent through pre- and post-processing of images. Thus, sometimes for immediate response activities, use of remote sensing products become obsolete (Cutter, Mitchell, and Scott 2000). Additionally, night vs daytime needs for optimal image acquisition, and cloud coverage augment these challenges for the immediate use in post-disaster situation (Coppock 1995).

In the context of mountain hazards, the use of geospatial technologies is limited by complex terrain and environmental factors such as atmosphere and land cover, which control irradiant and radiant flux (Campbell and Resler 2015, Fischer et al. 2011). Further, model calibration and verification are limited by mountainous terrain and remote locations that preclude
or complicate accessibility of field verification data (Gritzner et al. 2001). Limitations arising from geospatial technologies take the form of inappropriate data models and data structures, 3-D representation and analysis, and uncertainties regarding how to address, most effectively, the issues of spatial scale and time in geomorphic processes. Limitations in our ability to calibrate and verify model predictions arise from the quality of the basic input data such as spatial and temporal resolution, accuracy, and the precision of data on soil, precipitation, and other biophysical variables along with a thorough understanding of the physical processes involved.

1.2.4 Challenges in multi-hazard risk analysis

Conventional risk assessment methods deal with each type of hazard separately. In general, the total risk is considered as the sum of all the individual risks. The interplay among the multiple hazards and the influence of one hazard on the vulnerabilities to other hazards are often not considered, which may lead to misjudgment of the risk profile and an inaccurate overall human risk. Although, hazard and risk assessment has grown as a discipline, multi hazard risk analysis is in its infancy.

Research has highlighted different problems while assessing the impacts of multiple hazards (Greiving, Fleischbauer, and Lückenkötter 2006, Hernandez 2014, Kappes 2011, Tate, Cutter, and Berry 2010). Because of different underlying assumptions to understand each hazard process, modeling principles, and uncertainties, it is hard to generalize and compare different hazards. The requirement of large amounts of data is another constraint limiting multi hazard research. In addition, scale of analysis is another important issue. Usually, scale is determined by stakeholders and the spatial extent of the area under consideration differs with the level of details at which researcher have to provide results (Kappes 2011). In most cases, the boundaries of
hazard zones are not congruent with administrative borders and/or do not overlap with institutions, which are created to manage risks.

Greiving, Fleischhauer, and Lückenkötter (2006) highlights the problem of data quality as, for some hazards, detailed loss data can be found while for other hazards only few qualitative historic records are available. Subsequently, potential for comparisons among hazards is greatly reduced, however, a geospatial based integrated methodology can address such problem. For example, Tate, Cutter, and Berry (2010) developed a GIS based integrated multi hazard methodology based on publicly available data to help local decision makers and emergency managers. Authors first developed three different outputs from frequency mapping, losses mapping and social vulnerability mapping, and then integrated to get multi-hazard vulnerability map.

1.2.5 Natural hazards in Nepal

Nepal is located in the central Himalayan region and is characterized by complex, fragile geophysical features and rugged topography with high relief ranging from less than 100 meters to over 8,000 meters above mean sea level. Steep, unstable slopes and active geological formations of a young mountain range along with heavy monsoon rainfall render Nepal one of the most hazardous areas in the world.
Figure 2: Physical map of Nepal

Figure 3: Administrative map of Nepal (numbers 1-7 are the newly created provinces that have yet to be named by the government)
**Floods**

In Nepal, there are about 6,000 streams, totaling, in length, about 45,000 km (Ministry of Home Affairs (MoHA) 2009). Collectively, these river systems sustain drinking water, agriculture, hydropower, recreation, and other livelihood options. However, they also create troubles in the country through flooding. According to Shanker (1985), the river drainage density is 0.3 km/km², which reveals the compactness of drainage channels and susceptibility to floods. Floods are responsible for damage to agricultural products, built infrastructure, human lives, and often result in waterborne diseases such as cholera, dysentery, and typhoid fever.

Floods are common during the monsoon period from June to September throughout the country as two-thirds of total precipitation occurs in this period. It is mainly caused by natural factors: intense rainfall, landslide and glacial lake outburst floods (GLOFs), co-occurrence of snow and glacial melt with monsoon precipitation, as well as several human factors: land use changes, drainage congestion caused by haphazard development activities, and dam failures (Pradhan 2007). These factors may act individually or in combination, and the intensity and magnitude depend largely on the location and pattern of occurrence. Moreover, continuous rainfall on saturated mountain slopes induces landslips resulting in flash floods along with high sediment and bed loads. In addition, ephemeral rivers originating in the Chure range cause significant damages in the southern part of the country (i.e., Tarai region). According to Dixit (2003), the continuous monsoonal rainfall in 1954 throughout the mountain regions resulted in damaging floods on the Koshi River, jeopardizing the livelihoods of mountain populations. As a result, a large number of affected families responding to a program initiated by the government as a response to resettle them in a less vulnerable area migrated to southern part of the country.
The literature shows that the occurrence of extreme precipitation events in mountain areas causes significant damage to properties and claims human lives. For example, an extreme precipitation event in 1993 in southern and central parts of the Nepal was estimated as a 78-year precipitation event (Dhital, Khanal, and Thapa 1993). The single event generated about 2,000 landslides of various sizes with major landslides in more than 200 places which significantly damaged transportation routes and claimed about 160 lives (Ministry of Home Affairs [MoHA] 2011).

Temporary formation of lakes due to damming by landslides during the monsoon is also common in the high and middle mountains of Nepal. Khanal, Shrestha, and Ghimire (2007) reported that 11 disastrous landslide dam outburst floods occurred from 1967-1989 due to breaching of landslide dams. In Larcha, this type of flood took place in July 1996 killing 54 people and sweeping away 22 houses. Such events occur randomly and cannot be precisely predicted. Approximately 27% of landslide dams burst within one day of their formation (Costa and Schuster 1988). Hence, they pose immense threats of flash flooding for downstream locations and require very quick reaction.

Floods are a routine part of life and have problematized the lives of poor people, often pushing them further into poverty. On 18 August 2008, a flood control embankment on the eastern side of the Koshi River breached and wreaked havoc downstream in the Sunsari District of Nepal and six districts of Bihar, a state in northeastern India (Dixit 2009). About 60 people were killed, 7,000 families were displaced and about 50,000 people were affected in Nepal (Ministry of Home Affairs [MoHA] 2011), in addition to 3.5 million affected in Bihar (Dixit 2009). Likewise, the Bagmati River was blocked by tree logs for a few hours in 1993, which caused an outburst flood killing 816 people (Khanal, Shrestha, and Ghimire 2007). Similarly,
embankments breaching in 1981 swept away one bridge, 41 people and 120 houses, and a check dam failure on the Rapti River in 1990 killed 26 people and swept away 880 houses (Khanal, Shrestha, and Ghimire 2007).

Earthquakes

Nepal is situated in the southern slopes of the Himalayan range, which is one of the most active mountain ranges in the world. The Himalayan range was formed due to collision between the Indian and Tibetan plates. As a result, there are active faults that pose constant threats of earthquakes in the country. The major active faults are classified into four groups: South Tibetan Detachment System (STDS), the Main Front Thrust (MFT), the Main Boundary Thrust (MBT), and the Main Central Thrust (MCT). Among these, the MFT and MBT are most dynamic and have the immense ability to produce big earthquakes (Chamlagain 2009). The existence of world’s highest peaks in the country indicates the continuous tectonic movement in the Himalayan region. Figure 4 shows the danger zone in the Himalayan region with slip potential and urban population. As this is a 2001 work, the urban population has risen considerably in last 17 years. From the seismic risk perspective, Nepal is considered one of the disaster hot-spots in the world (Dixit 2014).

Nepal has an historical record of devastating earthquakes. The earliest recorded major destructive event was in the year 1255 followed by 1833, 1934, 1960, 1988, 2011, and 2015. The recent 2015 Gorkha earthquake caused more than 9,000 deaths, injured approximately 22,500, damaged approximately one million traditional masonry as well as reinforced concrete buildings. The built environment was mainly responsible for human hazard as 80% of fatalities are caused
by buildings whereas about 10% are caused by lack of medical facilities and about 10% are because of emergency response systems (Picard 2011).

![Image](image.png)

**Figure 4: Indo-Asian collision zone with estimated slip potential along the Himalaya (Bilham, Gaur, and Molnar 2001)**

Identifying the location and time of earthquakes is fundamental for planning measures to lessen the impacts of earthquakes in future. The instrumental records of seismic events in the Himalayan regions are sporadic and available only for shorter periods. However, a major trend has been identified with the help of available data. This trend depicts a narrow distribution of earthquakes just south of the MFT (Chamlagain 2009).
Based on the scenario of the 1934 earthquake, National Society for Earthquake Transition (NSET) (1999a, b) studied a loss estimation of infrastructures in Kathmandu and Bhaktapur if a similar magnitude of the earthquake were to strike again. It estimates that about 75% of the buildings in Bhaktapur would be damaged, and about 60% heavily damaged. Given the increment of population as well as centralized development in Kathmandu valley in recent decades, the infrastructure damages and mortality would significantly increase (Dixit 2014).

**Landslides**

Landslides are commonly occurring events in a highly sloped environment on Earth. In many cases, ‘landslide’ would be a misnomer as they do not contain sliding. The concept of landslide is used “to describe a range of processes that result in downward and outward movements of slope forming material composed of rock, soil and artificial materials” (Petley 2010). In this context, the term ‘mass movement’ might be desirable, but here the term landslide will be used as it is commonly used and better addresses the case of Nepal (Petley et al. 2007). The occurrence of landslides is influenced by factors such as steep slopes, geologic structure, and groundwater conditions and they are triggered by basal erosion, intense and prolonged rainfall, earthquakes, and melting of permafrost (Harvey 2012).

Being one of the most active mountain ranges in the world, frequent landslide activity can be expected in the Himalayan region. It is one of the primary geophysical activities which plays a leading role shaping landscape in both glaciated and non-glaciated mountain environments through a dynamic balance of erosion and uplift. Hence, all landslides should not be attributed to human activities or landslide risk be considered “socially constructed”. However, studies have identified that human activities are playing a significant role in mountainous region of Nepal to
generate landslides (Petley et al. 2007, Gerrard and Gardner 2002). Such human-induced landslides are of small-scale and do not get much attention at the national level. At the local level, primarily agricultural productivity is severely damaged which creates huge economic burdens for mountain populations. For example, every year landslides disrupt the Pritvhi highway, the only road connecting the capital city Kathmandu with the South. In August 2000, the road was disconnected for 11 days causing huge economic disruption in the Kathmandu valley.

The occurrence of landslides is not even throughout the country. The Tarai region, flat plains in the southern part of the country, has a very low occurrence of landslides as do the Mountain districts, whereas the Hill districts have the highest distribution of landslides. The occurrence of landslides in Nepal can possibly be explained by two reasons, the impact of deforestation and degradation, and second, development. Deforestation and degradation is generally considered one of the major contributors to landslide occurrence in mountain environments, especially in Nepal (Gerrard and Gardner 2002). The quest of development in the country has resulted in unplanned construction of mountain roads without proper investigation of water volume, soil properties, channel geometry, and other environmental factors. The “access” of mountain communities and “connectivity” to the markets is playing fundamental role for such an extensive expansion of road networks which is exerting significant pressure on a young and active Himalayan environment.

1.2.6 Problem statement

Nepal is one of the least developed countries in the world, with approximately one quarter of its population living below the poverty line (CBS 2014). Additionally, a decade-long
conflict from 1996-2006 further jeopardized Nepal’s economy and development activities. Social vulnerability has also escalated by emerging risks such as globalization and climate change in the Himalayan region. Consequently, the number of ‘at risk’ communities is increasing day by day. The Himalayan environment is strongly interconnected by upstream-downstream effects and hence hazards such as floods and landslides in upstream regions pose serious threats to downstream regions. The underlying risk of natural hazards has been further intensified by human factors arising from poverty, land use, infrastructure development, poor governance, and inadequate policies and policy implementation.

*The Natural Disaster Relief Act, 1982* is the first and principal guiding document to manage all natural hazards and disasters in Nepal. As this document is mainly focused on relief approaches, a new disaster management act was drafted in 2010 to include all components of disaster management (e.g. preparedness, mitigation, relief, reconstruction, recovery). However, this updated guiding document is still under consideration in the legislative assembly, which has been delayed due to ongoing political processes started in 2006 for transitioning from a centralized monarchy to federal governance. Lack of political willingness combined with inadequate manpower and a nominal budget allocated for disaster management have further exacerbated the situation. In the backdrop of these issues, it is important to examine the environmental, social, and economic implications of hazards at different levels: national, regional, and local. Further, there is a need to gather physical, scientific, as well as social data to assist in analyzing the different natural hazards, their inter-linkages, and their cumulative impacts. Based on the literature, the following major gaps/challenges have been identified in the domain of disaster management in Nepal. These gaps/challenges were considered in the formulation of relevant, context-specific research questions.
1) **Data unavailability/inaccessibility/patchiness**: There is no single dedicated institution to collect disaster-related information and data. Often, data are scattered, erratic, scanty, and of poor quality. Additionally, the data obtaining process is opaque. The majority of Nepal’s hydrological and meteorological stations were established as recently as the early 2000s.

2) **Reactive rather than proactive approach**: Disaster events have been treated as single events, usually on an ad-hoc basis. Furthermore, rescue and relief have been the central components without giving priority to preparedness activities that can significantly reduce losses to events in the first place.

3) **Structural vs. non-structural mitigation**: Structural measures are defined as “any physical construction to reduce or avoid possible impacts of hazards, or application of engineering techniques to achieve hazard resistance and resilience in structure or systems” whereas non-structural measures are defined as “any measure not involving physical construction that uses knowledge, practice or agreement to reduce risks and impacts, in particular through policies and laws, public awareness raising, training, and education” (UNISDR 2009, 28). Thus, structural measures include built-environment structures such as floodwalls, levees, and tornado shelters, while non-structural measures include building codes, zoning, and education campaigns. In Nepal, natural hazards are typically viewed in isolation and structural, technocratic measures are envisioned as the only solution. Mainly, floods are dealt with through this strategy whereas landslides, debris flow, avalanches, glacial lake outburst floods (GLOFs), and earthquakes are left as is. Despite the failure of structural measures to
control such hazards, government authorities continue to rely on them as their primary strategy. Because of the high cost and short lifetime of structural measures, and lack of financial and human resources in the country, non-structural measures may serve the Himalayan region better. In addition, non-structural measures have low environmental impacts and high sustainability due to involvement of local resources and local communities at risk. Ultimately, a combination of structural and non-structural measures represents the best approach, but in this case the nonstructural measures are largely absent.

4) **Single hazard approach:** In Nepal, disaster risk reduction (DRR) activities are focused on single hazards. Hazards are perceived as isolated natural processes and their cascading effects are completely neglected. As a result, the preparedness and mitigation efforts are deficient. Sometimes one hazard event triggers another hazard which amplifies risk in the vicinity and downstream region. The recent experiences of large landslides causing flooding downstream, and the occurrence of medium and shallow landslides on highways after earthquakes clearly show the need for a more holistic approach. Thus, a multi-hazard approach should be taken to understand the overall risk of an area and devise relevant programs and policies. In addition, it also helps to reduce the risk from cascading effects of multiple natural hazards.

5) **Lack of involvement of local people and their knowledge in the DRR process:** While instituting DRR programs and policies, local people are rarely involved. There is scarce representation of vulnerable communities and their know-how in DRR activities. In addition,
they are not commonly used by scientists, practitioners and policymakers although local knowledge and practices are identified as crucial in DRR (Hiwasaki, Luna, and Shaw 2014).

6) **Inadequate consideration of social vulnerability:** Thus far, studies focus on physical vulnerability. Most researchers focus on physical processes, but human interactions with these natural processes are largely ignored. The concept of social vulnerability acknowledges that sensitive populations may be less likely to respond to, cope with, and recover from natural disasters (Cutter and Finch 2008). This perspective is missing in disaster research, programs and policies. The identification of socially vulnerable regions and populations is a critical element for emergency preparedness, immediate response, mitigation planning, and long-term recovery from disaster. Hence, the major factors of social vulnerability (e.g., lack of access to resources, limited political power and representation, low social capital and networks, beliefs and customs, and physically limited individuals (Cutter, Boruff, and Shirley 2003) should be incorporated in Nepal to arrive at an integrated approach.

7) **Inadequate human, economic, and government resources:** The concerned authorities lack trained manpower and their work is constrained by low staffing and an inadequate budget allocation. Most staffs have no relevant background and have additional responsibilities beyond disaster management. Furthermore, staff turnover is high; staff often serves for a very short period, sometimes less than a year. The rapid through-flow of staff affects employee motivation, human capital, and institutional memory, which creates constant challenges to coordinate disaster preparedness activities. This context is further complicated by a scarcity of resources, funding and overall capacity.
8) **Political transition**: The constitution writing process completed in 2015 started in 2006 after the end of active monarchy and a decade long armed conflict. The writing process has delayed many programs, in particular the promulgation of the draft Disaster Management Act. Although the constitution is completed, the demarcation of federal boundaries and allocation of ethnic rights at the province level are making the execution of the document very difficult. The debate surrounding the structure of the federal government in a newly forming constitution has considerably impeded DRR programs and policies.

9) **Remoteness/isolation**: The rugged topography and altitudinal variation have isolated many villages from the central government. This not only constrains local people to access the resources and government facilities, but also limits the number of researchers and government authorities to implement DRR infrastructure in areas of great need.

### 1.3 Statement of purpose, significance, and dissertation outline

**1.3.1 Statement of purpose and significance of research**

This dissertation research evaluates the combination of multiple hazards vulnerability and risk in the Nepal Himalaya. Further, this research assesses the confluence of disasters and vulnerability at spatial different scales, which will contribute to the overall understanding of natural hazard risk and help to formulate more disaster resilient policies. This work considers three comprehensive research questions, each leading to three different objectives of the dissertation project.
• **Research Question 1:** *How is natural hazard mortality distributed across the country of Nepal, and can any patterns be discerned?*

• **Research Question 2:** *Can an index of vulnerability from the United States setting be applied to Nepal, and what would such an instrument look like?*

• **Research Question 3:** *Using the city of Dharan, Nepal as a case study, how can geospatial technologies be used to inform multi-hazard risk in a data scarce environment?*

The objective of the first research question is to better understand spatial and temporal patterns of mortality from natural disasters in Nepal. The second question results in the quantification of social vulnerability to natural hazards using a modified, contextualized social vulnerability index (SoVI). Finally, the third question, with the assistance of geospatial techniques, computes cumulative risk to multiple natural hazards. Given the three research questions, key outcomes of this study are to:

1) Identify spatial dimensions of mortality and social vulnerability

2) Identify a strategy for developing a geospatial model to measure multi-hazard risk, and

3) Contribute to disaster studies.

### 1.3.2 Structure of the dissertation

The dissertation is organized in five chapters: Chapter 1 provides a review of the literature pertinent to hazard, vulnerability, risk, and geospatial analyses. Gaps in these analyses are identified. Chapter 2 delves into spatial and temporal patterns of fatalities at the village level due to various natural hazards across the country. Chapter 3 focuses on the evaluation of social
vulnerability. Here I present an index to identify the major social processes and factors contributing to social vulnerability. Chapter 4 details a geospatial model created to assess multiple hazard risk in data-scarce regions. Additionally, work presented in this chapter assimilates qualitative data to enhance the understanding of the risk posed by different hazard in a specific location. Chapter 5 provides the overall conclusions reached as a result of the previously mentioned research. It also identifies research obstacles and limitations of this work, and includes future avenues for research.

1.4 Data sources

Data required to conduct this study are outlined in Table 1. Physical as well as social data were collected from publicly available sources, secondary sources, and field investigations.

Table 1: Data required and source

<table>
<thead>
<tr>
<th>DATA</th>
<th>SOURCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data and sources for physical analysis</td>
<td></td>
</tr>
<tr>
<td>Aspect</td>
<td>ASTER</td>
</tr>
<tr>
<td>Elevation</td>
<td>ASTER</td>
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<tr>
<td>Geology</td>
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<tr>
<td>High resolution satellite images</td>
<td>DigitalGlobe Foundation</td>
</tr>
<tr>
<td>Land use land cover</td>
<td>ICIMOD</td>
</tr>
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<tr>
<td>Slope</td>
<td>ASTER</td>
</tr>
<tr>
<td>Soil</td>
<td>Department of Mines &amp; Geology, GoN</td>
</tr>
<tr>
<td>------</td>
<td>-----------------------------------</td>
</tr>
</tbody>
</table>

**Data and source for social analysis**

<table>
<thead>
<tr>
<th>Mortality</th>
<th>DesInventar database</th>
</tr>
</thead>
<tbody>
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<td>CBS, GoN</td>
</tr>
<tr>
<td>Employment</td>
<td>CBS, GoN</td>
</tr>
<tr>
<td>Gender</td>
<td>CBS, GoN</td>
</tr>
<tr>
<td>Age</td>
<td>CBS, GoN</td>
</tr>
<tr>
<td>Rural/Urban</td>
<td>CBS, GoN</td>
</tr>
<tr>
<td>Education</td>
<td>CBS, GoN</td>
</tr>
<tr>
<td>Trade</td>
<td>CBS, GoN</td>
</tr>
<tr>
<td>Other socio-economic variables</td>
<td>Field collection</td>
</tr>
</tbody>
</table>

**ASTER** = *Advanced Spaceborne Thermal Emission and Reflection Radiometer*

**CBS** = *Central Bureau of Statistics*

**GoN** = *Government of Nepal*

**ICIMOD** = *International Centre for Integrated Mountain Development*
References


Gencer, Ebru A. 2013. "Natural disasters, urban vulnerability, and risk management: a theoretical overview." In The interplay between urban development, vulnerability, and risk management, 7-43. Springer.


*Proceedings of the national academy of sciences* 100 (14):8074-8079.


Chapter 2. Spatial patterns of natural disaster mortality in Nepal

2.1 Introduction

This chapter analyzes temporal and spatial patterns of fatalities due to natural hazards in Nepal at the village level using a publicly available disaster database. The objective is to examine which patterns, if any, exist as well as to compute which hazard contributed most to fatalities from 1971-2011. To achieve the objectives, mortality records from DesInventar database from 1971-2011 were extracted, aggregated, and georeferenced.

2.2 Publication

The manuscript related to this chapter was published in Environmental Hazards journal and can be found in the Appendix 1.

3.1 Introduction

This chapter quantifies social vulnerability to natural hazards at the village level using a modified Social Vulnerability Index (SoVI). SoVI is a method developed by Cutter, Boruff, and Shirley in 2003 for the US context. This method is adapted to Nepali context, and 39 variables are used to assess factors that contribute to vulnerability, their spatial distribution, and clustering patterns across the country.

3.2 Manuscript

Appendix 2 contains the draft of the original manuscript submitted to an academic journal for review on 26 January 2018.

References

Chapter 4. Multi-hazard risk assessment using geospatial techniques

4.1 Introduction

This chapter models cumulative risk to floods, landslides, and earthquakes in Dharan, Nepal, using geospatial techniques. Since any given geographical location is exposed to multiple natural hazards, a single hazard risk assessment either overestimates or underestimates natural hazard risk. Furthermore, developing countries such as Nepal are often constrained by limited financial and human resources, and in many cases such scenarios are exacerbated by a lack of robust data to model the total risk of a place. Research findings have potential to inform local officers, planners, and disaster risk reduction practitioners on how to more effectively to deploy disaster risk reduction programs, policies, and resources.

4.2 Manuscript

The draft of the manuscript for this analysis is found in the Appendix 3. It is currently being revised for submission to a peer reviewed journal.

Chapter 5. Conclusions

Understanding physical processes of natural hazards in combination with social processes is required to develop a comprehensive picture of risk in a geographic location. Furthermore, the integration of spatial components enhances this approach and can provide place-based insight on disaster planning, resource allocation, and the provision of humanitarian assistance in times of emergency. Using Nepal as a case study, this dissertation broadly aimed to: (1) understand the spatial and temporal distribution of natural hazards; (2) assess the contribution of social factors and processes to social vulnerability; and (3) model multi-hazard risk of a specific geographic location. The dissertation research resulted in several findings that are useful to disaster researchers and practitioners, particularly in Nepal.

First, this dissertation quantified social vulnerability at the village level and demonstrated its spatial distribution and clustering throughout the country. This research not only advanced the SoVI methodology and represents the first-of-its-kind in Nepal, but it also provides much-needed insight on social aspects of vulnerability, which are currently absent in Nepal’s disaster planning. This work has potential to draw attention to social vulnerability in Nepal and forms a benchmark study for future analyses of social vulnerability in Nepal and similar contexts that demand a modified SoVI approach.

Second, thus far risk assessment in Nepal focuses on a single natural hazard type, which often results in the over or underestimation of risk to populations residing in a particular geographic location. This dissertation work leverages a multi-hazard risk assessment approach and proposes a methodological framework using geospatial techniques. Multi-hazard approaches are emerging in risk assessment, and this research contributes to the literature by providing a case study in which geospatial techniques can be used to quantify cumulative risk in a place.
This methodological framework can be replicated in other parts of the world, especially in lesser-developed countries that are constrained by data availability.

Third, this research emphasizes the importance of non-structural mitigation in disaster preparedness programs and policies. The dominant approach of mitigating natural hazards through structural means fails to address the complex, underlying social phenomena that often combine to create a disaster. Furthermore, such infrastructure-based approaches may actually aggravate physical and social systems, serving to increase the vulnerability and risk of already susceptible communities. This dissertation provides strong evidences that there are several benefits to understanding and addressing both physical and social dimensions of disasters.

Lastly, this dissertation advances knowledge on natural hazards, vulnerability, risk, and disasters in Nepal by providing empirical assessments on these topics. Disaster-related studies in Nepal are scattered across the development sector and many are not published or available to the general public. This research fills the gap by providing a comprehensive, publicly available study for future discussion among scholars, government officials, nonprofits, and the public.
Appendix – Publications related to this Research
Spatial and temporal analysis of natural hazard mortality in Nepal


Department of Geography, Virginia Tech, Blacksburg, VA, USA; Department of Geography and Virginia Water Resources Research Center, Virginia Tech, Blacksburg, VA, USA

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 < 0.001) and village (0.256, p < 0.001) 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 policymakers, planners, and local officers to more efficiently allocate scarce capital and human resources to reduce mortality.

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, & Huyot, 2004), a several fold increase since the 1950s (De Haen & Hemrich, 2007). Though the linear-temporal approach provides insight on disaster losses over
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 (Comfor 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.](image)
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 lesserdeveloped 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 disproportionately (Osti, Tanaka, & Tokioka, 2008). While a

<table>
<thead>
<tr>
<th>Hazard type</th>
<th>Vulnerable areas</th>
<th>Total mortality</th>
<th>Percent total mortality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landslide</td>
<td>Mid-mountain, mid-hills, Siwalik, and valleys</td>
<td>3302</td>
<td>41.91</td>
</tr>
<tr>
<td>Flood</td>
<td>Terai, mid-hills, and valleys</td>
<td>2502</td>
<td>32.52</td>
</tr>
<tr>
<td>Thunderstorm</td>
<td>Entire country</td>
<td>913</td>
<td>11.69</td>
</tr>
<tr>
<td>Cold wave</td>
<td>Mid-mountain and mid-hills</td>
<td>542</td>
<td>6.88</td>
</tr>
<tr>
<td>Strong wind</td>
<td>Mostly Terai regions</td>
<td>143</td>
<td>1.82</td>
</tr>
<tr>
<td>Avalanche</td>
<td>Mid-mountain and Himalaya</td>
<td>80</td>
<td>1.01</td>
</tr>
<tr>
<td>Snowstorm</td>
<td>Mid-mountain and Himalaya</td>
<td>69</td>
<td>0.88</td>
</tr>
<tr>
<td>Forest fire</td>
<td>Mid-hills and Terai (forest belt at foot of Siwalik)</td>
<td>61</td>
<td>0.77</td>
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<tr>
<td>Earthquake</td>
<td>Entire country</td>
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<td>Rain</td>
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<td>Storm</td>
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<tr>
<td>Heat wave</td>
<td>Terai</td>
<td>30</td>
<td>0.38</td>
</tr>
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</table>

*Source: Desiventar 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 8,519 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 9,000 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 Deshventar 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 (Velas-
quez, 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 rela-
tively 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 com-
prehensive 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 com-
pared 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 classifi-
cations. 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
Society for Earthquake Technology-Nepal (NSET), a well-known nongovernmental organi-
ization based in Kathmandu, consistently updates the database. In addition to disaggrega-
tion 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 DesIn-
ventar 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 facili-
tate 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, earth-
quake, 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.
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 DesInventar 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 mortalities 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 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 Udayapur 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.

**ORCID**

Sanam K. Aksha  http://orcid.org/0000-0003-4824-0882
Luke Juran  http://orcid.org/0000-0002-5313-2694
Lynn Resler  http://orcid.org/0000-0002-5135-1797

**References**


Appendix 2. Social vulnerability manuscript submitted to IJDRS
An analysis of social vulnerability to natural hazards in Nepal using a modified Social Vulnerability Index

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An analysis of social vulnerability to natural hazards in Nepal using a modified Social Vulnerability Index

Abstract

Social vulnerability influences the ability to prepare for, respond to, and recover from disasters. The identification of vulnerable populations and factors that contribute to their vulnerability are crucial for effective disaster risk reduction. Nepal exhibits multihazard risk and has experienced socioeconomic and political upheaval in recent decades, further increasing susceptibility to hazards. However, we still know little regarding social vulnerability in Nepal. Here, we investigate social vulnerability in Nepal by adapting Social Vulnerability Index (SoVI) methods to the Nepali context. For example, variables such as caste and populations who cannot speak/understand Nepali were added to reflect the essence of the Nepali context. Using principal component analysis, 39 variables were reduced to seven factors that explained 63.02% of variance in the data. Factor scores were summarized to calculate final SoVI scores. The highest levels of social vulnerability are concentrated in the central and western Mountain, western Hills, and central and eastern Tarai regions of Nepal, while the least vulnerable areas are in the central and eastern Hills. These findings, which are supplemented with smaller scale analyses, have potential to assist local officers, policy makers, and emergency managers in the development of more effective and geographically targeted disaster management programs.

Keywords: Social Vulnerability Index, Nepal, Natural hazards, Disasters, PCA, Disaster risk reduction

https://mc03.manuscriptcentral.com/jdrs
1. Introduction

The frequency and intensity of disasters are increasing globally (de Haen and Henrich 2007, CRED 2015, Huggel et al. 2015). This escalation parallels increases in human-environment interaction and in the number of people and value of assets exposed to hazards. Vulnerability measurement and assessment are recognized as key components for reducing losses from disasters and facilitating a culture of disaster resilience (Birkmann 2006b, Cutter and Finch 2008, Montz and Tobin 2011).

Vulnerability has been applied in various fields, such as disaster studies, sustainable development, urban growth, gender studies, and climate change, to better understand susceptibility to stresses and shocks originating in environmental and social change. Interpretations of vulnerability depend on disciplinary perspective and context. For example, physical scientists tend to conceptualize vulnerability in terms of the likelihood of occurrence of a specific process and associated impacts on the built environment (Papatheo-Kohle et al. 2011, Fuchs, Birkmann, and Glaed 2012). On the other hand, social scientists tend to situate vulnerability as a set of social, economic, and demographic factors that coalesce to determine people’s ability to cope with stressors (Wisner et al. 2004, Juran and Trivedi 2015). In reality, the biophysical environment interacts with social attributes and systems to reveal vulnerability, meaning that vulnerability is socially constructed. Vulnerability ultimately manifests in stratification and unequal impacts among different groups of people across space. Consequently, vulnerability reduction requires knowledge of the factors that influence vulnerability coupled with a holistic understanding of the social, economic, and political contexts in which they operate (Hewitt 1997, Cutter, Boruff, and Shirley 2003, Wisner et al. 2004).
Much vulnerability research relies on qualitative assessments (Laska and Morrow 2006, Few and Pham 2010, Mallick, Rahaman, and Vogt 2011), but there is growing interest in measuring vulnerability empirically (Armas 2008, Myers, Slack, and Singelmann 2008, de Oliveira Mendes 2009), especially social vulnerability. Among the most recognized methods is the Social Vulnerability Index (SoVI). Developed by Cutter, Boruff, and Shirley (2003), the SoVI framework uses place-based indicators in order to quantify and identify the biggest drivers of social vulnerability. The SoVI has undergone continuous evolution given deeper understandings of the nature and drivers of vulnerability (Cutter and Morath 2014), and it has been applied in various geographical and social contexts, such as Africa (Letsie and Grab 2015), Asia (Zhou et al. 2014), Caribbean Islands (Boruff and Cutter 2007), Europe (Holand and Lujala 2013), and Latin America (Hummell, Cutter, and Emrich 2016).

Quantitative assessments of social vulnerability in Nepal are scarce due to the availability of social data for analysis and mapping. Thus, previous studies on vulnerability in Nepal have focused on either a specific physiographic region of Nepal (TU-CDES 2016) or a single hazard type, such as floods (Dixit 2003, Dixit et al. 2007, Devkota et al. 2013), landslides (Sudmeier-Rieux et al. 2012), earthquakes (Dixit et al. 2013, Dixit 2014), or severe weather events (Shrestha 2005). Furthermore, these studies fail to explicitly quantify social vulnerability. A recent study Mainali and Pricope (2017) used social data in combination with high-resolution images to investigate vulnerability to climate change in Nepal. This study is valuable because it uncovers spatial variations of vulnerability across the country. However, the study does not consider social, economic, and demographic variables (e.g., unemployment and elderly, children, and minority populations), which would add much needed social dimensions of vulnerability to the study. Meanwhile, the Ministry of Environment of the Government of Nepal (2010), in a
district level analysis of vulnerability to climate change, recommends a scale-dependent approach that focuses on the local level (i.e., villages and municipalities). The argument is that such analyses reveal finer-scale dynamics of vulnerability that may be concealed at larger scales. Thus, there exists a need for the quantification of social vulnerability across the entire country of Nepal at the local level.

To address this research gap, we deploy a modified SoVI to quantify social vulnerability to natural hazards in Nepal at the village and municipal level. The specific research questions are: (1) who are the most vulnerable populations in Nepal? and (2) where do they live? The objectives are to: (1) quantify social vulnerability at the village and municipal levels using indicators relevant to the Nepali context, and (2) assess spatial dynamics of social vulnerability in Nepal. This study contributes a SoVI index to the country of Nepal for the first time. Furthermore, the SoVI, which is applied at the local level across the entire country, provides statistical and spatial findings that have the potential to improve disaster preparedness in Nepal.

2. The Nepali context

2.1 Socioeconomic context

Social, economic, and demographic attributes of Nepal, which intersect with geophysical and hydrometeorological processes, reflect directly on social vulnerability of the country. The status of such attributes is rooted in a sluggish development process. Official development activities began only after 1950 when democracy was achieved by overthrowing a century-long rule of the Rana family. At the time, Nepal lacked systems for civil service, national accounting, and recordkeeping of vital statistics (Devkota 2007). Then, the 1960 coup introduced the party-
less Panchayat system, which stalled development for three decades until democracy was re-established in 1990. Nepal finally adopted a multiparty democratic system. As a result, development activities began to reach beyond the ruling elites and urban areas, neoliberal approaches were adopted, and non-governmental organizations (NGOs) and foreign aid began to enter the country. However, the pace of development was obstructed by numerous bouts of political unrest, including a ten-year Maoist insurgency from 1996-2006; appropriation of power by the Monarchy afterwards; the People’s Movement of 2006; abolition of the Monarchy in 2007; and a political impasse from 2008-2015 due to a delayed constitution-making process.

The socioeconomic situation of Nepal is further problematized by a lack of infrastructure, energy, government accountability, and financial resources. As a result, Nepal is struggling to escape the poverty trap and remains one of the least developed countries, ranking 144th in a recent Human Development Index (HDI) report (UNDP 2016). According to the latest census of 2011, Nepal’s population of 26.5 million has been growing steadily at greater than 2% and stands close to triple its 1961 population of 9.5 million (CBS 2014). The total adult literacy rate is 59.6% with a female literacy rate of just 48.8%. Nepal is predominantly an agrarian society with roughly 60% of the population dependent on subsistence agriculture. The majority of land is not arable due to steep slopes and rocky soils characteristic of the mountainous region, and agriculture is highly monsoon-dependent. Poverty has compelled many to emigrate to neighboring countries and the Middle East in search of employment, which provides much needed remittances. The recent census reports that one in every four households (25.4%) have at least one member living outside of Nepal, and the greatest proportion of absentee population (44.8%) is among the economically productive 15-24 year cohort (CBS 2014). Most migrants are male and, thus, female-headed households have increased from 14.9% in 2001 to 25.7% in 2011.
Nepal exhibits great demographic diversity, which ultimately influences social vulnerability. Hinduism is followed by greater than 80% of the population (Buddhism and Islam are other common religions), but is comprised of many castes and sub-castes. Furthermore, the latest census also accounts for 125 ethnic groups and 123 languages across the relatively small country (CBS 2014), and these demographics are geographically clustered. Only a few ethnic and caste groups are dispersed throughout the country—in fact, modern day Nepal was formed in the 18th century by unifying numerous small principalities that were primarily based on caste, ethnicity, and language. Some of these social markers, specifically the caste system, lead to discrimination and social exclusion, especially in rural areas. Thus, the concentration of demographic features in space may be revealed through spatial patterns of social vulnerability.

Adding to the socioeconomic and demographic contexts is risk to a multitude of hazards—such as earthquakes, floods, landslides, thunderstorms, debris flow, avalanche, glacial lake outburst floods (GLOFs), and forest fires—and these hazards are distributed unevenly throughout the country (Aksha, Juran, and Resler 2017). The 2015 Gorkha earthquake alone killed about 9,000 and damaged or destroyed more than 750,000 buildings. A majority of the losses occurred in rural areas where low quality, traditional masonry is the predominant housing material. Due to competition for resources (e.g., jobs and land that is accessible, arable, and easily developable), people are pushed to high-risk areas (Aryal 2014).

2.2 Physical context

Nepal is situated in the Himalayan range between India and China. Elevation ranges from just 57 masl to the world’s highest peak of Mt. Everest at 8,848 masl in a relatively small latitudinal extent. Nepal is divided into three ecological regions: Tarai, Hill, and Mountain.
(Figure 1). The Tarai region is the southernmost part of Nepal. This ‘grain basket’ of the country has relatively low, flat, and fertile land comprised of alluvial soils. The Tarai covers roughly 24% of the total area of Nepal, but contains roughly 50% of the population. The Hill region rises from 1,000-4,000 masl and comprises about 42% of the Nepal’s total area. The Hill region is the first orographic barrier to monsoon winds, which produce heavy precipitation on its southern flanks. The increasingly urbanized Kathmandu and Pokhara valleys lie in this region. Further north of the Hill lies the Mountain region, which covers about 34% of the total land area of Nepal. The Mountain region has sub-alpine to alpine climates and is characterized by river valleys, tectonic basins, snow-capped peaks, glaciers, rocky slopes, and colluvial deposits. This region is sparsely populated.

2.3 Political context

For administrative purpose, Nepal was divided into five development regions, 14 zones, 75 districts, 53 municipalities, and 3,918 village development committees (VDCs). However, in 2015, a new constitution was adopted that created three levels of governance: the federation, the province, and local bodies. Now, Nepal is divided into seven provinces and 744 various local bodies (including four metropolitan cities, 13 sub-metropolitan cities, 246 municipalities, and 481 rural municipalities), although administration through these bodies has not yet commenced. This study is based on the previous administrative bodies (i.e., 3,918 VDCs and 53 municipalities). The previous bodies were chosen because the scale is smaller (total of 3,971 spatial compared to just 744), which allows statistical and spatial analyses to produce finer results. Further, the new administrative bodies were formed by simply combining groups of the previous bodies, so the new administrative bodies are still captured in our analyses, but at a finer...
scale. Ultimately, use of the previous bodies supports analyses across more observations and more spatial units while still being administratively relevant. Finer scale analyses are especially important in the Nepali context, which exhibits great socioeconomic, cultural, and physiographic diversity across short expanses of space.

3. Materials and methods

3.1 Data and SoVI modification

This study adopts the SoVI method developed by Cutter, Boruff, and Shirley (2003), which employed more than 200 variables to quantify and analyze social vulnerability in the United States. Conceptualizations of social vulnerability and the SoVI methodology have been refined over time and applied in several contexts (see Boruff and Cutter 2007, Holand and Lujala 2013, Zhou et al. 2014, Hummell, Cutter and Emrich 2016). Similarly, this study analyzes individual factors such as education, employment, ethnicity, and health as well as community characteristics such as level of urbanization, access to medical services, and built environment attributes to construct an original SoVI for Nepal.

Since the original SoVI was applied to the United States context, modifications were necessary to adapt the model to Nepal’s distinct sociophysical context. To construct the modified SoVI, we extracted data from the full dataset of the most recent 2011 census, which was provided by the Central Bureau of Statistics (CBS), Government of Nepal. CBS conducted the census using two household level questionnaires. The first questionnaire collected basic demographic data, and the second questionnaire included more detailed questions on topics such as migration, fertility, and economic activity. A systematic sampling method was adopted and
roughly 15% of the entire population of Nepal were sampled. Using all available data from this most recent census, Table 1 provides a list of concepts and variables used to construct the SoVI.

Modifications to the original SoVI were made to capture fundamental demographic differences between Nepal and the United States. For example, the original SoVI includes a race and ethnicity variable comprising the percentage of African American, Native American, Asian, and Hispanic populations. However, demographics are different in Nepal. To capture ‘Ethnicity,’ we included Dalit (the lowest strata of the Hindu caste system) and Minority Populations. Dalits are considered ‘untouchable’ and confront systemic social and economic oppression. About 15.6% of the total population are Dalits, and there are 26 distinct, concentrated Dalit groups distributed heterogeneously throughout Nepal—each with a different language, culture, religious practices, and means of employment (Dahal et al. 2002). Minority Populations encompasses indigenous populations and other historically disadvantaged groups. Indigenous populations in Nepal are defined as people who possess distinct cultural traditions, languages, and religious faiths based on animism (Bhattachan 2008). Fifty-nine separate groups are considered Minority Populations, and they are further divided into five categories based on their status: endangered, highly marginalized, marginalized, disadvantaged, and advanced. The advanced category, which consists of the Newar and Thakali castes, actually have the highest HDI values (Sharma, Guha-Khasnobis, and Khanal 2014) and were thus excluded from Minority Population status in our SoVI. However, Muslims and Sikhs/Punjabis were included since they are considered disadvantaged groups that together account for less than 5% of Nepal’s total population.

We also included ‘Built Environment’ variables to reflect physical attributes of housing and public services such as electricity, water, and sewer infrastructures, as similarly included in a SoVI in Brazil by Hummell, Cutter, and Emrich (2016). According to the 2011 census, 25% of
houses have external walls constructed from low quality materials such as bamboo and wood, and only 10% of houses have Reinforced Cement Concrete (RCC) foundations. As the entirety of Nepal lies in a highly active seismic belt, housing foundations and wall materials significantly impact vulnerability. For example, many fatalities from the 2015 Gorkha earthquake were among people residing in low quality houses. Furthermore, severe damages were sustained to traditional mud and stone houses, especially in rural areas. In addition to housing quality, only 52% of households are connected to a piped water supply, only 39% have a toilet or latrine, and 33% are without electricity as their primary source of energy.

Populations who do not speak/understand Nepali were added to the ‘Special Needs Populations’ indicator because inability to speak or understand Nepali substantially restricts access to critical and timely knowledge on disaster warnings as well as post-disaster recovery and rehabilitation programs. In the census questionnaire, individuals were asked to report their mother tongue and second language. Those who did not report Nepali were identified as individuals who do not speak/understand the Nepali language. Knowing the most widely spoken language is important because it is used extensively for basic communication and relaying information on disasters. Furthermore, such populations confront linguistic issues (e.g., completing and submitting official forms) when attempting to receive compensation and other support from the government. In fact, although Nepali is no longer the official national language, it is the only language used for administrative and government communications, which constitutes a major disadvantage for non-speakers, especially in emergency situations.
3.2 Methods

A total of 39 variables were selected for construction of the modified SoVI (Table 1). All variables were normalized using percentage, density, or per capita functions prior to statistical analysis. Principal component analysis (PCA) via Statistical Package for the Social Sciences (SPSS) version 21.0 software generated a set of independent factors. PCA is a factor reduction methodology that identifies a smaller number of components to explain the variance observed in a larger dataset (Abdi and Williams 2010). The purpose of performing PCA is to distill a broad explanation of the data by grouping like-variables into components that adequately account for covariation among the larger number of analysis variables. PCA also facilitates the interpretation of component groups and provides insight when data are examined with further analyses. Following methods developed by Cutter, Boruff, and Shirley (2003), Kaiser Normalization and Varimax rotation were employed as extraction methods for components. Only components with eigenvalues higher than 1.0 were extracted and named to indicate the latent variables. Each component was named and assigned cardinality (±). Next, the index was calculated by adding the scores of each component to arrive at total SoVI scores. An equal weighting and additive approach was used in the absence of empirical and justifiable evidence for weighting components differently, as has been exercised in similar studies (e.g., Cutter, Boruff, and Shirley 2003, Humnall, Cutter, and Emrich 2016). Our modified SoVI for Nepal is calculated for each spatial unit (i.e., 3,918 VDCs and 53 municipalities) by adding the principal components, as shown below and as detailed in Table 2 of the results section:

$$SoVI_{allage} = PC1 + PC2 - PC3 + PC4 + PC5 + PC6 - PC7$$
SoVI scores of each spatial unit were mapped using ArcMap version 10.3 to visualize the most and the least vulnerable villages in Nepal based on standard deviation from the mean value. Further, we used global and local Moran’s I tests of spatial autocorrelation to investigate whether social vulnerability is clustered or random across space in statistical terms. Global and local tests calculate autocorrelation among all villages and determine statistically significant patterns of similarity and dissimilarity in the spatial location and distribution of social vulnerability. Global Moran’s I determines whether the geolocations of index results exhibit a spatial pattern. The interpretation is similar to that of correlation coefficients: values close to +1 indicate strong positive spatial autocorrelation (i.e., clustering of either high or low values of social vulnerability), while values close to -1 indicate strong negative spatial autocorrelation (i.e., alternation of high and low values for adjacent observations). Values near zero indicate the absence of spatial patterns, or randomness. Next, local Moran’s I was deployed to classify identified clusters according to type of association. These results were used to map four typological gradations of social vulnerability at the village and municipal level: (1) ‘High-High’ (HH), a village with a high SoVI score surrounded by villages with high SoVI scores; (2) ‘Low-Low’ (LL), a village with a low SoVI score surrounded by villages with low SoVI scores; (3) ‘High-Low’ (HL), a village with a high SoVI score surrounded by villages with low SoVI scores; and (4) ‘Low-High’ (LH), a village with a low SoVI score surrounded by villages with high SoVI scores. HH (i.e., ‘hot spots’) and LL (i.e., ‘cold spots’) denote positive spatial autocorrelation, indicating clusters of similar values, whereas the LH and HL denote negative spatial autocorrelation, indicating clusters of dissimilar values. Together, global and local spatial analyses identify patterns of social vulnerability that are either not visible (i.e., masked) or appear visually meaningful yet are not statistically significant (i.e., ‘false positives’).
4. Results

PCA uncovered seven components with eigenvalues greater than 1.0. Based on loaded variables and their cardinality, the seven components were named ‘Renters and Occupation’, ‘Poverty and Poor Infrastructure’, ‘Favorable Social Conditions’, ‘Migration and Gender’, ‘Ethnicity’, ‘Medical Services’, and ‘Education’. In total, the principal components explain 63.02% of the variance of the data. Descriptions of the seven components, signs denoting their effect on social vulnerability, and loadings are presented in Table 2.

Total SoVI scores were calculated by summing all seven principal components based on their cardinality, and the mean and standard deviation (SD) of scores were also calculated. Based on SD values, vulnerability scores were grouped into five quintiles from most (>1.5 SD) to least (≤-1.5 SD) vulnerable. Using ArcMap, we subsequently mapped total SoVI scores (Figure 2) and the value of each component to visualize social vulnerability across Nepal (Figure 3). Total SoVI scores (Figure 2) reveal that the most socially vulnerable villages are located in the eastern and central Tarai; western Hill; and central and western Mountain regions. Conversely, the least vulnerable villages are located in eastern and central Hill region. The capital city of Kathmandu is also highly vulnerable. In terms of districts, the Hill districts of Achham, Doti, Dailekh, Jajarkot, Rukum, and Rolpa; Mountain districts Humla, Mugu, Jumla, Kalikot, Dolpa, Mustang, and Manag; and Tarai districts of Morang, Sunsari, Saptari, Siraha, Mahottari, and Bara contain a predominant number of villages and municipalities with high social vulnerability.

Alternatively, the eastern Hill districts of Ilam, Panchthar, Terhathum, Dhankuta, and Bhojpur contain a majority of the villages and municipalities with low SoVI scores.

The geographic distribution of each principal component is displayed in Figure 3. Highly vulnerable areas for the Renters and Occupation component are concentrated in urban centers,
particularly in Kathmandu and the Mountain region. Vulnerability for Poverty and Poor Infrastructure is concentrated in the Tarai region. For example, almost every village and municipality in the Tarai districts of Morang, Sunsari, Saptari, Siraha, Dhanusa, Mahottari, Sarlahi, Rautahat, Bara, Parsa, Rupandehi, and Kapilbastu exhibit high vulnerability in terms of Poverty and Poor Infrastructure. The third component, Favorable Social Conditions, exhibits greater levels of vulnerability across the entire Tarai as well as pockets of the eastern and central Hill region. Relatively vulnerable areas for Migration and Gender, the fourth component, are distributed across the entire Tarai and Hill regions with a distinct concentration in the geographic center of Nepal. The highest levels of social vulnerability for component five, Ethnicity, are located in the western part of all regions of Nepal, as well as the eastern Tarai. The Medical Services component reveals relatively high vulnerability in the Mountain region, with vulnerability decreasing with elevation. The final component, Education, reveals higher vulnerability in central and eastern Nepal—especially the eastern Tarai—with pockets of the western Mountain region also revealing high levels of social vulnerability.

To test for clustering, we calculated global Moran’s I statistics of SoVI scores in an ArcMap environment. We used the polygon contiguity concept to specify spatial relationships among villages and municipalities, which defines neighboring villages as those that share a boundary. The global Moran’s I test positively confirmed positive spatial autocorrelation with a value of 0.41 (p < 0.001) and z-score of 44.13. Next, we employed a local’s Moran’s I test to decompose global statistics into local clusters and identify pockets of association in terms of high and low values (Figure 4). Results indicate that HH clusters are present in the western Hill and Mountain regions, although there are smaller, isolated pockets in the eastern Tarai. Clusters of LL values were detected in eastern and central parts of the Hill and Mountain regions.
5. Discussion

The objective of this study was to quantify social vulnerability at the local level of Nepal using indicators relevant to Nepal’s distinct social and physical landscapes. Following Cutter, Boruff, and Shirley’s (2003) SoVI methodology, we derived seven components via PCA that contribute to social vulnerability in Nepal. The seven significant components explain 63.02% of the variance (in descending order): Renters and Occupation, Poverty and Poor Infrastructure, Favorable Social Conditions, Migration and Gender, Ethnicity, Medical Services, and Education (Table 2). Individual component and total SoVI scores are not evenly distributed across Nepal. Thus, clustering is evident (Figure 4) with relatively high levels of social vulnerability in the western Hill, western and central Mountain, and central and eastern Tarai ecological regions (Figures 2 and 4), and relatively low social vulnerability was detected in the eastern and central Hill region.

A major finding of this study is that areas with similar hydrometeorological and geophysical characteristics may exhibit differences in social vulnerability. Marked differences are observed in the spatial distribution of social vulnerability among the three ecological regions. The central and western Mountain, western Hill, and central and eastern Tarai regions exhibit relatively higher social vulnerability, while the central and eastern Hill region reveals comparatively less vulnerability. This finding is interesting because elevation, natural hazard risk, and geophysical and hydrometeorological regimes are similar within each ecological region, but social vulnerability is not. Thus, while populations residing within each region are subjected to similar natural environments (and thus exhibit similar exposure to the same natural hazards), findings suggest that social, economic, and built environment attributes make the places different, which in turn influences levels of social vulnerability. A majority of villages and

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municipalities in the central and eastern Tarai, which contain a disproportionate amount of the population, are categorized in the High and Medium-High vulnerability classes, whereas population centers in the western Tarai are primarily classified as Medium or lower. These results parallel the fact that the central and eastern Tarai lag behind in education and health while also being home to a large number of poor, Dalit, and minority groups (Sharma, Guha-Khasnobis, and Khanal 2014). As for the Hill and Mountain regions, the decade-long armed political conflict emerged in the western Hill region and then expanded. Due to geographic proximity, villages and municipalities in the western Hill and central and western Mountain regions were acutely affected, further paralyzing the development trajectory of already isolated segments of the country.

Our regional findings both correspond and contrast with previous studies. For example, while Mainali and Pricope’s (2017) investigation of climate change vulnerability similarly contends that western portions of the Hill and Mountain regions exhibit relatively greater vulnerability, they classify the central and eastern Tarai in a low to moderate category. This classification contrasts with our identification of the central and eastern Tarai as relatively highly vulnerable. Our results also indicate that villages and municipalities in the central and eastern Hill region are relatively less vulnerable, but the Ministry of Environment (2010), in a report on climate change and climate-related disasters, claims that these areas are highly vulnerable. Finally, a study by K. C. (2013), which investigated flood and landslide vulnerability between Tarai and non-Tarai districts through the lens of education, found that vulnerability is greater in the Tarai compared to the remainder of the country. However, our analyses reveal that the western Tarai performs relatively well in educational attainment and is less vulnerable than the rest of the Tarai and many other parts of the country. Observed collectively, discrepancies with
similar studies are likely linked to (1) the spatial units of analysis, and (2) the type(s) of hazard(s) considered. That is, the studies by K. C. (2013) and Ministry of Environment (2010) used districts as the spatial unit of analysis, whereas our study uses smaller scale villages and municipalities. Additionally, our study considered all hazard types (rather than only floods, landslides, and/or climate-related hazards) and used more variables. While other studies are certainly valuable, we argue that our smaller scale analyses and consideration of more variables jointly generated more refined and spatially explicit results. Further, we argue that incorporating all hazards (as opposed to a single hazard type) is more realistic in a complex, dynamic, and compounding sociophysical environment such as Nepal.

Social vulnerability is discussed above at the SoVI and regional scales; however, drivers of vulnerability vary at the component and local scales. The Medical Services component, for example, exhibits a distinct geographic pattern: Mountain villages are highly vulnerable with decreasing vulnerability as elevation decreases. Mountain villages are sparsely populated and are characterized by remoteness and isolation, which results in poor access to health facilities. Conversely, as elevation decreases, population size and concentration increase and thus result in greater numbers of health facilities. We also overlaid the new province boundaries (see Figure 1) and found that a majority of villages in provinces 2, 4, 6, and 7 are classified in the High vulnerability category, whereas a majority of villages in provinces 1 and 3 are classified as Low.

At the district level, the spatial distribution of social vulnerability reflects historical development patterns of the country. In terms of HDI values, the ten lowest districts—which are predominantly in the western Hill and western Mountain regions—are Bajura, Bajhang, Kalikot, Humla, Achham, Rautahat, Mahottari, Jajarkot, Rolpa, and Mugu. These districts are also identified as highly vulnerable in our study, with a majority of villages and municipalities from
the districts classified in the High and Medium-High vulnerability classes. Historically, districts in western Nepal are relatively poorer, exhibit lower literacy rates, lack infrastructure (e.g., transportation and hospitals), and have been alienated from mainstream development projects, although they have received greater allotments of development aid in recent years. It is also worth reiterating that western districts were substantially impacted by the 1996-2006 armed conflict. Due to geographic isolation, push factors, and the vicious cycle of poverty, these districts have a dependence on natural resources, such as forests, and high rates of migration to the Middle East as laborers.

Major cities of Nepal fall into different vulnerability categories. Table 3 provides an overview of the ten most populous cities and their vulnerability classes. Kathmandu and Butwal are identified as the most vulnerable cities, and Biratnagar and Dharan are classified as Medium-High. None of Nepal’s major urban centers are classified as Low vulnerability. Among urban centers, major drivers of social vulnerability are Renters and Occupation and/or Poverty and Poor Infrastructure. According to the latest census, the population growth rate of Nepal was 1.35% from 2001-2011, but all major cities exceed this rate—particularly the two most vulnerable cities of Kathmandu and Butwal. Urban centers have experienced significant rural-to-urban migration in recent years, thus exposing increasing numbers of people to natural hazard risk. Furthermore, infrastructure, public services, and utilities are already serving more users than they can accommodate. In our study, Kathmandu was identified as the most vulnerable city in Nepal, but similar studies disagree. For example, K. C. (2013) found that educational attainment is highest in Kathmandu and thus the city is relatively less vulnerable compared to other cities, while Ministry of Environment (2010) found that Kathmandu is less vulnerable to climate-related disasters compared to the rest of the country. Again, we argue that our analysis of smaller
spatial units, inclusion of more variables, and consideration of multiple hazards helps to explain differences in research findings.

Only 206 of close to 4,000 villages and municipalities (roughly 5%) are classified in the Low vulnerability class. Even more striking, this categorization of ‘low’ is solely in relation to other jurisdictions in Nepal, meaning that it does not consider the larger international context. The entirety of Nepal is located in a high risk zone for natural disasters. Thus, a classification of Low in our study—which only considers Nepal—may actually be quite vulnerable compared to places that are classified as low in other countries. For example, a measure of ‘low’ vulnerability in a country that is less hazard prone and socially, economically, and politically well off does not mean the same as ‘low’ vulnerability in Nepal.

Nepal is extremely vulnerable to climate change given its hydrometeorological and physiographic extremes, which expose the country to flash and riverine floods; landslides, mudslides, and debris flows; and GLOFs (Shrestha and Aryal 2011, Immerzeel et al. 2012). In terms of social vulnerability, these risks are compounded by a reliance agriculture, natural resource extraction, and primary sector economic activities—all of which perturb Nepal’s already fragile landscape. Further, the fifth assessment report of the Intergovernmental Panel on Climate Change not only projects a higher warming trend for South Asia (e.g., Nepal) compared to the global mean (Christensen et al. 2014), but warming is expected to be more pronounced in high altitude regions compared to lowlands (Shrestha et al. 1999, Aryal, Cockfield, and Maraseni 2014). This study identified the high altitude Mountain villages and municipalities of Nepal as highly vulnerable, and predictions of global warming threaten to exacerbate such vulnerability with greater risk to floods, landslides, GLOFs, etc. (Bajracharya and Mool 2009, Shrestha and Aryal 2011). Further adding relevance to social vulnerability, disaster mitigation programs and
policies in Nepal have historically been reactive, focusing on structural solutions on an event-by-event basis (Dixit 2003). This approach is not proactive and fails to address many underlying factors of social vulnerability, including education, poverty alleviation, and communication of disaster information via several languages and media.

Data availability is typically the most limiting factor in measuring social vulnerability to natural hazards. This can lead to a reliance on easily measurable variables and result in the misrepresentation (e.g., concealment or masking) of people and the complex physical and politico-economic contexts in which they reside (Birkmann 2006a, Zhou et al. 2014, Burton 2015). This study used complete, long-form data from the most recent census (2011) of Nepal, which sampled roughly 15% of the population. Based on our knowledge, this represents the largest, most comprehensive, and geographically extensive dataset for the country of Nepal. However, one critique is that this study was unable to explicitly include data on income, which may have influenced our measurements of social vulnerability. CBS utilizes a ‘living standard survey’ that measures consumption as a surrogate for income. Thus, consumption was used as a surrogate for income, but we supplemented these data with several related measurements of employment, occupation, educational attainment, literacy, and vehicle ownership. As another critique, other factors that are generally considered to shape social vulnerability—such as access to resources (including information and political power), age of infrastructure, and risk perception and awareness—could not be included in this study. Future analyses of social vulnerability in Nepal should attempt to account for these shortcomings.
6. Conclusions

Based on the underlying socioeconomic and demographic profiles of close to 4,000 villages and municipalities, this study investigated spatial patterns of social vulnerability in Nepal using an adapted SoVI methodology. In terms of ecological regions, the western Hill, central and western Mountains, and central and eastern Tarai were determined the most vulnerable. The central and eastern Hill region was determined the least vulnerable.

Demographics and historical development processes are essentially reflected in the geographic distribution of social vulnerability. That is, social vulnerability is particularly high in areas that have concentrations of Dalit and minority populations and/or a history of armed conflict, with mountain communities (which have poor access to infrastructure and critical services) overrepresented. As far we are aware, this analysis is the first attempt to quantify social vulnerability at the local level across the entire country of Nepal.

Nepal is attempting to make progress in disaster risk reduction. Unfortunately, the 2015 Gorkha earthquake set the country back and added additional urgency to the daunting task of making communities more resilient. Furthermore, the recent earthquake brought much needed attention to social components of vulnerability that have primarily remained unaddressed in favor of structural mitigation. This shift is important, and our study can help to provide a science-based starting point. Additionally, because this study is based on census data, it can be periodically revised to monitor changes over time and measure the impacts of disaster programs and policies. This study provides a visual understanding of the geographic distribution of social vulnerability in Nepal, which may inform policy making, resource allocation, and disaster management among government officials and NGOs at the local level.
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Influencing Population and Societal Vulnerability to Natural Disasters." Risk Analysis 34
Table 1. Concepts and variables used to construct the modified Social Vulnerability Index in Nepal

<table>
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<tr>
<th>Concept</th>
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<th>Description</th>
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<tr>
<td>Age</td>
<td>1</td>
<td>PAGE65</td>
<td>Percent elderly population (65+ years)</td>
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<tr>
<td></td>
<td>2</td>
<td>PAGE5</td>
<td>Percent children under 5 years</td>
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<td>Built Environment</td>
<td>3</td>
<td>PNORCC</td>
<td>Percent households without Reinforced Cement Concrete (RCC) foundation</td>
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<tr>
<td></td>
<td>4</td>
<td>PNOWATER</td>
<td>Percent households without piped water connection</td>
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<td></td>
<td>5</td>
<td>PNOELECT</td>
<td>Percent households without electricity</td>
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<td></td>
<td>6</td>
<td>PNOSEWER</td>
<td>Percent households without sewage infrastructure</td>
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<td></td>
<td>7</td>
<td>PLOWALL</td>
<td>Percent population living in houses with low quality external walls</td>
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<td>Education</td>
<td>8</td>
<td>PILIT</td>
<td>Percent population who cannot read and write</td>
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<td></td>
<td>9</td>
<td>PSLC</td>
<td>Percent population who completed School Leaving Certificate (SLC)</td>
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<td></td>
<td>10</td>
<td>PCOLLEGE</td>
<td>Percent population who completed college degree</td>
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<td>Ethnicity</td>
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<td>PDALIT</td>
<td>Percent Dalit population</td>
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<td></td>
<td>12</td>
<td>PMINOR</td>
<td>Percent minority population</td>
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<tr>
<td>Family Structure</td>
<td>13</td>
<td>PFEMHEAD</td>
<td>Percent female-headed households</td>
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<td>Average number of people per household</td>
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<td>PFEM</td>
<td>Percent females</td>
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<td>Percent households that are female owned</td>
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<td>PFEMOWNL</td>
<td>Percent households with land owned by female</td>
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<td>PUNEMPLOY</td>
<td>Percent unemployed</td>
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<td>Medical Services</td>
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<td>19</td>
<td>PBHEALTH</td>
<td>Number of basic health institutions per capita</td>
</tr>
<tr>
<td>20</td>
<td>PHEALTHPOP</td>
<td>Percent employed in health care and social services</td>
</tr>
<tr>
<td>Migration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>PFOREIGN</td>
<td>Percent non-Nepali (foreigners) population</td>
</tr>
<tr>
<td>22</td>
<td>PABSENTPOP</td>
<td>Percent absentee population</td>
</tr>
<tr>
<td>Occupation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>PAGRI</td>
<td>Percent employed in agriculture, forestry, fishing, mining, and quarrying</td>
</tr>
<tr>
<td>24</td>
<td>PMANU</td>
<td>Percent employed in manufacturing and construction</td>
</tr>
<tr>
<td>25</td>
<td>PTRANS</td>
<td>Percent employed in transportation, communication, and other public utilities</td>
</tr>
<tr>
<td>26</td>
<td>PACCOM</td>
<td>Percent employed in accommodation and food services</td>
</tr>
<tr>
<td>27</td>
<td>PPUBADM</td>
<td>Percent employed in public administration, defense, and social security</td>
</tr>
<tr>
<td>28</td>
<td>PTRADE</td>
<td>Percent employed in trade and commerce</td>
</tr>
<tr>
<td>Population Change</td>
<td>29</td>
<td>POPCHAN</td>
</tr>
<tr>
<td>-------------------</td>
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<td>----------</td>
</tr>
<tr>
<td>Renters</td>
<td>30</td>
<td>PRENTER</td>
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<tr>
<td>Socioeconomic Status</td>
<td>31</td>
<td>PMOFAM</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>PRAUDIO</td>
</tr>
<tr>
<td></td>
<td>33</td>
<td>PPONE</td>
</tr>
<tr>
<td></td>
<td>34</td>
<td>PVEHICLE</td>
</tr>
<tr>
<td></td>
<td>35</td>
<td>PNOCOM</td>
</tr>
<tr>
<td>Special Needs Populations</td>
<td>36</td>
<td>PDISABILITY</td>
</tr>
<tr>
<td></td>
<td>37</td>
<td>PNONEPALI</td>
</tr>
<tr>
<td>Urban/Rural</td>
<td>38</td>
<td>PFUEL</td>
</tr>
<tr>
<td></td>
<td>39</td>
<td>POPDEN</td>
</tr>
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</table>
### Table 1. Components, cardinality, variables, and explained variance for the modified Social Vulnerability Index in Nepal

<table>
<thead>
<tr>
<th>Component name</th>
<th>Cardinality</th>
<th>Variables</th>
<th>Loadings</th>
<th>Explained variance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Renters &amp; Occupation (PC1)</td>
<td>(-)</td>
<td>PRENDER</td>
<td>0.824</td>
<td>15.97</td>
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<tr>
<td></td>
<td></td>
<td>PTRADE</td>
<td>0.773</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>PAGRI</td>
<td>-0.764</td>
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<tr>
<td></td>
<td></td>
<td>PTRANS</td>
<td>0.674</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>PPIBADM</td>
<td>0.647</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>PMANU</td>
<td>0.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>PACCOM</td>
<td>0.537</td>
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<td></td>
<td></td>
<td>PCOLLEGE</td>
<td>0.681</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>PSLC</td>
<td>0.594</td>
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<tr>
<td></td>
<td></td>
<td>PHEALTHPOP</td>
<td>0.589</td>
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<tr>
<td></td>
<td></td>
<td>PNORCC</td>
<td>-0.739</td>
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<td></td>
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<td>POPDEN</td>
<td>0.407</td>
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</tr>
<tr>
<td>2. Poverty &amp; Poor Infrastructure (PC2)</td>
<td>(--)</td>
<td>PNOWATER</td>
<td>0.824</td>
<td>14.65</td>
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<td></td>
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<td>PNOSEWER</td>
<td>0.675</td>
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<tr>
<td></td>
<td>PLOWALL</td>
<td>0.778</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------</td>
<td>---------</td>
<td>-------</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PVEHICLE</td>
<td>0.806</td>
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<tr>
<td></td>
<td>PRADRO</td>
<td>-0.738</td>
<td></td>
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<td></td>
<td>PMOREFAM</td>
<td>0.428</td>
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<tr>
<td></td>
<td>PLOWALL</td>
<td>0.778</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Favorable Social Conditions (PC3)</td>
<td>(-)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>PELOWNL</td>
<td>0.762</td>
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<tr>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PEMOWNH</td>
<td>0.703</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PNOCOM</td>
<td>-0.781</td>
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</tr>
<tr>
<td></td>
<td>PHONE</td>
<td>0.748</td>
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</tr>
<tr>
<td></td>
<td>PAGES</td>
<td>-0.685</td>
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</tr>
<tr>
<td></td>
<td>PNOELECT</td>
<td>-0.684</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>PSLC</td>
<td>0.444</td>
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https://mc03.manuscriptcentral.com/ljhrs
<table>
<thead>
<tr>
<th>Item</th>
<th>Variable</th>
<th>PILLIT</th>
<th>( \beta )</th>
<th>( \hat{\beta} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>4. Migration &amp; Gender (PC4)</td>
<td>PAABSENTPOP</td>
<td>0.833</td>
<td>7.03</td>
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<tr>
<td></td>
<td>PFEM</td>
<td>0.732</td>
<td></td>
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<tr>
<td></td>
<td>PFFMHEAD</td>
<td>0.791</td>
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</tr>
<tr>
<td></td>
<td>AVGHH</td>
<td>-0.452</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Ethnicity (PC5)</td>
<td>PDALIT</td>
<td>0.727</td>
<td>4.86</td>
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</tr>
<tr>
<td></td>
<td>PMINOR</td>
<td>-0.819</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>PMORFAM</td>
<td>0.521</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Medical Services (PC6)</td>
<td>PHHEALTH</td>
<td>0.789</td>
<td>4.68</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PAGE65</td>
<td>0.476</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>PACCACOM</td>
<td>0.401</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Education (PC7)</td>
<td>PCOLLEGE</td>
<td>0.445</td>
<td>3.47</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PSLOC</td>
<td>0.431</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\( \text{SovTalle} = \text{PC1} + \text{PC2} - \text{PC3} + \text{PC4} + \text{PC5} + \text{PC6} - \text{PC7} \)
Table 3. Level of social vulnerability among Nepal’s ten largest cities

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Kathmandu Metropolitan</td>
<td>1,003,285</td>
<td>4.01</td>
<td>6.1742</td>
<td>High</td>
</tr>
<tr>
<td>2 Pokhara Sub-Metropolitan</td>
<td>264,991</td>
<td>5.28</td>
<td>4.9379</td>
<td>Medium</td>
</tr>
<tr>
<td>3 Lalitpur Sub-Metropolitan</td>
<td>226,728</td>
<td>3.30</td>
<td>0.9253</td>
<td>Medium</td>
</tr>
<tr>
<td>4 Biratnagar Sub-Metropolitan</td>
<td>204,949</td>
<td>2.07</td>
<td>3.4703</td>
<td>Medium-High</td>
</tr>
<tr>
<td>5 Bharatpur Municipality</td>
<td>147,777</td>
<td>5.03</td>
<td>0.5845</td>
<td>Medium</td>
</tr>
<tr>
<td>6 Birgunj Sub-Metropolitan</td>
<td>139,068</td>
<td>2.12</td>
<td>0.7854</td>
<td>Medium</td>
</tr>
<tr>
<td>7 Butwal Municipality</td>
<td>120,982</td>
<td>4.73</td>
<td>4.9134</td>
<td>High</td>
</tr>
<tr>
<td>8 Dharan Municipality</td>
<td>119,915</td>
<td>2.29</td>
<td>1.7084</td>
<td>Medium-High</td>
</tr>
<tr>
<td>9 Bhimdatta Municipality</td>
<td>106,666</td>
<td>2.77</td>
<td>-1.2839</td>
<td>Low-Medium</td>
</tr>
<tr>
<td>10 Dhadingdi Municipality</td>
<td>104,047</td>
<td>4.34</td>
<td>-2.7208</td>
<td>Low-Medium</td>
</tr>
</tbody>
</table>
Figure 1. Physical and administrative map of Nepal (numbers 1-7 are the newly created provinces that have yet to be named by the government).

230x253mm (300 x 300 DPI)

https://mc03.manuscriptcentral.com/ijdr
Figure 2. Spatial distribution of vulnerability in Nepal using a modified Social Vulnerability Index

159x103mm (300 x 300 DPI)

https://mc03.manuscriptcentral.com/ijdr
Figure 3. Geographic distribution of principal components of the modified Social Vulnerability Index in Nepal

148x210mm (300 x 300 DPI)

https://mc03.manuscriptcentral.com/ijdr
Figure 4. Spatial clustering of vulnerability in Nepal based on a Local Moran’s I test

159x103mm (300 x 300 DPI)

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Appendix 3. Multi-Hazard risk assessment manuscript
Multi-hazard risk assessment in Dharan, Nepal using geospatial techniques

Manuscript for ‘Applied Geography’

Abstract

Natural hazard risk assessment generally focuses on a singular hazard type, such as earthquakes, landslides, or floods. However, this emphasis tends to view physical processes in isolation. Rather, it is common for areas to be at risk simultaneously from multiple interacting hazards that may generate cascading effects or synergies. While scholars have proposed a multi-hazard risk framework based on probabilities, the quality and quantity of data required for this approach are rarely available in developing countries. Using geospatial and socioeconomic data, this study assesses multi-hazard risk in the city of Dharan, Nepal. Three hazards—landslides, floods, and earthquakes based on 12 relevant criteria—were considered for a composite hazard assessment using statistical methods and the Analytic Hierarchy Process (AHP). We employed a Social Vulnerability Index (SoVI) to create a vulnerability map of the study area, which was then combined with the multi-hazard hazard map to produce a total risk map. The resulting map identifies the spatial extent of low to high risk areas. Our results indicate that eastern Dharan along the Seuti River and southwestern Dharan on the left bank of the Sardu River are high risk areas. Central Dharan as well as the hills in the west are categorized as low risk areas. This analysis could be helpful to local officials and stakeholders to devise better disaster risk reduction programs and policies. Also, the model can be adjusted and applied at different scales and in different territories.
1. Introduction

Disaster risk reduction requires the identification and quantification of risk in a given geographic location (Garcia-Aristizabal, Gasparini, and Uhinga 2015, van Westen et al. 2014). The primary objective of risk quantification is to assess probability of loss due to the occurrence of a hazardous event, defined here as an event or process that causes loss or harm (Wohl 2000). Hence, risk assessment requires knowledge of both physical and social processes to calculate the cumulative level of risk posed by multiple natural hazards.

Vulnerability is a product of physical exposure to natural hazards combined with the human capacity to prepare for, mitigate, and recover from (or cope with) their negative impacts (Aksha, Juran, and Resler 2018, Juran and Trivedi 2015). The dependence and overlay of social systems upon natural systems leads to their frequent interaction, resulting in increased risk, damage, and economic losses. Vulnerability to natural hazards is rising as populations, infrastructure, and human settlements expand; especially problematic is construction without sufficient buffers between communities and the potential spatial extent of hazardous natural processes (Hernandez 2014, Kappes et al. 2012, Schmidt et al. 2011). As a result, disaster mortality in developing countries and economic losses in the developed world are increasing (Peduzzi et al. 2009, Dilley et al. 2005).

Human and economic losses to natural hazards have escalated in recent decades (Bouwer 2011, Guha-Sapir, Hargitt, and Hoyois 2004). Lessening losses from hazard risk necessitates a holistic assessment of risk that involves the identification of hazards that may affect a particular location combined with knowledge on the physical, built, and social environments that are likely to be affected. To do this effectively, a spatial approach must be employed. A spatial approach in risk assessment supports disaster risk mitigation and reduction by providing crucial information,
on hazard source areas, possible impact zones, and the distribution of populations and infrastructure in and around hazardous areas (Greiving, Fleischhauer, and Lückenkötter 2006). Also, spatial approaches help to identify optimal locations for disaster mitigation infrastructure and can assist in evacuation, resource allocation, and policymaking.

For any risk assessment work, the term risk (R) needs definition. In the literature of hazards and geography, risk has been understood as the combination of hazard exposure (H) and societal vulnerability (V). This relationship can be expressed in a “pseudo-equation”: $R = H \times V$ (Varnes 1984, Wisner et al. 2004). Thus, there would be no risk if a hazard and a vulnerable population do not interact in a particular location.

The majority of risk assessment work either focuses on a single hazard type or gives little attention to vulnerability of society to natural hazards. To address the gap, this study combines an integrated spatial assessment of hazards, based on the approach of Greiving, Fleischhauer, and Lückenkötter (2006), with the hazards of place model developed by Cutter, Mitchell, and Scott (2000) (Fig. 1). While Greiving, Fleischhauer, and Lückenkötter (2006) consider all spatially relevant hazards that produce total risk in a particular location, the Cutter, Boruff, and Shirley (2003) Social Vulnerability Index method considers various social, economic, and demographic indicators that influence vulnerability of a society. This hybrid model conceptualizes risk as the joint product of (1) spatially relevant hazards in a particular place, and (2) level of vulnerability present in the social systems in a particular place. The combination of both models includes provides a holistic assessment risk.

Specifically, this study introduces a model for spatial multi-hazard risk assessment and applies it to the data scarce city of Dharan, Nepal, using publicly available geospatial data. The purpose is to assist local decision and policy makers in the efficient deployment of resources for
disaster risk reduction. The overall study objectives are to: (1) produce individual hazard assessments (i.e., for earthquakes, floods, and landslides) for the rapidly developing city of Dharan, Nepal; (2) estimate Social vulnerability for the city of Dharan; and (3) combine results from objectives 1 and 2 into a comprehensive multi-hazard risk assessment for the city of Dharan. In doing so, this study overcomes the formidable issue of inadequate data (quality, quantity, and access) to develop a scientifically sound procedural model that generates a composite risk map.

1.1 Multi-hazard risk analysis: challenges and opportunities

Studies of natural hazards have traditionally emphasized the impacts of individual hazards, including landslides (Althuwaynee et al. 2014, Devkota et al. 2013); floods (Kabenge et al. 2017, Kazakis, Kougias, and Patsialis 2015); earthquakes (Dhar, Rai, and Nayak 2017, Theilen-Willige 2010); droughts (Lehner et al. 2006); sea level rise (Hinkel 2011); tropical cyclones (Hoque et al. 2018); and wildfires (Adab, Kanniah, and Solaimani 2013). Although valuable for assisting local and national disaster risk reduction programs and policies, they do not provide an holistic understanding of risk that perceives geographic locations and groups of people to be exposed to multiple natural hazards, simultaneously.

Few studies have explored integrating multiple hazards in risk and impacts assessments (Barrantes 2018, Gallina et al. 2016, van Westen et al. 2014), not surprisingly given the many associated constraints. These include availability of geospatial data, access to comprehensive (and reliable) social data, and financial and human resources remain limiting factors (Kappes et al. 2012). The use of remote sensing data, geographic information systems (GIS) software, and publicly available social, demographic, and economic data has potential to support modeling
efforts in terms of increased spatial resolution, computing capacity, rigor in quantitative
techniques, and sharing of data for public good (Hoque et al. 2018, Bishop et al. 2012, Wohl and
Oguchi 2004).

Despite these challenges, a multi-hazard approach that integrates natural hazard risk and
social vulnerability offers a more realistic assessment of potential impact at a given location
because social, economic and cultural elements, are considered simultaneously with physical
geography. Modeling natural hazard risk in terms of single hazard types underestimates total risk
since it does not consider the spatiotemporal overlap of hazards and the possibility of cumulative
synergistic and cascade effects. Moreover, the inclusion of socioeconomic factors such as income,
education, ethnicity, and elderly populations provides insights on levels of capacity and resilience
before a disaster happens. Since the pre-disaster context either accentuates or attenuates the
impacts of any disaster, a multi-hazard approach that considers the spatio-cultural context and its
various linkages and feedbacks could play a significant role in saving human and economic losses.
2. Study area

Nepal is susceptible to a multitude of natural hazards, ranging from frequent, regularly occurring hazards such as floods, landslides, and avalanches, to less frequent but higher magnitude hazards such as earthquakes. For example, floods are a commonality during heavy precipitation events and the annual monsoon season, whereas large-scale earthquakes occur periodically to ‘shock’ the country. The recent 2015 Gorkha earthquake alone claimed more than 9,000 lives and destroyed tens of thousands of houses. The combination of these serial and
sporadic hazards makes apparent the high level of risk and low level of disaster preparedness that characterize the country of Nepal.

The city of Dharan (192.03 km² area and located at 26°51’ N, 87°13’ E) is situated in Sunsari District in eastern Nepal, approximately 600 km southeast of the capital Kathmandu (Fig. 2). Dharan is one of three major urban centers in eastern Nepal, and the latest 2011 census reports the population at 137,705 (CBS 2014). Dharan is situated at the foothills of the Siwalik range and is characterized by the presence of very young sedimentary rocks such as mudstones, shale, sandstone, and conglomerates. Furthermore, the Main Boundary Thrust (MBT) runs along the north side of Dharan, placing the entire city at seismic risk. The MBT is an active thrust running east-west along the Himalayas that is capable of initiating major earthquakes at any time (Upreti 2001).

Figure 2. Map of Nepal and the study area of Dharan.
Dharan is rapidly urbanizing and many settlements are expanding on fan deposits of the flanking Sardu and Seuti Rivers (Fig. 2), which flood frequently during the annual monsoon season. A large agglomeration of squatter settlements has also emerged along the banks of Seuti and Sardu Rivers. This highly vulnerable area contains about 6,500 households scattered across several administrative wards. Risk to wet and dry landslides is severe in Dharan due to riverbank cutting by the Sardu and Seuti Rivers. Serial flooding and landslides during the monsoon season continually deteriorate agricultural land and pose constant, increasing risk to recent settlements that have sprung up as part of urban sprawl processes (Dharan Municipality 2014). Efforts to reduce vulnerability are further exacerbated by weak institutional memory of past disaster events, scarcity of financial and capital resources, and limitations in quantitative, geospatial, and socioeconomic data and their applications.

3. Materials and methods

3.1 Data and sources

We collected imagery, hundreds of geolocations, topographic data, environmental factors, triggering factors, and social data (Table 1) for hazard and risk assessment from publicly available sources (e.g., most recent 2011 census), the Dharan sub-metropolitan office, and field investigations. These data were managed in a GIS environment. High resolution WorldView-3 imagery (1.24 m) dated 31 October 2016 was obtained from the DigitalGlobe Foundation to produce a land use land cover map. Monthly rainfall data for the 2016 calendar year were obtained from the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) available at the Center for Hydrometeorology and Remote Sensing, University of California (http://chrsdata.eng.uci.edu). River flow data were not
available for the Seuti and Sardu Rivers because no gauging stations are installed. Based on visual interpretations of WorldView-3 images and Google Earth, an inventory of active landslides was prepared. Landslide locations were field-checked during a field visit in summer 2016.

The methodological framework described in Fig. 1 guided our overall analysis. We used binomial logistic regression to assess landslide hazards in the study area, with the presence-absence of a landslide used as a response factor. A GIS database of 12 conditioning factors was prepared (Fig. 3). Each spatial layer was transformed into a grid spatial database at a pixel size of 30x30 m. All raster layers were referenced using World Geodetic System (WGS)-1984 and the Universal Transverse Mercator (UTM) zone 45 North. Hazards were modeled individually based on causative factors and were subsequently integrated to generate a composite hazard map of the study area. Finally, social, demographic, and economic data (as documented in Table 1) were used to assess social vulnerability at the ward level, which was overlaid on the integrated hazard map to produce a composite risk map of Dharan.

<table>
<thead>
<tr>
<th>Type</th>
<th>Data</th>
<th>Source/Characteristics</th>
</tr>
</thead>
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<td>WorldView-3 (1.24 m resolution) obtained from DigitalGlobe Foundation</td>
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<tr>
<td></td>
<td>satellite imagery</td>
<td></td>
</tr>
<tr>
<td><strong>Topographic Data</strong></td>
<td>Contour lines</td>
<td>20 m interval contour lines obtained from Department of Mines &amp; Geology, Government of Nepal</td>
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<tr>
<td></td>
<td>DEM</td>
<td>ASTER-DEM (30 m resolution) downloaded from United States Geological Survey Earth Explorer</td>
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<tr>
<td></td>
<td>Slope angle</td>
<td>Slope steepness derived from DEM</td>
</tr>
<tr>
<td></td>
<td>Slope aspect</td>
<td>Slope direction derived from DEM</td>
</tr>
</tbody>
</table>

Table 1. Input data for modeling multi-hazard risk in Dharan, Nepal
<p>| Plan curvature | Concavity-convexity derived from DEM (positive values indicate convexity, negative values indicate concavity) |
| Flow accumulation | Flow accumulating in downslope pixel derived from DEM (ESRI 2014) |
| Topographic wetness index (TWI) | Calculated from DEM based on equation (Sörensen, Zinko, and Seibert 2006): TWI = ( \ln(\alpha/\tan\beta) ) where ( \alpha ) is upslope area and ( \beta ) is slope |
| <strong>Environmental Factors</strong> | NDVI | Band difference derived from WorldView-3 based on equation (Rouse 1973): ( \text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} ) |
| Land use | Land use prepared from WorldView-3 |
| <strong>Triggering Factors</strong> | Precipitation | Monthly rainfall (mm) downloaded from PERSIANN |
| <strong>Hazard Inventory Data</strong> | Fault lines | Geologic fault lines obtained from Department of Mines &amp; Geology, Government of Nepal |
| Landslide inventory | WorldView-3 (1.24 m resolution) obtained from DigitalGlobe Foundation and field verified |
| Lithology | Lithological units obtained from Department of Mines &amp; Geology, Government of Nepal |
| Streams | Drainage networks obtained from Department of Mines &amp; Geology, Government of Nepal |
| <strong>Social Data</strong> | Age | Population 65+ years |
| Built environment | Percent households without piped water connection |
| | Percent households without electricity |
| | Percent households without sewerage infrastructure |
| | Percent population living in houses with low quality external walls |
| Education | Percent population who cannot read and write |
| | Percent population who completed school |</p>
<table>
<thead>
<tr>
<th>Ethnicity</th>
<th>Percent Dalit population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family structure</td>
<td>Percent female-headed households</td>
</tr>
<tr>
<td></td>
<td>Percent average number of people per household</td>
</tr>
<tr>
<td>Gender</td>
<td>Percent females</td>
</tr>
<tr>
<td>Level of employment</td>
<td>Percent unemployed</td>
</tr>
<tr>
<td>Occupation</td>
<td>Percent employed in agriculture</td>
</tr>
<tr>
<td>Renters</td>
<td>Percent families occupying rented houses</td>
</tr>
<tr>
<td>Socioeconomic status</td>
<td>Percent households with &gt;1 family</td>
</tr>
<tr>
<td></td>
<td>Percent households with cell phone or landline</td>
</tr>
<tr>
<td>Special needs</td>
<td>Percent population with disability</td>
</tr>
<tr>
<td>Urban/Rural</td>
<td>Percent households that use firewood as fuel source</td>
</tr>
</tbody>
</table>

### 3.2 Hazard assessment

Three types of natural hazards (i.e., landslides, floods, and earthquakes) were included in this study. Based on selected conditioning factors (Fig. 3), individual hazards were first mapped separately, and subsequently the three layers were overlaid to prepare a composite hazard map. These processes are described throughout Section 3.2.
Figure 3. Conditioning factors for hazard assessment: (A) Aspect, (B) Plan curvature, (C) Distance from faults, (D) Distance from streams, (E) Elevation, (F) Flow accumulation, (G) Land use, (H) Lithology, (I) NDVI, (J) Rainfall intensity, (K) Slope, and (L) TWI.
3.2.1 Landslide hazard assessment

Based on visual interpretations, 71 landslide locations were identified in the study area and 63 of those were verified in the field during the month of July 2016. Due to inclement weather and steep slopes, 8 landslide locations could not be field-verified but were cross-checked in Google Earth. For purposes of using landslide presence-absence as a binomial predictor in a logistic regression model, 71 non-landslide points were randomly generated in ArcGIS 10.3 (Althuwaynee et al. 2014, Devkota et al. 2013). These points were randomly divided into training (70%) and validating (30%) datasets for model fitting and validation.

Hillslope failure results from interacting factors that may weaken shear strength and/or increase shear stress. Influencing factors are often related to the nature of the topography, such as slope angle, aspect, elevation, and surface curvature (Devkota et al. 2013). Further, local hydrology, soil moisture, and climatic triggering events are key. Rivers and streams are also important triggering factors for landslides as they can control slope cutting movements (Van Westen, Castellanos, and Kuriakose 2008). Land use and vegetation cover influence slope failure by increasing slope stability and affecting hydrological regimes via the interception of precipitation, changes in runoff speed, and perturbations in groundwater flow (Van Westen, Castellanos, and Kuriakose 2008). Finally, underlying geology (e.g., location of faults) and underlying lithology are important to consider (Devkota et al. 2013).

We selected ten relevant variables for inclusion in the landslide model. These include aspect, plan curvature, distance from faults, distance from streams, elevation, land use, lithology, normalized difference vegetation index (NDVI), slope, and topographic wetness index (TWI) (Fig. 3).
Slope angle, slope aspect, plan curvature, and TWI were derived from a DEM using Spatial Analyst toolsets in ArcGIS 10.3. We also measured distance from a fault and river using the Euclidean Distance tool in ArcGIS. Additionally, we classified high-resolution satellite images into four classes (forest, urban area, water body, and agriculture/open/barren) to obtain a land use map of the study area (Table 1). Aspect, land use, and lithology were defined as categorical variables, and the remaining variables were defined as nominal variables. Values for each landslide and non-landslide point were extracted and imported into R version 3.3.3 environment (R Core Team 2017) to perform binomial logistic regression using the GLM function. Using the Variance Inflation Factors (VIF) function, multicollinearity of the data was tested. Two variables, distance from faults and slope, were removed due to high collinearity.

3.2.2 Flood hazard assessment

Flood hazard assessments are generally based on meteorological, hydrological, and geomorphological data and typically use hydraulic modeling to predict flood depth based on rainfall-runoff relationships (Vojtek and Vojteková 2016). However, many developing nations, including Nepal, lack adequate sets of such data. The use of hydraulic modeling is limited in these contexts and instead a GIS-based Flood Hazard Index (FHI) can be used to estimate flood hazards (Kabenge et al. 2017).

Given the absence of river discharge data for Dharan, we adopted the GIS-based FHI method. Based on the results of previous studies, seven criteria-parameters were selected to construct the FHI: distance from streams (Butler, Kokkalidou, and Makropoulos 2006), elevation (Chen et al. 2015), flow accumulation (Kazakis, Kougias, and Patsialis 2015), lithology (Nyarko
Distance from drainage networks is crucial as flood inundation is resulted from the overflow of drainage channels. Areas closer to drainage channels have high risk of inundation than farther away (Butler, Kokkalidou, and Makropoulos 2006). Water flows from higher elevations and slope to lower elevations and slopes. Lower slopes decrease the speed of runoff and get quickly inundated than higher slopes (Kabenge et al. 2017). The high values of flow accumulation indicate the concentrated flow and consequently higher flood hazard zone (Kazakis, Kougias, and Patsialis 2015). The geology of an area comprising soil type and parent rock information may amplify or extenuate the magnitude of flood events. Soil type determines the infiltration and water holding capacity of an area thus affecting flood susceptibility (Nyarko 2002). Land use and land cover plays role on precipitation interception reducing speed of rainfall, infiltration, evapotranspiration, and underground water holding capacity of an area. Natural vegetation cover such as forests and grassland reduces the speed and amount of runoff than built-up areas (Yalcin and Akyurek 2004). Higher rainfall intensity could result quicker infiltration capacity. Thus, the likelihood of flood increases in an area where the amount of rainfall increases (Kabenge et al. 2017, Nyarko 2002).

To generate the index, we extracted elevation, flow accumulation, and slope from a DEM. Geological information was obtained from engineering geological maps of the study area. Euclidean distance was used to calculate distance from drainage networks and a modified Fournier index was applied to calculate rainfall intensity from rainfall measurements (De Luis, González-Hidalgo, and Longares 2010). The relative importance of each parameter was determined based on the Analytic Hierarchy Process (AHP), detailed in section 3.2.4.
3.2.3 Earthquake hazard assessment

Advancements in satellite technologies and computing capacity have allowed earthquake hazard assessment using geomorphometric parameters based on DEMs (Geiß and Taubenböck 2013). Several studies have analyzed geomorphic/topographic features in earthquake-prone areas, primarily including five criteria-parameters: distance from faults, elevation, flow accumulation, lithology, and slope (Dhar, Rai, and Nayak 2017, Theilen-Willige 2010, Allen and Wald 2009, Wald and Allen 2007) (Fig. 3). Damage from earthquakes varies mainly due to local lithological and hydrogeological conditions. The presence of tectonic structures such as faults and folds can influence seismic hazards and their secondary effects such as land subsidence, liquefaction, and building collapse (Dhar, Rai, and Nayak 2017). Higher slope angles and elevations contribute to mass movements more than lower slopes and elevations. Higher flow accumulation is characterized by young unconsolidated deposits and high groundwater tables, which increase the chance of liquefaction during earthquakes (Theilen-Willige 2010).

3.2.4 Weighting the criteria using AHP

To integrate various parameters in a spatial decision making process and determine their relative importance, weighting and ranking of the parameters for each individual hazard type (landslide, flood, and earthquake) is required. For the landslides hazard assessment, a statistical method, described above, was adopted (Althuwaynee et al. 2014, van Westen et al. 2014, Devkota et al. 2013). The weight of each parameter for floods and earthquakes was calculated using the AHP method (Saaty 1990). AHP is a widely used multi-criteria decision making tools that serves a basis for integrating and determining the importance of criteria-parameters (Hoque et al. 2018, Kabenge et al. 2017, Kazakis, Kougias, and Patsialis 2015, Althuwaynee et al. 2014).
To do so, we prepared a pairwise comparison matrix for flood and earthquake hazards. Three
experts (local officer from Dharan municipality, a professor from Tribhuvan University, and the
first author) have filled up the matrix. The relative importance between criteria was assessed
from 1 to 9 implying from low to high importance, respectively (Saaty 1990) (Table 2). A
consistency ratio (CR) is used to justify the consistency of comparisons in the pairwise
comparison matrix and if CR is less than or equal to 0.1, comparisons are considered consistent
(Hoque et al. 2018).

Table 2. Scale of relative importance for hazard parameters (Hoque et al. 2018,
Kabenge et al. 2017, Saaty 1990))

<table>
<thead>
<tr>
<th>Relative Importance</th>
<th>Definition</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
<td>Two criteria are equally important</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance</td>
<td>One criteria is slightly favored over another</td>
</tr>
<tr>
<td>5</td>
<td>Strong importance</td>
<td>One criteria is strongly favored over another</td>
</tr>
<tr>
<td>7</td>
<td>Very strong</td>
<td>One criteria is very strongly favored over another</td>
</tr>
<tr>
<td></td>
<td>importance</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Extreme importance</td>
<td>The evidence favors one criteria over another and is of the highest possible order of validity</td>
</tr>
<tr>
<td>2,4,6,8</td>
<td>Intermediate values</td>
<td>When compromise is needed</td>
</tr>
</tbody>
</table>
3.2.5 Integrated hazard assessment

Susceptibility to individual hazards was identified based on the weightings of relevant parameters. Then, we overlaid the individual hazard maps using the Weighted Overlay Function tool in ArcGIS 10.3 to prepare an integrated hazard map of the study area. The city of Dharan is affected by all three hazards. Dharan experiences floods and landslides every year, and there was a damaging earthquake in 1985. Since the study area is at constant risk to all three hazards, we assumed that each had the same relative importance and employed equal weights when preparing the composite hazard map (Collins, Grineski, and Aguilar 2009).

3.3 Vulnerability assessment

Vulnerability is primarily controlled by social, economic, and demographic factors that coalesce to influence the capacity of individuals and communities to mitigate, cope with, and reduce disaster risk. In general, a population with relatively greater socioeconomic status, access to resources, and built environment attributes is less vulnerable and typically performs better during and after disaster events. We calculated and mapped social, demographic, and economic data (see Table 1) to assess social vulnerability at the ward level of Dharan (total of 25 wards). The quantification and mapping of social vulnerability was based on the Social Vulnerability Index (SoVI) method, which was overlaid on the integrated hazard map to produce a composite risk map of Dharan.

We used the SoVI method, adapted from the approach of Cutter, Boruff, and Shirley (2003), to assess hazards vulnerability in the study area. Social, economic, and demographic variables were obtained from the most recent Nepal census as well as from the city office of Dharan. Among the variables, 18 total on topics such as age, built environment, education,
ethnicity, family structure, gender, level of employment, occupation, renters, socioeconomic status, special needs, and urban/rural were included to model vulnerability (see Table 1). Data were aggregated at the ward level and then normalized and standardized for further processing. Principal component analysis (PCA), using the Dimension Reduction tool in SPSS version 22.0, was used to reduce the 18 variables into a smaller number of more meaningful components (Hummell, Cutter, and Emrich 2016). Varimax rotation and Keiser criterion were employed to identify components with eigenvalues higher than 1. Based on the cardinality of the components, all components were summed to obtain SoVI scores of the study area. The values were then brought into ArcGIS to create a vulnerability map.

3.4 Overall risk assessment

The composite risk of Dharan was based on spatial intersections of hazard risk and social vulnerability in the study area (Fig. 2). The integrated hazard and social vulnerability layers were multiplied in ArcGIS to obtain a multi-hazard risk map. The Jenks natural breaks method was applied to obtain five classes of risk ranging from low to high (Hoque et al. 2018, Devkota et al. 2013).
4. Results

4.1 Individual hazard assessments

The binomial logistic regression for prediction of landslide presence and absence revealed that distance to streams, elevation, lithology (Siwalik), and lithology (Midland) are significant predictors of landslide presence or absence in Dharan. Based on the coefficients of each significant predictor, a landslide hazard susceptibility map was prepared (Fig. 4A). The results indicate that 45% of the study area is located in high hazard zones for landslides, meaning that these areas are highly susceptible to landslide occurrence. The forested areas in the south and stable hills in the north are delineated as regions that are relatively safe from landslides. The results are significantly influenced by the lithology (Midland) variable, which has the highest coefficient values among others in the logistic regression equation (Table 3). Due to such a heavy influence of lithology (Midland), the central part of Dharan is classified as a high landslide hazard zone (Fig. 4A).

Table 3. Coefficients of the conditioning factors in GLM model

<p>| Factor            | Estimate | Std. Error | z value | Pr(&gt;|z|) |
|-------------------|----------|------------|---------|----------|
| Intercept         | -1.43E+01| 3.96E+03   | -0.004  | 0.9971   |
| Aspect (North)    | 8.61E-02 | 4.82E+03   | 0       | 1.0      |
| Aspect (Northeast)| 1.46E+01 | 3.96E+03   | 0.004   | 0.9971   |
| Aspect (East)     | 1.27E+01 | 3.96E+03   | 0.003   | 0.9974   |
| Aspect (Southeast)| 1.36E+01 | 3.96E+03   | 0.003   | 0.9973   |
| Aspect (South)    | 1.41E+01 | 3.96E+03   | 0.004   | 0.9972   |</p>
<table>
<thead>
<tr>
<th>Aspect (Southwest)</th>
<th>1.44E+01</th>
<th>3.96E+03</th>
<th>0.004</th>
<th>0.9971</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspect (West)</td>
<td>1.34E+01</td>
<td>3.96E+03</td>
<td>0.003</td>
<td>0.9973</td>
</tr>
<tr>
<td>Aspect (Northwest)</td>
<td>1.37E+01</td>
<td>3.96E+03</td>
<td>0.003</td>
<td>0.9972</td>
</tr>
<tr>
<td>Plan curvature</td>
<td>-3.83E-01</td>
<td>3.92E-01</td>
<td>-0.978</td>
<td>0.3282</td>
</tr>
<tr>
<td>Distance to streams</td>
<td>-1.06E-03</td>
<td>6.38E-04</td>
<td>-1.661</td>
<td>0.0967*</td>
</tr>
<tr>
<td>Elevation</td>
<td>6.93E-03</td>
<td>3.22E-03</td>
<td>2.154</td>
<td>0.0312**</td>
</tr>
<tr>
<td>NDVI</td>
<td>-6.32E-01</td>
<td>2.63E+00</td>
<td>-0.24</td>
<td>0.81</td>
</tr>
<tr>
<td>TWI</td>
<td>-2.39E-01</td>
<td>1.94E-01</td>
<td>-1.236</td>
<td>0.2163</td>
</tr>
<tr>
<td>Land use (Forest)</td>
<td>-6.18E-01</td>
<td>1.15E+00</td>
<td>-0.538</td>
<td>0.5905</td>
</tr>
<tr>
<td>Land use (Agri)</td>
<td>-5.30E-02</td>
<td>1.03E+00</td>
<td>-0.052</td>
<td>0.9587</td>
</tr>
<tr>
<td>Land use (Water)</td>
<td>-1.61E+00</td>
<td>2.20E+00</td>
<td>-0.73</td>
<td>0.4652</td>
</tr>
<tr>
<td>Lithology (Siwalik)</td>
<td>3.05E+00</td>
<td>1.46E+00</td>
<td>2.093</td>
<td>0.0364**</td>
</tr>
<tr>
<td>Lithology (Gondwana)</td>
<td>1.23E+01</td>
<td>3.96E+03</td>
<td>0.003</td>
<td>0.9975</td>
</tr>
<tr>
<td>Lithology (Midland)</td>
<td>-7.53E+00</td>
<td>3.82E+00</td>
<td>-1.97</td>
<td>0.0488**</td>
</tr>
</tbody>
</table>

** = Significant at 0.01, * = Significant at 0.05

The relative importance of seven indicators of the Flood Hazard Index (FHI), obtained via Analytic Hierarchy Process (AHP), were used as inputs for the weighted overlay function in ArcGIS. The thematic layers were then overlaid to prepare a final flood hazard map (Fig. 4B). The map shows that roughly 47% of the study area lies in low flood hazard zones. The majority of high flood hazard zones are near the Seuti and Sardu Rivers. Flow accumulation and distance from drainage networks are listed as relatively important indicators, so riverbanks and lowland...
agricultural areas are categorized as high flood hazard areas. The hills in east, north, and west, as well as comparatively elevated regions in Bijayapur, show low risk to flood hazards.

An earthquake hazard map (Fig. 4C) was prepared for the study area using five different thematic maps: distance from faults, elevation, flow accumulation, lithology, and slope. AHP determined the weightage of the variables and those values were used while overlaying layers in GIS. The map indicates that high hills in the north have lower seismic risk, while central Dharan is categorized in a high earthquake hazard zone. Since MBT passes just north of Dharan and a few local faults are also present in the study area, a majority of the human settlements in Dharan lie in high earthquake hazard areas. The forested areas in south are classified as a medium hazard zone, likely because their low elevation allows for soil liquefaction due to high groundwater table movement (Theilen-Willige 2010).

The integrated multi-hazard map—prepared by combining the landslide, flood, and earthquake hazard maps—is presented in Fig. 4D. The map portrays that approximately about 35% of the study area is classified in the medium hazard risk range, while 7% is classified as low risk, 26% as low to medium, 30% as medium to high, and only 2% of the study area lies in a high risk area. The adjoining areas of rivers are predominantly under high risk to hazards, whereas the forested lands in the north and south are categorized as low risk to hazards.
Figure 4. Hazard risk of the study area.
4.2 Vulnerability assessment

PCA reduced 18 variables into four components that explained 86.62% of the variance of the data: Socioeconomic Status, Education and Built Environment, Ethnicity, and Disability. Socioeconomic Status explained 45.12% of the variance Education and Built Environment explained 19.74%, Ethnicity explained 10.98%, and Disability explained 10.78%. Based on the cardinality of the components, they were summed to calculate SoVI scores for the 25 wards of Dharan assessed in this study, which were then mapped (Fig. 5).

Figure 5. Spatial distribution of social vulnerability in Dharan at the ward level.
SoVI scores revealed three wards categorized as high vulnerability, six as medium-high, seven as medium, six as low-medium, and three wards as low (Fig. 5). The social vulnerability map (Fig. 5) reveals that wards 20, 21, and 22 are the most vulnerable, and wards 1, 4 and 5, located at the core of Dharan, are the least vulnerable.

4.3 Total risk assessment of the city of Dharan

The final risk map (Fig. 6) portrays greatest risk areas in the eastern part of Dharan along the Seuti River, as well as southwest part of Dharan along the left bank of the Sardu River. The southern part of the study area is classified as low risk. This area is relatively lower in elevation, flatter, and forested. The slope along the Sardu river and its headwater is also categorized as low risk. Central Dharan, the oldest settlement in the city, is classified as low risk.
Figure 6. Total risk map from landslides, floods, and earthquakes for Dharan, Nepal, obtained after overlaying social vulnerability (Fig. 5) and integrated hazard (Fig. 4) maps.
5. Discussion

The overall objective of the study was to assess the multi-hazard risk of Dharan, Nepal, using socioeconomic data and geospatial techniques. Based on the literature and methodology used in other studies (e.g., van Westen et al. 2014, Collins, Grineski, and Aguilar 2009, Greiving, Fleischhauer, and Lückenkötter 2006), we generated landslide, flood, and earthquake hazard maps. Subsequently we weighted and combined these maps to delineate low to high risk areas of Dharan based on the combined influence of the hazards. Finally, we incorporated vulnerability into a final composite risk map, using a SoVI map generated using the SoVI method.

Lithology (Siwalik) was the most important predictor of landslide presence (Table 3) within the study area (Fig. 4A). Siwalik group is characterized by the presence of loose materials, comprised of grained sandstones, mudstones, siltstones, and shales (Chamlagain 2009, Upreti 2001). Such lithology makes the area more susceptible to slope failures on stream banks, the formation of steep cliffs, differential erosion forming scraped ridges, and frequent landslides on the steep slopes. The flood hazard assessment (Fig. 4B), indicates that the higher flood risk regions are distributed along the banks of Sardu and Seuti Rivers. This is mainly because both rivers are characterized by active channel shifting likely due to loss of high sediment loads (Stoffel, Wyżga, and Marston 2016) during the monsoon season in combination with human encroachment from the construction of buildings along the banks as well as sand mining and stone quarrying (Sudmeier-Rieux et al. 2012, Dixit 2003). During low flow of the river in the winter, commercial exploitation of the river bed deepens the channel, which later is filled during monsoon season. One example of river bank encroachment and expansion of human settlements towards the rivers is clearly visible in Fig. 7A and 7B. Results of the earthquake hazard assessment (Fig. 4C) depict that most of Dharan is under high to medium risk; however, in
reality the entire country of Nepal is considered to be at high seismic risk (Chamlagain 2009). From multiple natural hazards point of view, almost all densely populated areas of study area are categorized under either medium, medium to high, or high hazard zones (Fig. 4D), which is likely a result of the compound nature of the hazard risk. For example, while any given location might have low susceptibility to one natural hazard (southern areas in Fig. 4B), it may be highly susceptible to other natural hazards (southern areas in Fig. 4C) making that area exceptionally risky to natural hazards overall.

The social vulnerability analysis revealed that central Dharan is less vulnerable than other parts of the city (Fig. 5). Central Dharan is the oldest part of the city and has better access to piped water, sewerage infrastructure, and electricity (Dharan Municipality 2014). In fact, this part of the city has no dependence on firewood as a fuel source, which helps to make environment clean and reduce health problems especially related to indoor air pollution. The region also boasts greater access to education (which helps to increase awareness on hazards, risk, and vulnerability) and other resources such as comparatively better access to preparedness materials, emergency shelters, and any other facilities provided by governmental and non-governmental institutions. Interestingly, the western part of the study area is classified as low risk although the area is characterized by low quality built environment attributes (e.g., no electricity connection, without sewerage infrastructure, low quality external walls) and a greater dependence on agriculture and firewood as fuel source (Dharan Municipality 2014). The areas depicted in medium and medium to high vulnerability categories are the fastest growing regions of the study area, and they are expanding towards the banks of Sardu and Seuti Rivers. Figure 7A and 7B provide context for such expansion along the banks of Seuti River (south eastern part of the study area) between 2004 and 2016.
Figure 7A. Google Earth image dated 22 Nov. 2004

Figure 7B. WorldView-3 image dated 16 Nov. 2016
The distribution of composite risk from landslides, floods, and earthquake (Fig. 6) is partly explained by the steep mountainous terrain, rapid unplanned urbanization, and encroachment on the Sardu and Seuti Rivers. Rapidly and poorly planned urbanization in combination with high river bed exploitation and river bank invasion are generating significant pressures. As a result, natural hazards become more complex and uncertain due to dynamic interactions between increasing populations, existing ecologies and ecosystem services, and environmental degradation (Liu, Shi, and Wang 2016, Sudmeier-Rieux et al. 2012, Dixit 2003). These factors favor a high susceptibility to landslides and floods, and risk in these areas could manifold due to spatial interactions with each other as well as earthquakes and other hazards.

In general, the results confirm general assumptions that riverbanks and regions near high slope gradients are at higher risk to natural hazards. Also supportive is that central Dharan is farther from the rivers, there are fewer ‘slums,’ and it acts as the city’s hub for economic activities. Interestingly, the hills in western Dharan, which contains numerous landslides, are categorized as a low risk zone. While landslide risk is high in the western hills (Fig. 4A), a low composite risk is explained by stable geology in the upper region, low density of human settlements, and relatively low levels of social vulnerability (Fig. 5). Although the western hills are surrounded by forests and low population density, active landslides in the area could threaten the expanding squatter settlement on the banks of the Sardu River.

The aggregate result (Fig. 6) of this work should not be considered a final product on the status of multi-hazard risk and vulnerability in Dharan, Nepal. Our aim here was to begin a conversation on how to assess risk from multiple hazards that occur in Nepal, which has several urban centers like Dharan that have rapidly expanding populations and exposure to multiple natural hazards on a regular basis. Since natural as well as social phenomena (e.g., employment,
age, built environment, and urban expansion) are dynamic, continuous measurement of variables could help risk assessment and projections in the study area.

We set out to determine how geospatial technologies can be used to inform multi-hazard risk in a data poor environment, using the city of Dharan, Nepal as a case study. Our experience here echoes the work of others (Kappes et al. 2012, Schmidt et al. 2011) —one of the major challenges of modeling multi-hazard risk is requirement of extensive databases, which are virtually absent in the developing world (Barrantes 2018). The databases are often absent and if it exists they are constrained by low accessibility for the researchers. Our model partially addresses this gap by using publicly available geospatial and social data gathered through intensive field works. Additionally, it is always a great methodological challenge to extract useful information from a large set of datasets in environmental decision making process (Runfola et al. 2017). With the help of geospatial techniques and a decision support system, our model is able to represent hazard processes in a spatial platform and conduct analyses to compare them. However, the final map should be interpreted carefully as we have used qualitative criteria to classify the risk category from low to high.

Although our model was able to identify risky areas in the study area, it demonstrated many challenges. Primarily, variables for such a data intensive model comprised of social, and topographic data are available in various temporal and spatial scales, across units of analysis, and in diverse data formats (Wilhelmi and Morss 2013). Social data are aggregated from the household level and are represented in discrete administrative boundaries, such as the ward level in our case, whereas topographic data such as elevation and rainfall are measured in continuous surfaces at different time scales. In addition, local level geological data are not available for
recent time periods and are measured in a different datum and coordinates than other recent spatial data such as high resolution WorldView-3 images.

Our model is limited in many ways. It could not consider the cascading effects of a hazard as it requires long term historic records of magnitude and intensity of the hazards. The available historic records related to natural hazards from the city office of Dharan was total sum of money either sanctioned for disaster mitigation work and/or compensation provided for a household after a disaster in a particular year.

The outcome of this study and the methods herein have utility in urban development, land use planning, and, most importantly, informed risk and policy planning at the local levels. GIS-based models, such as the one presented here, are promising in data scare regions such as Nepal and countries that make up the Himalayan belt, which encounter numerous natural hazards and have poor record keeping systems. By overlapping the current administrative map, it is evident that the newly developing settlement areas are under medium to high risk. As rural to urban migration is ever increasing in Nepal, Dharan has a high demand for land to build, especially for residential purposes. This study could assist local managers how to pursue local development and shed light on risky areas in their jurisdiction.

6. Conclusion

This study offers a composite risk assessment model for the data scarce city of Dharan, Nepal, based on geospatial data and techniques in combination with social data. This was accomplished by assessing and combining risk from three natural hazards (landslides, floods, and earthquakes) and subsequently merging the multi-hazard risk model with a social vulnerability analysis to produce a composite risk map. The model is primarily based on publicly available
remote sensing imagery and socioeconomic data collected through field work. Hence, this method can be replicated in other data poor regions that are at risk to multiple natural hazards. Additionally, results from this approach can assist decision makers to better understand risk and design programs and policies to increase capacity and resilience.

Risk is dynamic as changes occur due to geophysical processes, human activities, and their interactions. Hence, risk assessment should be measured routinely to capture changes in the natural and social environments thus to delineate high risk regions, vulnerable populations, and changes over time. One of the major challenges to risk quantification is inadequate long-term, historical information on hazard occurrence. This could partially be addressed with the help of satellite imagery, but the process can be tedious and sometimes not sufficient to accurately model risk. Still, with the help of geospatial data and techniques, a risk assessment of multiple hazards can be conducted and used to inform decision-making process.
References


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