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Who Is Vulnerable and Where Do They Live? Case Study of Three Districts in the Uttarakhand Region of India Himalaya

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Uttarakhand, India, is a dynamic region. It is frequently exposed to natural hazards and is experiencing rapid urbanization. However, the interaction of the increase in people, the built environment, and vulnerability to natural hazards is poorly understood. We model the relationship between urbanization and hazards for 3 cities (Almora, Nainital, and Champawat) and their surrounding subdistricts in the region using a social vulnerability framework. We apply the framework by using principal component analysis to identify socioeconomic vulnerability indicators and built-environment vulnerability indicators. The results show that higher access to assets reduces vulnerability and that larger households are less vulnerable. We also find that the presence of a bathroom and higher-quality building materials are associated with reduced vulnerability. Bathroom presence is more frequent in cities than in surrounding areas, and the quality of building materials was mixed within cities. Access to assets is higher in the cities than in surrounding areas, but households are smaller in cities. These indicators of vulnerability help to close the knowledge gap and identify who is vulnerable and where they live. This analysis continues to expand the conversation about vulnerability to disasters related to natural hazards in mountain regions.

Keywords: *socioeconomic vulnerability; built-environment vulnerability; natural hazards; principal component analysis; Hindu Kush Himalaya.*

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Introduction

Mountains are unique landscapes that are frequently exposed to various natural hazards. They have also seen rapid population increases in villages, towns, and cities (Gardner and Dekens 2007; Stäubli et al 2017). People are vulnerable to disasters related to natural hazards in mountain regions, but there is limited information about who is vulnerable and where they are located. Narrow gorges, steep slopes, and intense seasonal precipitation make mountain regions susceptible to frequent flash flooding events (Shrestha and Chhophel 2010; Elalem and Pal 2015). These intense rain events are often linked with landslide occurrence. Urbanization and human impacts have altered the ability of the landscape and human population to absorb and recover from these events (Haigh and Rawat 2011). The geophysical characteristics of a region, such as terrain, slope, and precipitation, are the first things considered when trying to understand where people may be exposed to natural hazards, because they give insight into where these hazards are likely to occur. However, this does not give us the whole picture about who is most vulnerable to disasters related to natural hazards (Borden et al 2007; Poonam et al 2017).

Infrastructure, social networks, cultural norms, and economic attributes of a region are just as important as geophysical characteristics in understanding the vulnerability of a region to disasters related to natural hazards (Tate 2012). However, many of these attributes are hard to measure. Because vulnerability is difficult to determine solely with biophysical and socioeconomic data, it is necessary to combine data analysis methods with on-the-ground research and expert regional knowledge to gain an in-depth understanding of the drivers of vulnerability in a particular region.

The Uttarakhand state of India is home to about 10 million people. They live at the confluence of 2 major forces that are transforming one of the most dynamic mountain systems in the world. First, the region is a hotspot for 4 natural hazards: earthquakes, fires, floods, and landslides (Panday 2013; Babu et al 2016; Khanduri 2019). Over the past few years, the region has experienced several devastating disasters related to natural hazards, including floods in 2013 that left nearly 6000 people dead and more than 100,000 people trapped by landslides, damaged roads, and flooded conditions (National Institute of Disaster Management 2015). Second is urbanization: cities and urban centers are expanding as people migrate from rural areas, valleys, and plains and as religious, ecological, and adventure tourism grows. Migration to urban centers is an increasingly important livelihood strategy for rural households, and household incomes are increasingly made up of nonfarm-dependent sources (Maharjan et al 2013). The growing urban

FIGURE 1 Study cities. (A) Almora; (B) Nainital; (C) Champawat. (Photos A and C by Bhagwati Joshi; Photo B by Corinne Grainger)

population, an urbanizing economy, and associated land use and land cover changes are transforming Uttarakhand (Pal 2015).

Vulnerability frameworks

There have been several international frameworks created for disaster risk reduction (DRR), the most recent being the 2015 Sendai Framework, which built upon the 2005 Hyogo Framework (Zimmermann and Keiler 2015). Vulnerability is defined in these frameworks as "the conditions determined by physical, social, economic, and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards" (UN 2005). In this study, we look at the social factors that influence people's vulnerability to disasters related to natural hazards, or their social vulnerability. Social vulnerability is made up of social inequalities that affect people's ability to withstand and recover from disaster impacts, as well as community and built-environment factors, such as urbanization and economic wellbeing (Cutter et al 2003). We use a framework for social vulnerability that includes measures of exposure, sensitivity, and adaptive capacity (O'Brien et al 2004). Exposure is a measure of the magnitude and frequency of disaster events, sensitivity is the degree to which a system will change in the face of a disaster event, and adaptive capacity is the ability of a system to adapt and respond to a disaster (O'Brien et al 2004). These 3 main components of vulnerability combine aspects of social networks, economic measures, and built-environment quality and examine them in relation to stressors. We use the interdisciplinary concept of social vulnerability to examine the social factors that contribute to the vulnerability of people living in the Indian Himalaya region to disasters related to natural hazards. Our findings provide information to the DRR community and increase our understanding of disaster risk, which is priority 1 of the Sendai Framework (UNDRR 2015).

The goal of this paper is to examine the socioeconomic characteristics of households vulnerable to disasters related to natural hazards in 3 cities and their surrounding subdistricts in Uttarakhand. We identify indicators that can serve as a starting point for further research. We apply an existing framework, established by Cutter et al (2003) and Borden et al (2007), to examine vulnerability and combine this with field surveys to identify potential indicators of vulnerability in the Uttarakhand region of India. We then investigate spatial variations for these indicators throughout the region.

Methods

Study area

This study was conducted in 3 districts (Almora, Nainital, and Champawat) in the Indian state of Uttarakhand in the Hindu Kush Himalaya (HKH). Study sites were selected based on the diversity in socioeconomic characteristics, the occurrence of urban development, and differences in the terrain. Urban development has a large impact on the dynamics of the mountain system in the region and can increase people's risk of being exposed to natural hazards. These become disasters related to natural hazards if there are losses of life or damage to property (Tiwari et al 2018). These disasters frequently compound one another, and existing risk analyses often overlook this (Zimmermann and Keiler 2015). The effects of these disasters are also compounded by increasing unplanned development and tourism in the region (Kala 2014). Although we understand that urbanization exposes more people to these hazards, there is an information gap regarding who is most vulnerable and where (Karki et al 2012; Elalem and Pal 2015).

Almora (29.5892°N, 79.6467°E; Figure 1A) is a town in the northern region of the HKH, is located 1642 masl, and has a population of about 35,000 people. The region is experiencing rapid urbanization, and the population in the town increased by 30% from 1991–2011 (Pushpa and Joshi 2016). It is one of the oldest cities in the region and has a mix of old and new development. Much of the development is along the main roads, which traverse the mountain in switchbacks. Development has continued to expand on the edges of the city, and homes have been built in areas previously deemed unsafe for building or have been built close together.

Nainital (29.3803°N, 79.4636°E; Figure 1B) is a resort town built on the mountains surrounding a mountain lake. It is located 2084 masl and has a population of around 41,000 people. Nainital is a wealthy city but has a transient population; it is a large tourist destination in the summer, filling with visitors from the nearby cities of Delhi and Haldwani looking to escape the heat. Although it is built in the mountain landscape, it is also built around a mountain lake, so the heart of the town is a valley and the homes and buildings are built into the mountains from the lake upward.

Champawat (29.3361°N, 80.0910°E; Figure 1C) is located 1615 masl and is home to about 4800 people. It has historic and religious significance: it was the former capital of the Chand Dynasty and has several important temples, including Baleshwar, and draws many religious pilgrims as tourists. The district of Pithoragarh was divided in 1997, creating the district of Champawat, with the city of Champawat as the district capital. It is also in a less severe landscape than the other 2 cities; rather than being built into a mountainside, it resembles a valley with rolling hills.

Household surveys

To identify variables that influence people's vulnerability to disasters related to natural hazards in the region, we conducted 17 household surveys in the 3 study areas (4 in Nainital, 10 in Almora, and 3 in Champawat) over 10 days in June 2018. Study sites were chosen using randomized points created from a remote-sensing product that classified urban areas using the continuous change detection and classification (CCDC) algorithm; surveys were conducted in the areas classified as urban by the CCDC algorithm and confirmed to be residences upon arrival in the field. The surveys gathered information about socioeconomic characteristics and household structure, as well as exposure to disasters related to natural hazards and risk awareness. Questions about socioeconomic characteristics included household size, expenditures, sources of income, loans, access to agricultural land and clean water, social relationships (caste), and work migration. Household structure questions were about the building materials used to construct the home and the condition the home was in. The results of these surveys were used to guide the construction and interpretation of the principal component analysis (PCA) to create a better view of vulnerability indicators in the region. Because of constraints on resources and time, we were not able to conduct more surveys and may not have a complete picture of the diverse households in the region. The goal of this analysis was to identify indicators that could lead to further research, our results can therefore be used as a starting point for follow-up surveys and analyses.

Data and vulnerability measures

We used the Household Enumeration Survey from the 2011 India census data for the state of Uttarakhand, which includes variables about the house structure (wall, floor, and roof material; presence of bathroom or kitchen; etc) and variables about social and economic factors (ie household size, access to assets, and household structure and married couples) (GOI 2011). The entire dataset has 128 variables.

Vulnerability to natural hazards is a function of socioeconomic characteristics that help or hinder a household's ability to respond to and recover from a hazard (adaptive capacity), the built environment that may increase or decrease the structural damage likely to occur when exposed to a hazard (sensitivity), and a measure of the potential risk of hazards (Borden et al 2007). To identify the strongest indicators of each of these components of vulnerability, we divided the variables in the larger dataset into subsets of variables associated with built-environment vulnerability (BEV) and socioeconomic vulnerability (SEV). Variables included in the BEV analysis described the physical structure of a household, and variables included in the SEV analysis described the social and economic characteristics. There were 70 BEV variables and 58 SEV variables.

Analysis

Following methods established by Cutter et al (2003) and Borden et al (2007), we modeled SEV and BEV. The India census data are published as percentages of households that are categorized under each variable; therefore, the data are already scaled. Certain variables are already grouped and the data are highly correlated; for example, the structures were classified as good, livable, or dilapidated, and every structure was defined, so the sum of the percentage of structures classified as good, livable, or dilapidated is 100%. To determine the main contributors to variation in the dataset, we conducted PCA. We separated the variables into socioeconomic factors and built-environment factors and ran 2 separate PCAs, because these are both important influences in a household's vulnerability but are distinct types of variables. Variables included in the SEV PCA represent the social and economic wellbeing of a household, and variables included in the BEV PCA describe the physical characteristics of the house. The variables included in each analysis were all characteristics that could contribute to a household's vulnerability, so by using PCA to create new orthogonal components that are combinations of the input variables and by identifying the strongest indicators of vulnerability from the results of the household survey, we can determine the strength of each indicator by the amount of variability in the dataset they explain. We ran each of these PCAs on correlations (Box 1).

Principal components 1 and 2 for both SEV and BEV were calculated for each village in the study area. The 4 components were joined to a shapefile of villages in the region and visualized as standard deviations from the mean. Local Moran I's spatial correlation statistics were run on this village-level data for each component in each subcategory to determine whether special patterns exist in the region.

Results and discussion

Household surveys

We found that most people did not perceive that they had experienced a disaster related to natural hazards. Flooding and landslides associated with monsoon rains were not considered disasters, because they are just a part of living in the region. Although people may not consider the monsoon rains to be flooding events, we did experience 2 heavy rainfall events during our fieldwork, and it was obvious that these events affect the landscape. Many people working in the region have temporary or seasonal jobs or rely on a pension from a government job, and most households have 1 or 2 sources of income. A large number of the households we surveyed rely on support from sons who have permanently moved to other regions of India for work. The official population of Almora is about 34,000 people, but it is estimated that the real population is more like 50,000–60,000 people. Many houses are not accounted for and therefore likely do not follow building codes. One of the homes we visited was a permanent structure but had been built on government land without permission. This is not uncommon. Although building codes exist, most people do not follow them. The large majority of the 17 homes we

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BOX 1: Steps of the applied PCA

In a PCA run on correlations, the data are normalized by the correlation matrix and are therefore weighted equally in the analysis. Even though the variable inputs into these analyses were already scaled, the way in which they were scaled (relative percentages) allowed paired variables to have a strong bimodal distribution, and this inherently represented a potentially large amount of variability. Running the analyses on correlations helps to moderate these extreme skews and allows us to better interpret how the input variables vary together. The PCA rotates the data to create new orthogonal (uncorrelated) component bands that explain a certain percentage of the variation in the dataset. A component is calculated by multiplying each variable by a loading coefficient determined in the rotation of the dataset. A component value for a certain village would be the sum of these scaled variables. Each variable that was included in the analysis will be represented in every component but will have a loading coefficient near zero and contribute little to the overall component value or will have a large loading coefficient and highly influence the component value. It is common as the next step in the published methods for vulnerability analysis using PCA to further rotate the data using varimax rotation (Kaiser 1958) to help increase the interpretability. This method takes a user-defined number of components from the PCA, often determined using a scree plot, a threshold of the amount of dataset variability explained, the Kaiser criterium (eigenvalues >1), or some combination of these and other criteria that can vary greatly. It then rerotates the data to create new components that explain more of the variance in fewer components; these new components also have a small number of large coefficient variables and a large number of near-zero coefficient variables, which is how interpretability is increased (Abdi 2003). We have chosen not to conduct this additional analysis for several reasons: we were able to sufficiently interpret the initial PCAs, this additional rerotation means that the new components are no longer orthogonal and are not based in normal coordinate space, and choosing the number of components to include in the rotation is arbitrary but has a large effect on the outcome of the analysis. The rerotated components do not explain any more of the overall dataset variability than the initial components, and the total explained variability is redistributed to the new components through the rotation, which is why the number of components chosen is so crucial.

surveyed had walls constructed of bricks or cement, floors of cement or mud, and roofs of cement or tin.

BEV analysis

The main built-environment indicators associated with reduced vulnerability are the presence of a bathroom and high-quality building material. The first component of the BEV PCA primarily represents the presence or absence of a bathroom or latrine in the home. Homes with bathing facilities and a latrine connected to closed drainage or a septic tank have decreased vulnerability, whereas homes without bathing facilities or a latrine, or those with an open latrine and no wastewater drainage, have increased vulnerability (Table 1). In addition, a few variables about the floor and roof materials and general condition of the home (good, livable, etc) are included in this first component. This finding is consistent with research in the water, sanitation, and hygiene (WASH) sector. Homes without access to sufficient sanitation are at higher risk of infectious diseases, and that risk is often exacerbated by climate variability and its associated natural hazards. People without sufficient access to sanitation are also disadvantaged in several other ways, such as lack of income, education, or political power, that limit their ability to adapt to climate-related natural hazards. They are therefore highly vulnerable to disasters related to natural hazards (WHO 2019). A study conducted in India by Singh et al (1996) found that 75% of households that were classified in the very-low-income bracket did not have bathroom or latrine facilities in the household and that most low-income households and almost all medium-, high-, and very-high-income households had bathroom or latrine facilities. Although it is not a new finding that poor households are more vulnerable, the absence of a bathroom in the home is an indicator of a poor, highly vulnerable home, which could be another way of identifying these households (Alcántara-Ayala 2002; Fothergill and Peek 2004; Brouwer et al 2007). It is often difficult to get an accurate measure of household income and expenditure, so having multiple ways to identify very-low-income households will help to improve the accuracy of this measure.

BEV component 2 measures the overall building material quality. Households with increased vulnerability were classified as temporary or semipermanent and serviceable or nonserviceable in the census. They are likely small (a single room) with no kitchen inside the home; have a roof made of grass, thatch, bamboo, wood, or mud; and have walls made of grass, thatch, bamboo, wood, mud, or burnt bricks. Households with decreased vulnerability have homes classified as permanent, in good condition, with roof and walls made of stone, and with a kitchen within the home (Table 1). Although the structural quality identified as an indicator of higher vulnerability is the traditional architecture in the rural context, it has been shown that structures constructed out of these natural materials are at greater risk from floods than those constructed with artificial materials such as concrete, whether in an urban or rural environment (Englhardt et al 2019). BEV component 2 is made up of many structural components of the home that can be improved individually and therefore is measured as more of a scale of vulnerability.

The presence of a bathroom is generally more common in the study areas than the surrounding areas, excepting the core of Almora, and building material quality was mixed within cities (Figure 2A–C). The presence of a bathroom and mixed building material quality within cities demonstrate that many homes surpass the basic wealth necessary to build a bathroom in their home and do not fall in the category of extremely vulnerable. However, there is still varied wealth (and vulnerability) demonstrated by the mix in building material quality. The income and job opportunities are greater within a city than rural areas, so people living in the city are often able to find enough income that they are not

TABLE 1 Variable loadings from the BEV PCA for components 1 and 2. Only loadings with coefficients greater than 0.4 are shown. Sign is not indicative of an increase or decrease of vulnerability.

BEV component	Increased vulnerability		Decreased vulnerability	
1. Presence/absence of bathroom	Households without a latrine facility within the premises	−0.869662	Households with bathing facility within the premises	0.870651
	Open latrine	−0.86184	Households with latrine facility within the premises	0.869662
	Households without a bathing facility within the premises	−0.828851	Material of floor: cement	0.715495
	Material of floor: mud	−0.650645	Material of roof: concrete	0.607382
	Material of roof: stone/slate	−0.563420	Material of wall: burnt brick	0.573735
	No waste water drainage	−0.542323	Waste water outlet: closed drainage	0.526749
	All structures: livable	−0.472136	Flush-pour, flush latrine connected to septic tank	0.520849
	Residence: livable	−0.453638	All structures: good	0.504551
			Residence: good	0.484912
2. Structure quality	Type of structure: temporary	0.698698	Type of structure: permanent	−0.72100
	Material of roof: grass, thatch, Bamboo, wood, or mud	0.646042	Material of roof: stone/slate	−0.57055
	Type of structure: nonserviceable	0.522184	Material of wall: stone packed with mortar	−0.561580
	Type of structure: serviceable	0.519602	All structures: good	−0.48522
	Material of wall: grass, thatch, bamboo, wood, or mud	0.516133	Residence: good	−0.464510
	Material of wall: burnt brick	0.515264	Kitchen facility inside house	−0.427980
	Material of wall: mud/unburnt brick	0.479967		
	Number of dwelling rooms: 1	0.477159		
	Type of structure: semipermanent	0.43355		
	Kitchen facility outside house	0.424073		
	All structures: livable	0.415693		
	Residence: livable	0.402682		

Note: Only loadings with coefficients greater than 0.4 are shown. The sign is not indicative of an increase or decrease in vulnerability.

extremely poor, but there is large variation in income level above that extreme poverty level alone.

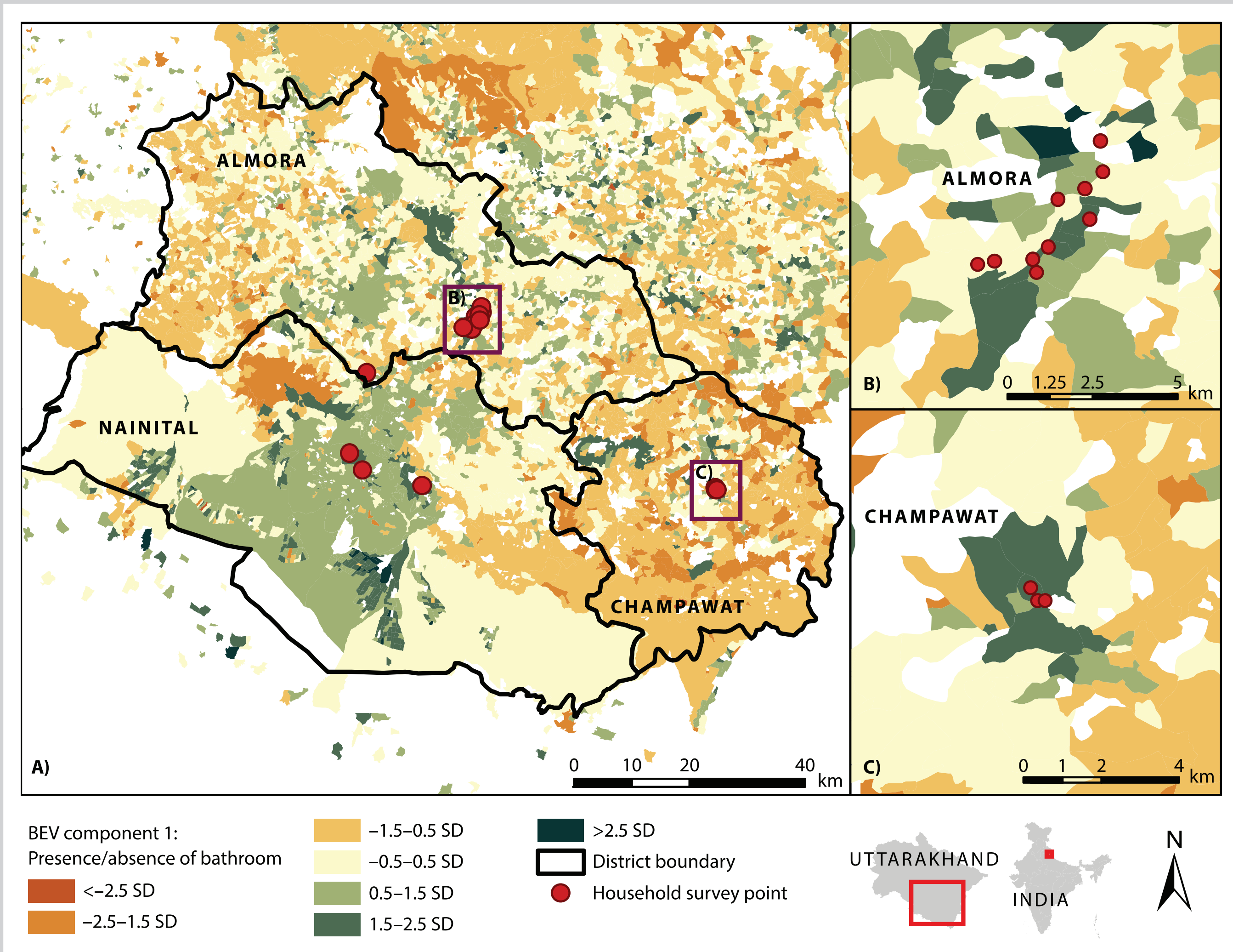
Almora is one of the oldest cities in the region, and although there is some tourism, much of the population resides there permanently. The city is built atop a ridge and extends down on either side of the ridge, with a mix of old and new development and a densely populated core region (Figure 2B). The slums, a group of informal settlements, are located in this core, which may be why that region shows mixed vulnerability for the presence or absence of a bathroom; households in the slums are basic, temporary structures and are not likely to have a bathroom (UN-Habitat 2005).

SEV analysis

The main SEV indicators are that access to a range of assets decreases vulnerability and that smaller households are more vulnerable. Component 1 from the SEV PCA is defined as access to assets; the main variables contributing to this component are availability of different assets, types of cooking fuel, and sources of lighting. Homes with decreased vulnerability have access to many types of assets, including some type of scooter, a car, a television, a mobile phone, and a computer with Internet; use liquified petroleum gas as a cooking fuel; and have electricity. Homes with increased vulnerability do not have access to assets, use fuelwood as their cooking fuel, and use kerosene for lighting (Table 2). Households with more capital assets have the means to absorb losses from a disaster and relocate or rebuild if necessary, whereas households with few capital assets are often not able to recover without aid (Cutter et al 2003; Holand et al 2011).

Component 2 of the SEV PCA represents household size. Homes with increased vulnerability have no married couples and only 1 or 2 people living there. Households with decreased vulnerability are larger; at least 6 people live in the home, and there are 2 or 3 married couples (Table 2).

FIGURE 2 Spatial distribution of BEV component 1 for the (A) districts of Nainital, Almora, and Champawat; (B) city of Almora; and (C) city of Champawat. Orange represents increased vulnerability, and green represents decreased vulnerability; the darker the shading, the greater the increase or decrease. SD, standard deviation.



Larger households have decreased vulnerability because they have an established social network and social capital; this network of support can help increase a household's ability to recover from a disaster (Moser 1998; Tierney 2006).

Access to assets is higher in the study cities than in surrounding areas, but household size is mixed in cities. There is an urban aggregation of resources, and it is easier to gain access to certain assets in cities because the infrastructure already exists. Household size being mixed in cities follows our survey findings; many of the homes we surveyed fit into the large household category defined earlier (2–3 married couples and greater than 6 people), but we also encountered several homes that fit into the small household category of having 1 or 2 people and no married couples. Because cities provide more job opportunities and ways to earn an income, 1 or a few members of a family will move to the cities from their village to earn enough income to support themselves and send resources back home to their families and villages. Some people moved to the city long enough ago to have established their own families and created a new social network, but those people who migrate to the cities and have small households are disconnected from their original social network and do not have access to their support system if a disaster were to occur. This may not be an issue if a small household has enough resources or a new social network to offset the disaster impact, but a larger household and social network often means more sources of income and the option to pool and share resources.

Spatial patterns

The regions surrounding Nainital and Almora largely have households with bathrooms (Figure 3A, B), but bathroom presence is less common in the region surrounding Champawat than within the city (Figure 3C). This means that most households within and surrounding Almora and Nainital have bathrooms and therefore have low associated vulnerability, but there is a clear difference in vulnerability between inside and outside of the city of Champawat.

Champawat is the capital of the newly established district (1997) of the same name, and although the city has been there for a long time, it has seen a lot more wealth and development in recent years. This influx of wealth and development likely explains the distinct difference in vulnerability shown by the presence or absence of a bathroom: most households outside of Champawat do not

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TABLE 2 Variable loadings from the SEV PCA for components 1 and 2.

SEV component	Increased vulnerability		Decreased vulnerability	
1. Asset index	Type of cooking fuel: firewood	−0.807921	Availability of assets: scooter, motorcycle, or moped	0.768283
	Availability of assets: none	−0.627915	Type of cooking fuel: LPG PNG	0.768274
	Ownership status: owned	−0.495441	Availability of assets: television	0.748832
	Main source of lighting: kerosene	−0.453643	Availability of assets: television, computer, laptop, telephone, mobile phone, and scooter or car	0.693960
			Location of drinking water source: within premises	0.649282
			Availability of assets: car, jeep, or van	0.642900
			Ownership status: rented	0.555306
			Availability of assets: bicycle	0.532856
			Availability of assets: telephone and mobile phone	0.530779
			Availability of assets: computer or laptop with internet	0.518930
			Main source of lighting: electricity	0.484346
2. Household size	Married couples: 0	−0.792705	Household size: 6–8	0.607194
	Household size: 1	−0.686640	Household size: 9+	0.541943
	Household size: 2	−0.405296	Married couples: 2	0.530025
			Married couples: 3	0.460137
			Ownership status: owned	0.444062
			Availability of assets: bicycle	0.411837

Note: Only loadings with coefficients greater than 0.4 are shown. The sign is not indicative of an increase or decrease in vulnerability.

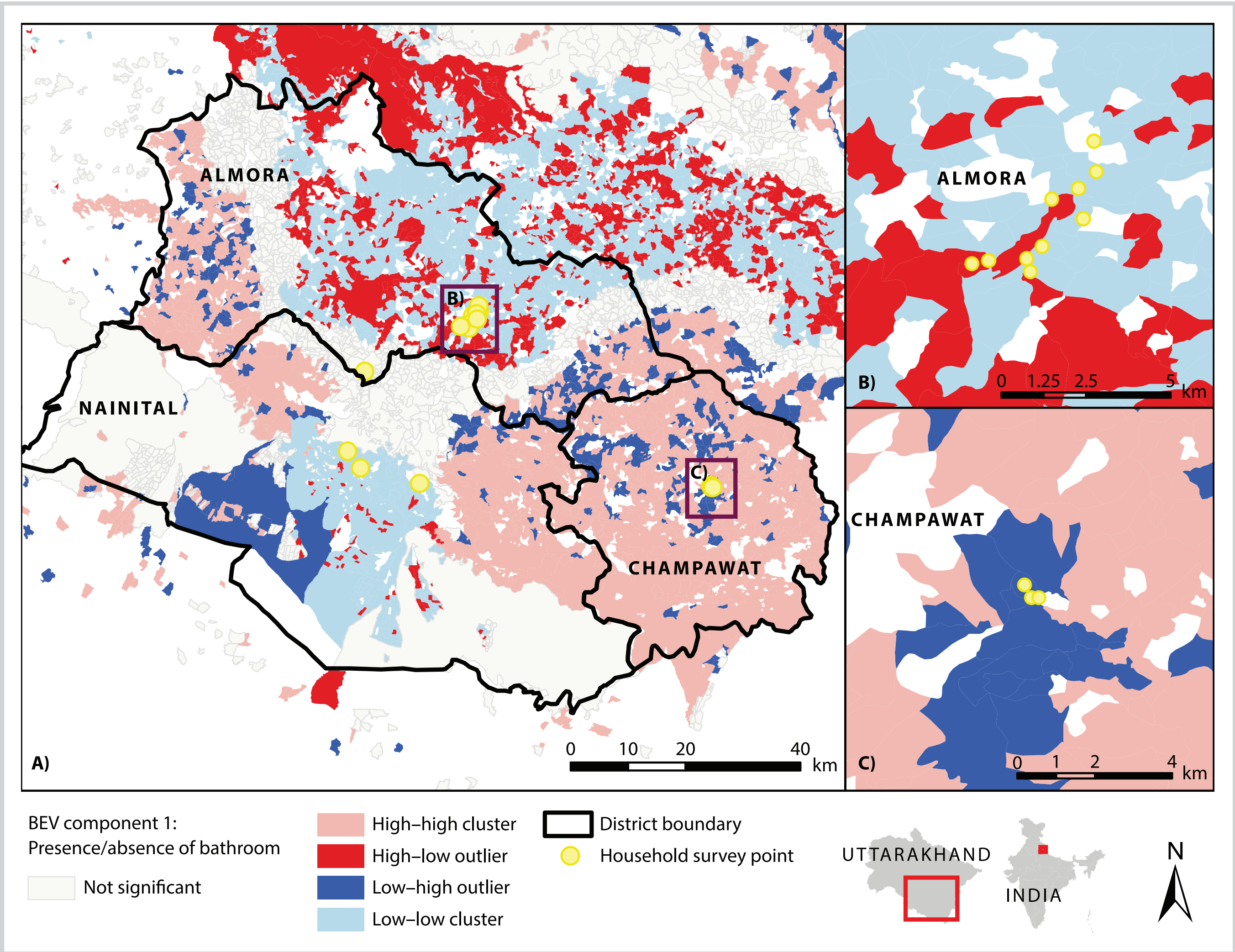
have the basic wealth necessary to build a bathroom in their home and are therefore more vulnerable than the regions within the city that are more likely to have a bathroom. Over time, as the city continues to grow, these resources reach further outside the city and the difference in basic vulnerability measured by the presence of a bathroom is not as stark between the city and the surrounding region.

Nainital and Champawat are both low-vulnerability outliers in regions of high vulnerability because of a low asset index; the regions surrounding Nainital and Champawat have low access to assets, but the cities have fairly high access. Almora is in a region where there are no significant spatial patterns of vulnerability associated with access to assets, and wealth is varied throughout the region. Nainital is a relatively wealthy city but has a variable population because of its status as a summer tourist destination. Although it is also built in the mountain landscape, it is built around a mountain lake, so the heart of the town is a valley and the homes and buildings are built into the mountains from the lake upward. These characteristics mean that the city is fairly self-contained, and the wealth seen within the city is far higher than in the surrounding region. Almora is a large city with a consistent year-round population. Because there are more permanent residents than in a city like Nainital, there is a higher variation in household types and wealth levels within the city. Much of the development in Almora occurred along the main roads, which traverse down the mountain in switchbacks, and new development is either built lower down on the steep slopes or between existing households. This pattern of development where people are building homes wherever they can find space has resulted in neighborhoods of varying wealth.

Conclusions

The goal of this analysis was to identify key indicators of vulnerability in the Uttarakhand region and examine patterns of kinds of vulnerability. The results provide information about the indicators and factors determining vulnerability in the region, but they are not necessarily the only drivers of vulnerability and addressing these issues does not guarantee that a home is no longer vulnerable. Multiple factors contribute to vulnerability, and especially in this analysis, vulnerability is relative. We look at the conditions in this dataset and use that information to gain insight into the factors influencing vulnerability, but more extensive field research and comprehensive data are necessary to draw conclusions about causality. Other studies have been conducted to examine social vulnerability in the state of Uttarakhand and can be used in conjunction with this study to define and direct further research. Studies such as the one

FIGURE 3 Spatial clustering of built-environment vulnerability (BEV) component 1 for (A) the region, (B) the city of Almora, and (C) the city of Champawat. Light red signifies clusters of high vulnerability, light blue signifies clusters of low vulnerability, dark red signifies high-vulnerability outliers in clusters of low vulnerability, and dark blue signifies low-vulnerability outliers in regions of high vulnerability.



conducted by Kumar and Bhattacharjya (2020) provide a statewide view of social vulnerability and complement this paper's city-based approach for examining patterns of household vulnerability in the region.

Our analysis contributes information about vulnerability in the region and provides a baseline of knowledge about who is vulnerable and where they live. We applied an existing framework for measuring vulnerability to the Uttarakhand region and expanded on this method by conducting household surveys. Through this work, we have identified that 2 prominent vulnerability indicators relating to the built environment are the presence or absence of a bathroom in the home and the structure quality of the home and that the strongest socioeconomic indicators of vulnerability are a household's asset index and the size of the household. We also looked at the spatial variation and spatial patterns of vulnerability and found that these spatial patterns were consistent with our findings from the household surveys, as well as with the knowledge we had for the region. The first priority of the Sendai Framework for DRR is understanding the many dimensions of disaster risk, and this analysis is a first step in creating a comprehensive view of vulnerability in a highly dynamic mountain region. Because mountain regions are complex, multihazard environments, it is crucial that we have as much information as possible about the many aspects that influence vulnerability. This analysis helps to close the knowledge gap about who is vulnerable and where they live at a village-level scale for this region.

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