https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Discussions

Integrated Seismic Risk Assessment in Nepal

Sanish Bhochhibhoya[1], Roisha Maharjan[1]

[1]Department of Civil Engineering, Pulchowk Campus, Lalitpur, Nepal

Correspondence to: Roisha Maharjan (072bce120.roisha@pcampus.edu.np)

Abstract. As Nepal is at high risk of earthquakes, the district-wide (VDC/Municipality level) study has been performed for vulnerability assessment of seismic-hazard, and the hazard-risk study is incorporated with social conditions as it has become a crucial issue in recent years. There is an interrelationship between hazards, physical risk, and the social characteristics of populations which are significant for policy-makers and individuals. Mapping the spatial variability of average annual loss (seismic risk) and social vulnerability discretely does not reflect the true nature of parameters contributing to the earthquake risk, so when the integrated risk is mapped, such combined spatial distribution becomes more evident. The purpose of this paper is to compute the risk analysis from exposure model of the country using OpenQuake and then integrate the results with socio-economic parameters. The methodology of seismic-risk assessment and the way of combining the results of the physical risk and socio-economic data to develop integrated vulnerability score of the regions has been described. This study considers all 75 districts and corresponding VDC/Municipalities using the available census. The combined vulnerability score has been developed and presented by integrating earthquake risk and social vulnerability aspect of the country and represented in form of map produced using ArcGIS 10. The knowledge and information of the relationship between earthquake hazard and the demographic characteristics of population in the vulnerable area is imperative to mitigate the local impact from earthquakes. Therefore, we utilize social vulnerability study as part of a comprehensive risk management framework to recuperate and recover from natural disasters.

Keywords: Socio-economic vulnerability, Physical vulnerability, Seismic risk, Hazard mitigation, OpenQuake, Principal Component Analysis (PCA), Integrated risk

1 Introduction

Nepal is one of the seismically active regions in the world with a long record of destructive earthquakes (Chaulagain et al., 2016). This is due to the intrinsic geological features with high exposure to earthquakes causing potential severe consequences. Most devastating earthquakes were reported in 1255, 1408, 1681, 1803, 1810, 1833, 1934, 1988, and 2015 (Pandey et al., 1999). From 2000 to 2015, 192 earthquakes greater than magnitude 5, 14 earthquakes greater than magnitude 6, and 1 earthquake greater than magnitude 7.5 took place in Nepal. Among these earthquakes, the most recent one in 2015 killed 8948 people, destroyed world heritage sites, and caused estimated damage of 10 billion dollars with the moment magnitude of Mw 7.8 (Mori et al., 2020). Around the globe, the impact of the seismic hazard has escalated due to increased population density,

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
Discussions

unmanaged urbanization, and other socio-economic parameters (Pachauri et al., 2014). Table 1 shows the number of deaths caused by the earthquake and poor hazard management in Nepal. The destruction or disaster is the combination of exposure to natural hazards and conditions of vulnerability characterized by the place and the inability to mitigate the negative repercussions (UNISDR, 2009). Although natural hazards are not escapable, hazard mitigation, vulnerability assessment, and their integration can significantly reduce the negative effect and aid in recovery (Frigerio et al., 2016).

Vulnerability is the key element and prerequisite of mitigating disaster, facilitating hazard resilient community (Guo and Kapucu, 2020). The core elements of vulnerability include resilience, exposure, and sensitivity (Cutter et al., 2003). The biophysical and natural components and the built-in environment under vulnerability have been meticulously examined; however, the social aspects of the vulnerability are highly undermined (Mileti, 1999). As a result, the loss estimation reports are usually unable to reflect social losses. It is imperative to include social vulnerability while assessing the natural hazards and their losses. According to Cutter et al. (2003), social vulnerability can be evaluated using the social vulnerability index (SoVI). For each country, SoVI is the corresponding measure of overall social vulnerability. Assessment of vulnerability and its mitigation necessitates the understanding of various factors like social, economic, and political contexts (Hewitt, 2007). SoVI analysis uses an all-inclusive framework where each factor is viewed to play an equal contribution to the country's vulnerability (Cutter et al., 2003). This concept has been applied under geographical and social contexts around the world such as the US (South Carolina) (Schmidtlein et al., 2011), Iran (Alizadeh et al., 2018), Bangladesh (Rahman et al., 2015).

To diminish the losses from natural and man-made hazards, individuals and policymakers need to be responsible for losses caused by disasters, reduce future risks, and finally make endeavours towards sustainable development accompanied by a resilient community. The knowledge transfer between individuals and policymakers is very constrained as hazard and risk assessment put limited focus on social components (Borden et al., 2007). In Nepal, the quantitative assessments of social vulnerability associated with seismic hazard are less owing to the lack of social data and seismic hazard mapping. Many studies in past are focused on geographical/physical vulnerability assessment of hazards like a flood (Dixit, 2003), landslides (Malakar, 2014), and extreme weather events (Shrestha, 2005). The study by Mainali and Pricope (2019) and (Aksha et al., 2019) incorporate vulnerability with climatic conditions and natural hazards in Nepal respectively with a wide range of socio-economic factors. However, such studies in Nepal do not include intricate analyses of social vulnerability assessment to earthquakes. Similarly, the extent of disaster caused by earthquakes depends on one place to another based on the local vulnerability factors such as socio-economic and cultural aspects. For example, the 2015 Gorkha Earthquake damaged more than 700,000 buildings, majority of which took place in underdeveloped rural areas with predominant traditional and low-quality masonry houses (Ulak, 2015). In this regard, risk assessment with proper forecasting measures plays prominent role in determining the areas vulnerable to seismic hazards and reducing the damage in the future. This signifies the need to incorporate the seismic risk assessment with social characteristics. In this study, the country-level earthquake risk estimates from the Global Earthquake Model OpenQuake, are analysed and integrated with vulnerability parameters (social and economic factors) in the districts of Nepal.

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

Studying social vulnerability identifies the sensitive areas and populations that are prone to high risk and are less likely to acclimatize and recover from a natural catastrophe. This study focuses on social vulnerability and explores the physical risk from earthquakes at the village and municipal levels. In this paper, we assessed the seismic impact potential by moving beyond the physical (direct) impact by integrating physical risk (economic loss) with measures of social vulnerability (features that create the potential for loss or harm). The main objective is to expand on the information and knowledge of features that are more socially vulnerable to seismic losses so that policymakers and individuals can carry out a sustainable procedure to reduce the effect in the country. To the author's best knowledge, no previous studies have been documented regarding integrating social vulnerability (preparation of society to any disaster) and seismic risk for Nepal.

Table 1: Deaths caused by Earthquakes in Nepal.

Year	Magnitude	Death
1255	7.8	2,200
1934	8.0	11,000
1966	6.3	80
1980	6.5	200
1988	6.9	1,091
2011	6.9	111
2015	7.8	8,857

2 Theory and background

2.1 Social Vulnerability Variables

As vulnerability is a multidimensional aspect, it cannot be integrated into a single variable (Cutter and Finch, 2008). The impact of natural hazards is based on social parameters such as socioeconomic status, geographical features, ethnicity (minority), renter, gender, and age. These intensify the impact of earthquakes; for instance, some people have the privilege to social advantages while some succumb to poverty and discrimination. The households with better economic status can recuperate from disasters better than low-income houses (Mileti, 1999). There have always been stories of high-class predation and low-class vulnerability. At the same time, the oppressed groups are not involved in the policy-making procedure due to the inequality prevalent in society. People are obliged to work overseas especially in gulf countries for employment opportunities due to poverty (Aksha et al., 2019). Similarly, ethnicity creates barriers in distribution and access to financial resources after disasters (Cutter et al., 2003). A significant number of minorities, females, and depending on age groups are more vulnerable (Borden et al., 2007). Moreover, another group of vulnerable populations is the renters because, in comparison to the homeowners, renters are financially unprepared for the recovery (Burby et al., 2003). According to the census of 2011, the population of Nepal is booming at more than 2% per annum. The topography of Nepal creates a barrier to distributing relief materials to the affected regions in time which exacerbates the impact of natural hazards. For example, in the Northern part of the country, especially in the far-western region most of the communities are not privileged with basic needs.

2.2 Earthquake risk assessment and OpenQuake

According to Stevens, et al. (2018), the probability of exceeding the shaking of 0.4g-0.6g is 10% and that of 1.0g-3.0g is 2% in the 50-year period. The seismicity in Nepal varies with the seismic source distribution with high risk in southern Nepal and is evenly distributed across the west-northwest–east-northeast direction. Such hazards could be devastating in a densely populated area. In this study, the physical risk assessment is evaluated using the OpenQuake platform. OpenQuake is a Python-based module that is used to model earthquake ruptures and calculate hazard and risk results by providing ground motion fields. The risk module of the platform where is the convolution of three parameters: hazard, seismic vulnerability model, and exposure data. The risk calculator includes a) classical damage b) classical BCR c) classical risk d) event-based damage e) scenario risk d) scenario damage (Pagani et al., 2014). In our research, first, the classical risk results are drawn from OpenQuake and these results are integrated with socio-economic models.

3 Materials and methods

In this research, an integrated approach for depicting the potential effects of earthquake events has been used. This approach assesses an event's potential impact by accounting for the seismic risk and the human dimensions within the hazard zone (Burton and Silva, 2016). Measuring risk necessitates multidisciplinary evaluation that takes into account both physical damage and social fragility/susceptibility conditions (Carreño et al., 2012). The integrated approach quantifies the direct impact of earthquake hazard in terms of physical risk descriptor, social parameters, and sustaining capacity of exposed societies (Fernandez et al., 2006).

3.1 Social vulnerability assessment

Social vulnerability helps to explain the reason behind the difference in consequences in communities, even though they are subjected to similar levels of ground shaking (Burton and Silva, 2016). We identified the meaningful variables incorporating the socioeconomic and physical context of Nepal. Moreover, to describe the vulnerability at the municipality and VDC level in Nepal, we computed a modified SoVI.

3.1.1 Data and SoVI modification

Social Vulnerability Index (SoVI) method was originally formulated by Cutter et al. (2003), which provides a comparative metric depicting an area's relative social vulnerability to hazard. This concept of social vulnerability has been applied in many contexts. For social vulnerability, we extracted data from the most recent national-wise census of Nepal held in 2011 (CBS), Nepal Human Development Report 2014 (UNDP). The administrative map at VDC and Municipality level is shown in Figure 1. Table 2 provides the list of all the variables used for social vulnerability assessment. Out of 45 variables, 22 variables are district-wise indicators and it is assumed that each sub-section (municipality and VDCs) has a uniform value. Similarly, 7 variables are a weighted combination of multiple variables as shown in Table 2. This technique of weighing variables is used

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

in PCR analysis exercised in NHDR (2014). NHDR (2014) also used the same weightage values for these variables. Hence, with 54 variables used in 7 weighted variables, there are altogether 92 variables considered for the social vulnerability index. The modification in the original SoVI is required due to the difference in demographic characteristics between Nepal and the USA and the availability of data. We have included variables from various categories. For instance, the housing unit status category reflects the features of the household, housing characteristics, and facilities. Population characteristics show female population characteristics, age structure, population density, population growth, child marriage, and disability population.
The cardinality of each indicator (variables) is indicated in Table 2. Positive cardinality (+) means variables have a positive relationship with social vulnerability, while negative cardinality (-) means they have a negative relationship. Each indicator should be normalized to obtain a relatively uniform dimension. Hence, based on cardinality, we used a MINMAX method for each indicator using Eq. (1) and (2), as exercised in Fang et. al. (2019).

For positively related indicators (+), $S_i = (X_i - X_{i,min})/(X_{i,max} - X_{i,min})$ (1)

For negatively related indicators (-), $S_i = (X_{i,max} - X_i)/(X_{i,max} - X_{i,min})$ (2)

Where, X_i is the original value of indicator i; $X_{i,max}$ and $X_{i,min}$ are the maximum and minimum values of the variable X_i. Si is the standard value of index i, which is in the range of 0 and 1.

Table 2: Variables used to construct social vulnerability index and their loading values after PCA.

S.N.	Description	Category	Data Source	Cardinality	Loadings
1	Percentage of households that owned a house	Housing Unit Status	a	-	-0.502
2	Weighted Foundation Index per household **	Housing Unit Status	a	-	0.863
3	Weighted Wall Index per household **	Housing Unit Status	a	-	0.872
4	Weighted Roof Index per household **	Housing Unit Status	a	-	-0.645
5	Weighted Drinking Water Index per household **	Housing Unit Status	a	-	0.498
6	Weighted Cooking Index per household **	Housing Unit Status	a	-	0.673
7	Weighted Electricity Index per household **	Housing Unit Status	a	-	0.72
8	Percentage of households without toilet facility	Housing Unit Status	a	+	0.533
9	Percentage of households without any of following facilities: radio, television, mobile, refrigerator, vehicles, internet	Housing Unit Status	a	+	0.653
10	Percentage of households with radio facilities	Housing Unit Status	a	-	0.395
11	Percentage of households with television facilities	Housing Unit Status	a	-	0.711

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

12	Percentage of households with internet facilities	Housing Unit Status	a	-	0.614
13	Percentage of households with vehicles	Housing Unit Status	a	-	-0.51
14	Percentage of absentee households	Housing Unit Status	a	+	-0.885
15	Average household size	Housing Unit Status	a	+	0.511
16	Percentage of households with child as household head *	Housing Unit Status	a	+	0.546
17	Percentage of households with female as household head *	Housing Unit Status	a	+	-0.797
18	Percentage of household with 5+ members *	Housing Unit Status	a	+	0.666
19	Housing Density *	Housing Unit Status	a	+	-0.914
20	Percentage of population that is females	Population	a	+	-0.84
21	Percentage of children under 5 years	Population	a	+	0.748
22	Percentage of children aged 5 to 14	Population	a	+	0.705
23	Percentage of people aged 30 to 49	Population	a	-	0.712
24	Percentage of elder population (65+)	Population	a	+	-0.483
25	Percentage of population with disabilities (blind, deaf, mental)	Population	a	+	-0.374
26	Percentage of child marriages *	Population	a	+	0.745
27	Population Growth (2001 - 2011) *	Population	b	-	-0.846
28	Net Migration Rate *	Population	b	-	-0.85
29	Population Density *	Population	a	+	-0.89
30	Population per each hospital and PHCC/HCC *	Health	e	+	0.51
31	Population per each health posts and sub-health post *	Health	e	+	0.773
32	Life Expectancy *	Health	b	-	0.776
33	Infant Mortality Rate (Per 1000 Birth) *	Health	b	+	0.706
34	Literacy Rate	Education	a	-	0.469
35	Weighted Education Level Index per capita **	Education	a	-	0.717
36	Population per each school *	Education	g	+	0.526
37	Human Poverty Index *	Economy	d	+	0.803
38	Human Development Index (2011) *	Economy	d	-	0.878
39	Budget allocation per capita *	Economy	f	-	0.835
40	Per capita income, Rs. at market price *	Economy	d	-	0.751
41	Percentage of population that are economically active *	Economy	d	-	0.488
42	Gross Domestic Product (Value Added) Rs. In Million (per Capita) *	Economy	d	-	0.739

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

43	Labour Productivity per capita *	Economy	d	-	0.871
44	Population per each small industry *	Economy	c	+	0.429
45	Percentage of employment that are female *	Economy	a	-	0.554

a National Population and Housing Census 2011 (CBS (2012))
b Population Monologue V01 (CBS (2014a))
c Population Monologue V03 (CBS (2014b))
d Nepal Human Development Report (Sharma et al., 2014)
e Department of Health Services (2013)
f Budget report for year 2070-71 (2013 - 14)
g Department of Education (2013 – 14)
* District-wise data
** Weighted index calculated as per Table 3

Table 3: Weights corresponding to the weighted variables, as defined in Table 2.

Variables	Weightage	Variables	Weightage
A. Weighted Foundation Index Types of foundation in houses		**E. Weighted Cooking Index** Main cooking fuel	
RCC with pillar	5	LP gas	6
Cement bonded bricks/stone	4	Electricity	6
Mud bonded bricks/stone	3	Kerosene	5
Wooden pillar	2	Bio gas	4
Others	1	Wood/firewood	3
Not Stated	1	Santhi/guitha (cow dung)	2
B. Weighted Wall Index Types of walls in houses		Others	1
Cement bonded bricks/stone	6	Not Stated	1
Mud bonded bricks/stone	5	**F. Weighted Electricity Index** Main source of light	
Wood/ planks	4	Electricity	5
Bamboo	3	Solar	4
Unbaked brick	2	Bio gas	3
Others	1	Kerosene	2
Not Stated	1	Others	1
C. Weighted Roof Index Types of roofs in houses		Not Stated	1
RCC	7	**G. Weighted Education Index**	

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Discussions

		Highest level of education of each individual	
Tile/slate	6	Post Graduate equiv. and above	9
Galvanized iron	5	Graduate and equiv.	8
Wood/planks	4	Intermediate and equiv.	7
Mud	3	S.L.C. and equiv.	6
Thatch/straw	2	Secondary (9 -10)	5
Others	1	Lower secondary (6 -8)	4
Not Stated	1	Primary (1-5)	3
D. Weighted Drinking Water Index Main source of drinking water		Beginner	2
Tap/piped water	7	Others	1
Covered well/kuwa	6	Non-Formal	1
Tubewell/handpump	5	Not Stated	1
Uncovered well/kuwa	4		
Spout water	3		
River/stream	2		
Others	1		
Not Stated	1		

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
Discussions

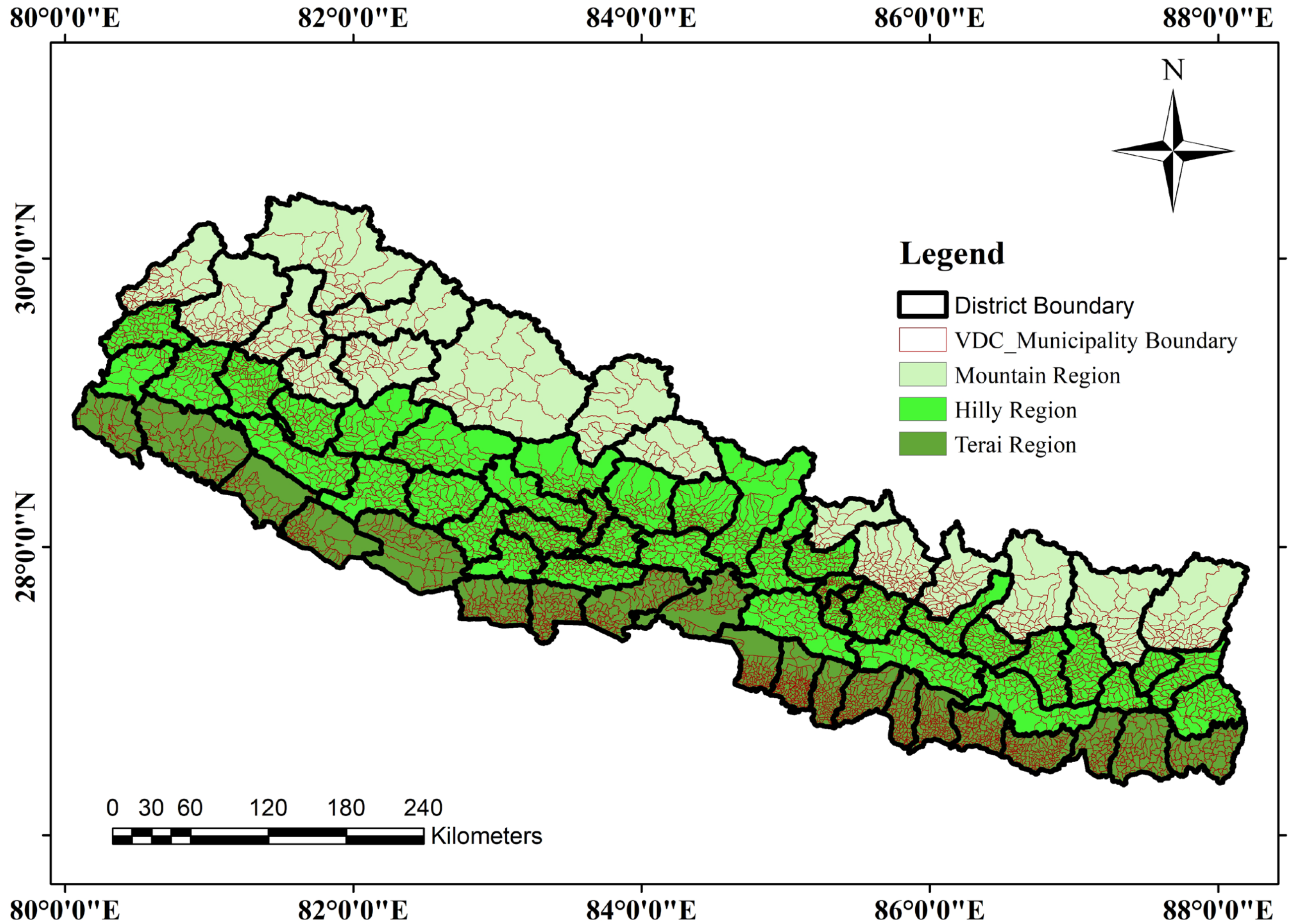


Figure 1: Administrative Map of Nepal showing 3983 VDCs and municipalities, 75 districts, and three geographical regions.

3.1.2 Principal component analysis

Social Vulnerability Index is created by synthesizing socio-economic variables through a mathematical procedure called Principal Component Analysis (PCA). PCA transforms a number of possibly correlated variables into a smaller number of uncorrelated components (Abdi and Williams, 2010). The main idea of PCA is to reduce the dimensionality of a dataset with a large number of inter-related indicators, whilst retaining the maximum possible variation present in the data set (Jolliffe, 2002).

3.1.2.1 Number of Principal Components

It is very crucial to determine the number of components to retain in PCA (Franklin, 1995). We used Parallel Analysis (PA) by Horn (1965). Various studies like Humphreys and Montanelli (1975), Zwick and Velicer (1986), and Thompson and Daniel (1996) have shown that PA is an appropriate method to determine the number of factors. These studies assert that this method

(PA) is the best available alternative to calculate the number of factors to be retained. Finally, in this method, Eigenvalues from PCA prior to rotation are compared with 'expected' eigenvalues which are obtained by simulating normal random samples with identical dimensionality (same number of samples and variables) using a Monte-Carlo simulation process. Initially, a factor was considered significant if the associated eigenvalue was bigger than the mean of those obtained from the random uncorrelated data. Currently, the default (and recommended) values for a number of random correlation matrices and percentile of eigenvalues are 100 and 95 respectively (Cota et al., 1993; Glorfeld, 1995; Velicer et al., 2000). We used a parallel analysis engine developed by Vivek et al. (2017) to calculate corresponding random Eigenvalues. From parallel analysis, there were eight components with larger associated Eigenvalues than one from the Monte-Carlo simulation as shown in Table 4. These eight components explained 77.51% of the variance in all variables.

We also used two rules-of-thumb to calculate the number of components to be retained for comparison. The first one is Kaiser's rule proposed by Kaiser (1960). As per this rule, only those principal components with Eigenvalues greater than 1.0 are retained. As seen in Table 4, just like parallel analysis, Kaiser's rule also indicated eight principal components. The second one is Cattell's Scree test ((Cattell, 1966) which is based on the scree-plot (Eigenvalues vs the number of components). According to this method, a point where the scree plot moves from steep to shallow is taken as a cutting-off point as shown in Figure 2 which also indicates eight principal components similar to parallel analysis.

Table 4: Initial Eigenvalues, variances, and results of Parallel analysis for first ten principal components.

Component	Initial Eigenvalues (a)	% of Variance	Cumulative %	95% Percentile Eigenvalue (Parallel Analysis) (b)	Parallel Analysis: Remarks
1	13.215	29.366	29.366	1.227612	a > b
2	9.201	20.447	49.813	1.199826	a > b
3	3.541	7.87	57.683	1.183024	a > b
4	3.096	6.88	64.563	1.170289	a > b
5	1.787	3.972	68.535	1.160148	a > b
6	1.488	3.308	71.842	1.147872	a > b
7	1.345	2.99	74.832	1.136596	a > b
8	1.206	2.681	77.513	1.126383	a > b
9	**0.929**	2.064	79.577	**1.11708**	**a < b**
10	0.79	1.755	81.332	1.107092	

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

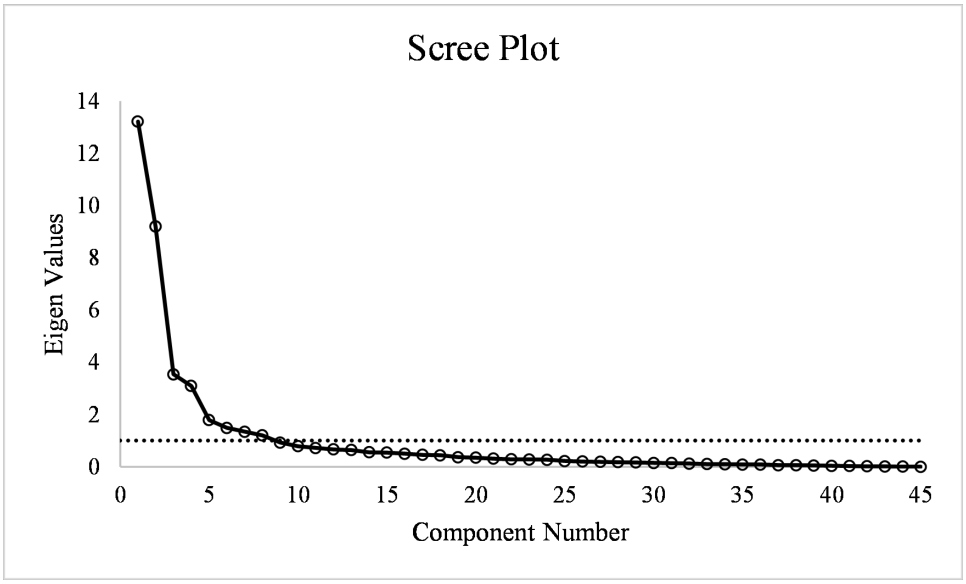


Figure 2: Scree plot (Eigen Values Vs Components).

3.1.2.2 Suitability of data for PCA

We performed two tests to check the adequacy of data for PCA. The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) depicts the proportion of variance in the variables that might be caused by underlying factors (Fekete, 2009; Kaiser, 1970). KMO-value greater than 0.8 is considered good, while KMO-value less than 0.5 requires some remedy, either by deleting or adding variables (IBM Support, 2020). Similarly, Bartlett's test of sphericity is the suitability test, where the value below 0.05 indicates the variables are related and suitable for structure detection. In this study, KMO value of 0.873 and Bartlett's test value of 0.000 passed the requirements of data for PCA.

3.1.2.3 Statistical Analysis

PCA is carried out in SPSS version 21.0. We employed Varimax rotation with Kaiser normalization as applied by Aksha et al. (2019), Fekete (2009) which maximizes the variance shared among data and eases the interpretation by rotating the axes of the components perpendicular to them. For the interpretation of the result, we suppressed the absolute loading value less than 0.30 and considered Eigenvalues greater than 1.0 as in Fekete (2009). Due to the lack of justifiable method and evidence for weighting components, an equal weighting, and additive approach is considered as exercised in similar studies Cutter et al. (2003) and Aksha et al. (2019). The loadings after PCA are presented in Table 2. Thereafter, SoVI scores are calculated by summing the scores of all principal components. SoVI scores are generally expressed as standard deviations (z-scores) or quintiles to emphasize their relative value (Tate, 2012). In this study, we used z-scores to classify the social vulnerability of each VDC and municipalities into five groups and we plotted the results in map form using ArcGIS.

3.2 Seismic Risk Assessment

The Classical PSHA-based risk calculator was performed to calculate the annual average loss using OpenQuake. This calculator combines numerical integration, physical vulnerability functions of the assets, seismic hazard curve at the location to calculate the loss distribution for the asset within a specified time period (Pagani et al., 2014). The calculator requires an exposure model describing the distribution of building typologies, physical vulnerability functions for each building type, and hazard curves calculated in the region of interest. The physical vulnerability function is solely hazard dependent. The hazard curves required are also calculated using the OpenQuake engine using the classical PSHA approach. For hazard curves derivation, a source model and ground motion prediction were provided. Finally, the value of annual average loss (AAL) for each VDCs and municipalities was rescaled into the range between 0 and 1 using MIN-MAX rescaling (Equation 1).

3.2.1 Source model

Nepal is one of the seismically active zones in the world, the geological formation of Nepal has been well documented in several studies (Gehrels et al., 2006; Hodges, 2000; Stevens et al., 2018; Taylor and Yin, 2009; Thapa and Guoxin, 2013; Upreti and Le Fort, 1999). For instance, Stevens et al. (2018) used a mix of fault and area source models — in total six seismic sources with the Gutenberg a and b values along with maximum magnitude estimated for each source zone. Similarly, Pandey et al. (2002) divided the whole Nepal region into ten area sources and twenty-four fault sources. Thapa and Guoxin (2013) divided the Nepal region into twenty-three seismic source zones. Chaulagain et al. (2016) also used the same sources to carry out a seismic risk assessment. In this study, the twenty-three source zones similar to that of Thapa and Guoxin (2013) are considered for probabilistic seismic hazard analysis. The seismic source zones are shown in Figure 3. The delineated sources are assumed to be homogenous in terms of their seismicity so that every point is assumed to have an equal probability of occurrence of an earthquake. Thapa and Guoxin (2013) determined ‘b’ value of 0.85 for the entire region. Here, we have also considered the same ‘b’ value as proposed in that study.

Generally, small magnitude earthquakes have a minute effect on engineering structures. Therefore, for the hazard analysis, the minimum magnitude within all source zone was considered 4.0. The surface wave of 4.0 can be damaging for engineering buildings in Nepal (Thapa and Guoxin, 2013). The devastating great earthquakes in Nepal occurred in 1505, 1934, 2015 with magnitude Mw of 8.1, 8.4, and 7.8 respectively. The maximum magnitude of each source zone is given in Table 5. Similarly, the hypocenter depth of 10 km is used for the entire region.

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
Discussions

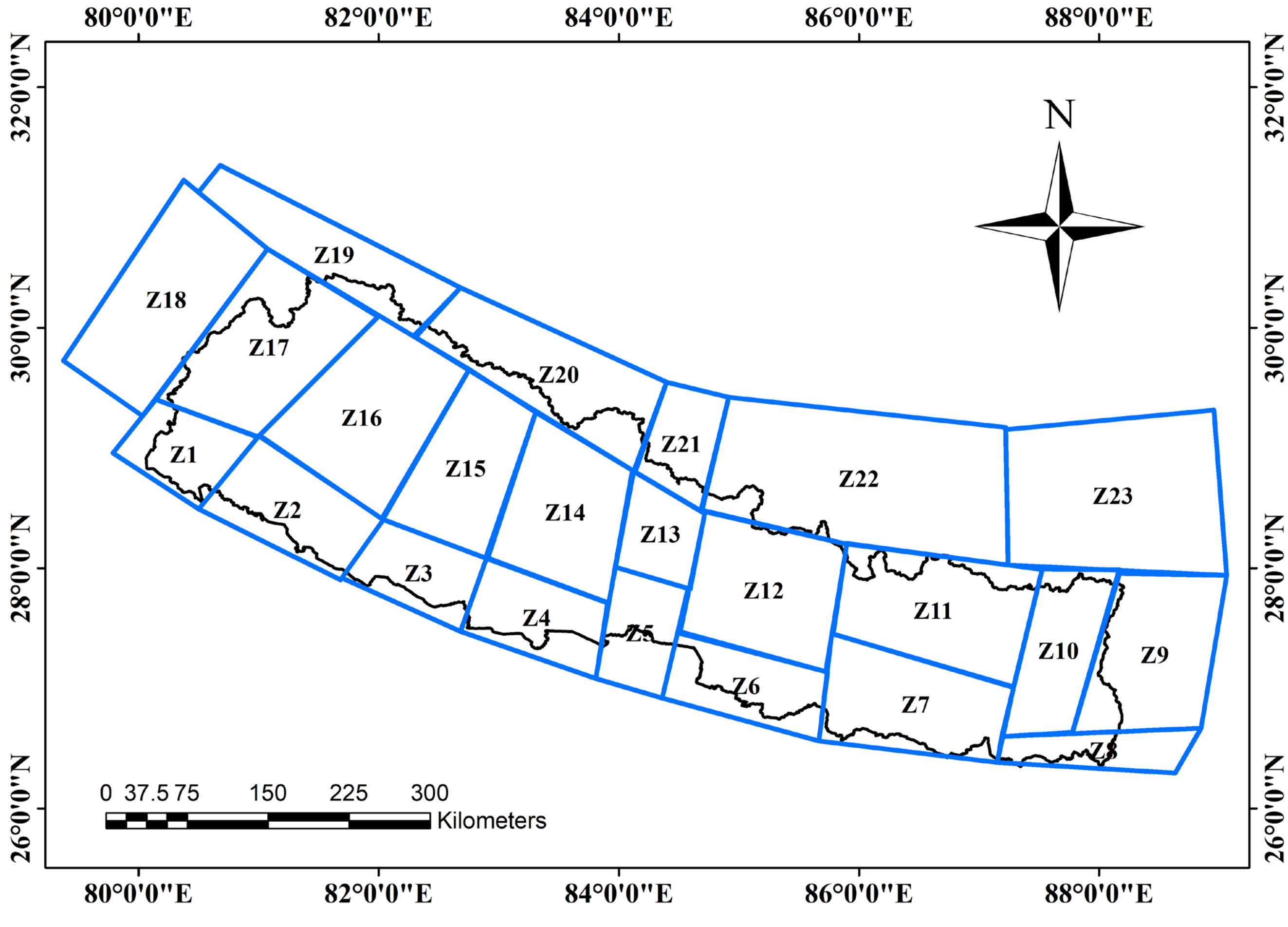


Figure 3: Seismic Source Zones of Nepal (Thapa and Guoxin, 2013).

225 **Table 5: Seismic history and maximum magnitude of source zones** (Chaulagain et al., 2015; Thapa and Guoxin, 2013)

Number	Source Zones	Historical Events	Maximum Magnitude
1	Z1	No records of strong earthquakes	6.5
2	Z2	No records of strong earthquakes	6.5
3	Z3	Magnitude (Mw) 6.2 earthquake	6.5
4	Z4	No records of strong earthquakes	6.5
5	Z5	No records of strong earthquakes	6.5
6	Z6	Magnitude (Mw) 6.3	6.5
7	Z7	Magnitude (Mw) 6.8	7
8	Z8	No records of strong earthquakes	6.5

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

9	Z9	Ms 6.3, Ms 7.0, Ms 6.1 in 1849, 1852, 1980 respectively	8
10	Z10	Ms 6.1 and Ms 6.8 in 1965 and 2011 respectively	8.5
11	Z11	Magnitude Mw 7.6 and Mw 8.2 in 1833 and 1934 respectively	8.5
12	Z12	Ms 7.6 in 1255, 1408, 1681, 1810	8
13	Z13	Moderate earthquakes	7.5
14	Z14	Mw 7, Mw 6.7 in 1936 and 1954 respectively.	8.5
15	Z15	Ms 8.1	8.5
16	Z16	Strong earthquakes	8.5
17	Z17	Strong earthquakes	8.5
18	Z18	Ms 6.7, 6, 6, 6.5, 6.3 in 1911, 1935, 1945, 1958 respectively.	8
19	Z19	No strong earthquakes	6.5
20	Z20	Strong earthquake of Ms 6.2	6.5
21	Z21	Less active	6.5
22	Z22	Moderate earthquakes	6.5
23	Z23	Moderate earthquakes	6.5

3.2.2 Attenuation relationship (Selection of ground motion prediction equation)

Selecting the ground motion prediction equation is one of the important steps in seismic hazard analysis. These equations govern the propagation of seismic ground motion from seismic source to site in terms of magnitude, distance, depth, and other site parameters (Cornell, 1968). In the context of Nepal, there are insufficient strong ground motion records to derive a precise equation capturing the actual response spectrum. On top of that, very few researches have been conducted in terms of attenuation relationship in Nepal. Previous studies like Chaulagain et al. (2015) and Stevens et al. (2018) have used combination of GMPEs within logic tree. To this end, we assume the tectonic region as a shallow crust and subduction interface like that in Chaulagain et al. (2016). The equations used herein are Atkinson and Boore (2003), Youngs et al. (1997), Campbell and Bozorgnia (2008), Chiou and Youngs (2008), and Boore and Atkinson (2008). These equations are used within a logic tree (equal weights for each equation) to conduct probabilistic seismic hazard and risk analysis in OpenQuake.

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

3.2.3 Exposure model and Physical Vulnerability model

In this study, the building description and data from Census 2011 are used to develop the exposure model without considering the industrial or commercial buildings. The total number of households according to Census 2011 is 5,423,297. Most of the regions in Nepal consist of mud-mortar/bonded brick masonry buildings. In remote areas, wooden buildings are abundant whereas, in the central region especially in Kathmandu and urban areas, cement bonded or reinforced concrete buildings are present. We have considered four types of buildings — mud bonded, cement-bonded, reinforced cement concrete (RCC), wooden, and adobe. The area and construction cost of each building type is shown in Table 8 as considered by Chaulagain et al. (2015). The spatial distribution of total buildings across the country is shown in Figure 4a and the individual building typology is summarized in Box and Whisker plot as shown in Figure 4b. The average values of RCC with pillar, Mud-Bonded, Cement-Bonded, Wooden-pillar, and Adobe are 135.73, 603.36, 239.91, 340, 46.33 respectively as presented in Figure 4 b.

On the other hand, the seismicity itself is not responsible for imposing seismic risk in Nepal, the risk is also driven by the physical vulnerability of infrastructures (Chaulagain et al., 2016). The average annual loss is evaluated using a vulnerability model. The physical vulnerability model is the probabilistic distribution of loss ratio for given intensity measure levels. In this research, the fragility model developed by Chaulagain et al. (2015) is adopted for different building types thereafter, the fragility curve is inputted in the vulnerability modellers toolkit (VMTK) developed by GEM OpenQuake to derive the physical vulnerability model. VMTK is a framework divided into six modules from deriving fragility function via non-linear dynamic analysis to deriving physical vulnerability model using fragility function and consequence model (Martins et al., 2021). In this process, the fractions of buildings in each damage state are multiplied by the associated damage ratio (from the consequence model), in order to obtain a distribution of loss ratio for each intensity measure type (Pagani et al., 2014). The fragility function used in this study is shown in Table 6. The consequence model used for developing the physical vulnerability model is presented in Table 7.

Table 6: Mean and standard deviation per damage state for each building type (Chaulagain et al. 2015).

Building type	Moderate Damage		Extensive Damage		Collapse	
	μ	σ	μ	Σ	μ	Σ
Adobe	-3.22	0.65	-1.99	0.77	-1.45	0.64
Mud Bonded	-2.14	0.72	-1.66	0.72	-1.05	0.66
Cement Bonded	-1.82	0.68	-1.06	0.67	-0.62	0.72
Wooden	-1.08	0.64	-0.39	0.64	0.00	0.64
RCC	0.35	0.17	0.85	0.2	1.35	0.32

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Table 7 Consequence model to develop physical vulnerability model (Chaulagain et al. 2015).

Damage Type	Damage ratio
Moderate damage	0.3
Extensive damage	0.6
Collapse	1.00

Table 8: Area and construction cost of different Building Type (Chaulagain et al. 2015).

Building Type	Area per building (m^2)	Construction cost (€/m^2)
Adobe	60	150
Mud Bonded	70	225
Cement Bonded	80	275
Wooden	60	200
RCC	80	325

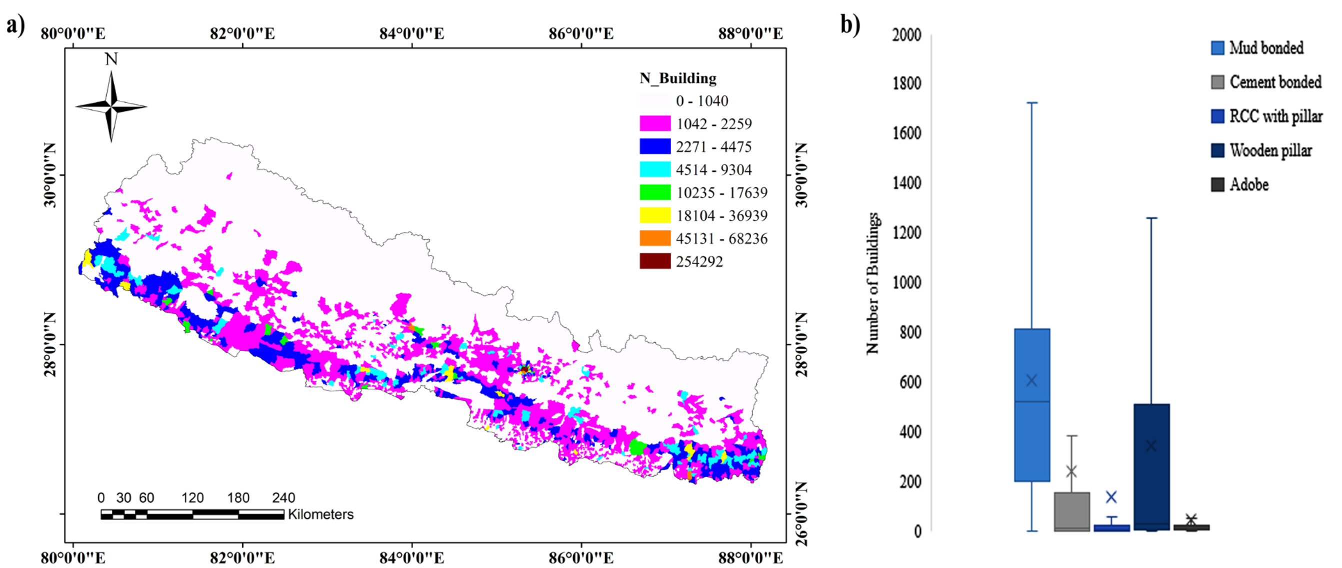


Figure 4: a) Spatial distribution of total buildings in Nepal b) Box and Whisker plot describing the distribution of each building types

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
Discussions

3.3 Integrated risk assessment

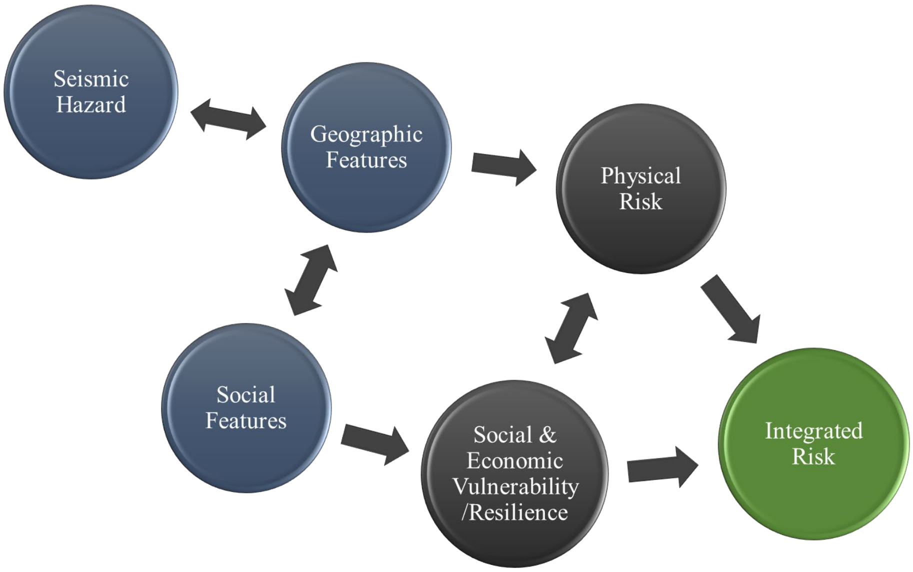


Figure 5: Framework for Integrated Risk Approach (Burton and Silva, 2016)

The mapping of average annual loss estimates and SoVI are useful, but they do not depict the true nature of the components contributing to the earthquake risk at a particular place (Burton and Silva, 2016). The compounding nature of risk becomes more evident when visualized in form of an integrated risk map. A total risk index was constructed by combining the social vulnerability index and estimates of average annual loss in rescaled metrics. Here, the seismic losses were recomputed by using the Min-Max rescaling method. The framework or workflow of the integrated risk assessment is shown in Figure 5. The first phase of integrated risk involves evaluating seismic hazards using OpenQuake's hazard toolkit developed by GEM Foundation. The seismic hazard analysis requires earthquake ruptures and ground motion fields. The hazard calculation when combined with exposure and physical vulnerability using QpenQuake's risk calculator gives the estimate of physical seismic risk in the form of human loss or economic loss. The physical vulnerability and exposure model interacts with the social and economic parameters or overall capacity of the population to sustain hazards (Burton and Silva, 2016). The total integrated risk is the combination of physical risk and a set of contextual and social vulnerability conditions (Carreño et al., 2012). In this regard, the paper evaluates the integrated risk grounded on direct factors or physical risk and indirect factors. In this paper, the integrated risk index (R_T) was calculated using Eq. (3):

$$R_T = R_f\ (1 + F) \tag{3}$$

The Moncho's equation (Eq (3)) is used to evaluate convoluted risk, where R_f is a physical risk index, in this case, average annual loss estimate, and F is a social fragility index or aggravating coefficient (Glorfeld, 1995). This technique and its successful application can be found in numerous studies due to its simplicity and successful applications. (Burton and Silva, 2016; Carreño et al., 2012; Fernandez et al., 2006; Khazai et al., 2013). In order to verify the calculated total risk, the OpenQuake integrated risk modelling toolkit was used. The integrated risk modelling toolkit (IRMT) is a plugin developed by

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

GEM Foundation and available in QGIS opensource platform that allows to build a composite framework to assess physical risk and social characteristics that affect the earthquake risk. The OpenQuake platform present within QGIS was used to develop probabilistic seismic risk models. The diagrammatic workflow of social and physical risk indicators developed by OpenQuake IMRT is shown in Figure 6. The integrated toolkit involves intricate details — selection of indicators to the detailing and mapping of composite risk assessment.

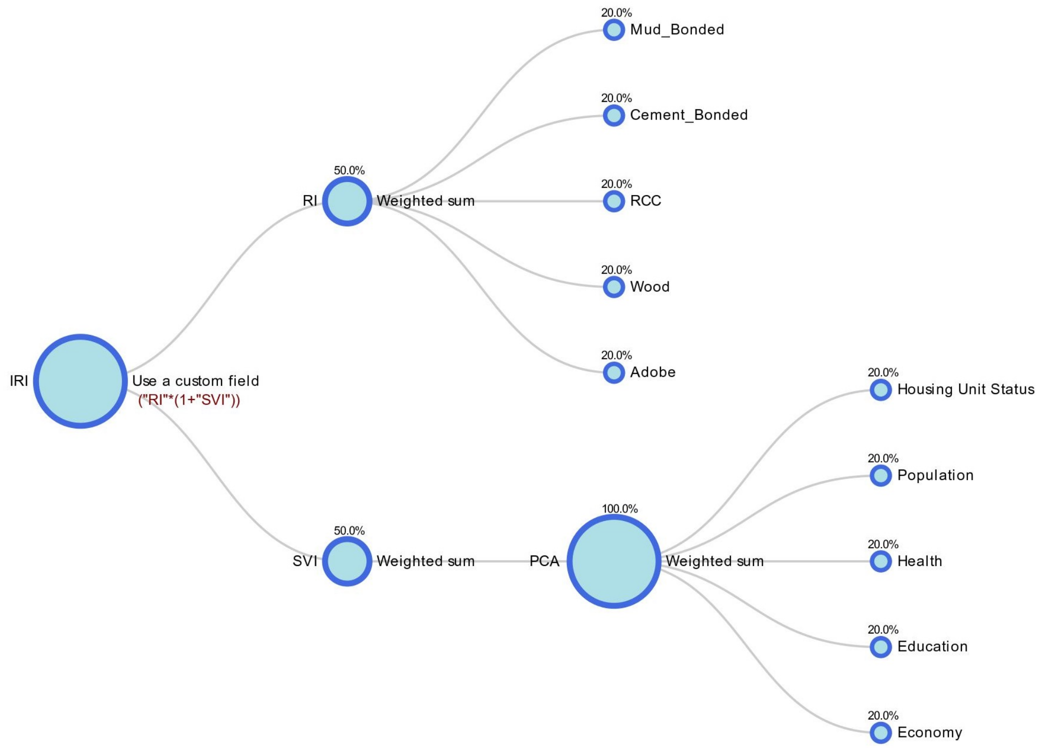


Figure 6: Workflow showing social and physical risk indicators in QGIS IRMT.

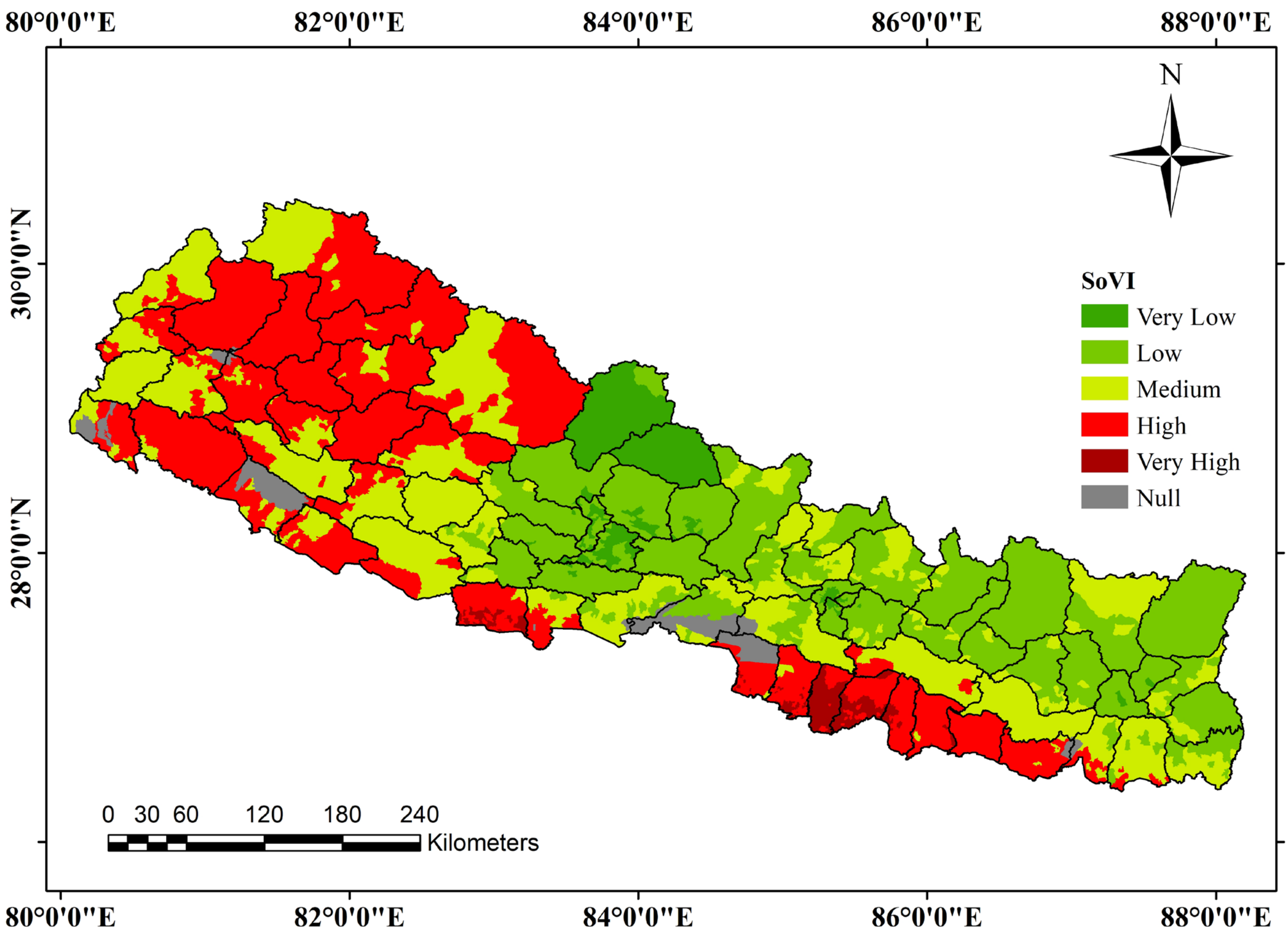
4 Results and discussion

4.1 Social vulnerability index (SoVI)

Based on z-scores, the total SoVI scores are classified into five quintiles from very low (< -1.5 standard deviation) to very high (> 1.5 standard deviations) vulnerability. Figure 7 depicts the distribution of total SoVI scores across the country. The total SoVI scores were calculated by summing all principal components. The most vulnerable places are located in the eastern region and western Terai region of Nepal. Aksha et. al (2019) and Gautam (2017) also found a similar vulnerability in their respective studies. Despite having similar geophysical characteristics (same ecological region), they exhibit differences in

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

social vulnerability. However, Aksha et. al (2019) classified Kathmandu valley as a high vulnerability class, while Gautam (2017) classified it as very low class. Our result agreed with the latter case. This variability in the result is due to differences in variables during the analysis. The geographic distribution of each sub-component is demonstrated in Figure 8. Highly vulnerable areas under the housing unit category are concentrated in the Western Hill and Eastern Terai regions. The population component exhibits a high level of vulnerability in Kathmandu, Butwal, and some parts of the Far-Western region. Under health component, there is an intense degree of vulnerability in the Terai region and the Northern part or Mountain parts of the Far-Western region. Similarly, the component, education, reveals great vulnerability in the Eastern Terai region. The final component economy shows a very high degree of vulnerability in the mid part of the Far-Western region and Terai region. One of the major takeaways of this study is that areas with the same geophysical features may demonstrate different levels of social vulnerability. Significant differences are observed among three regions eastern Terai, Mountain, and Western Hills. The least vulnerable areas are the central and eastern Hill regions. A high level of vulnerability is concentrated in the areas with dense populations of minorities, regions with limited access to infrastructures and important facilities.



https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Figure 7: Spatial distribution of Social Vulnerability Index in districts of Nepal.

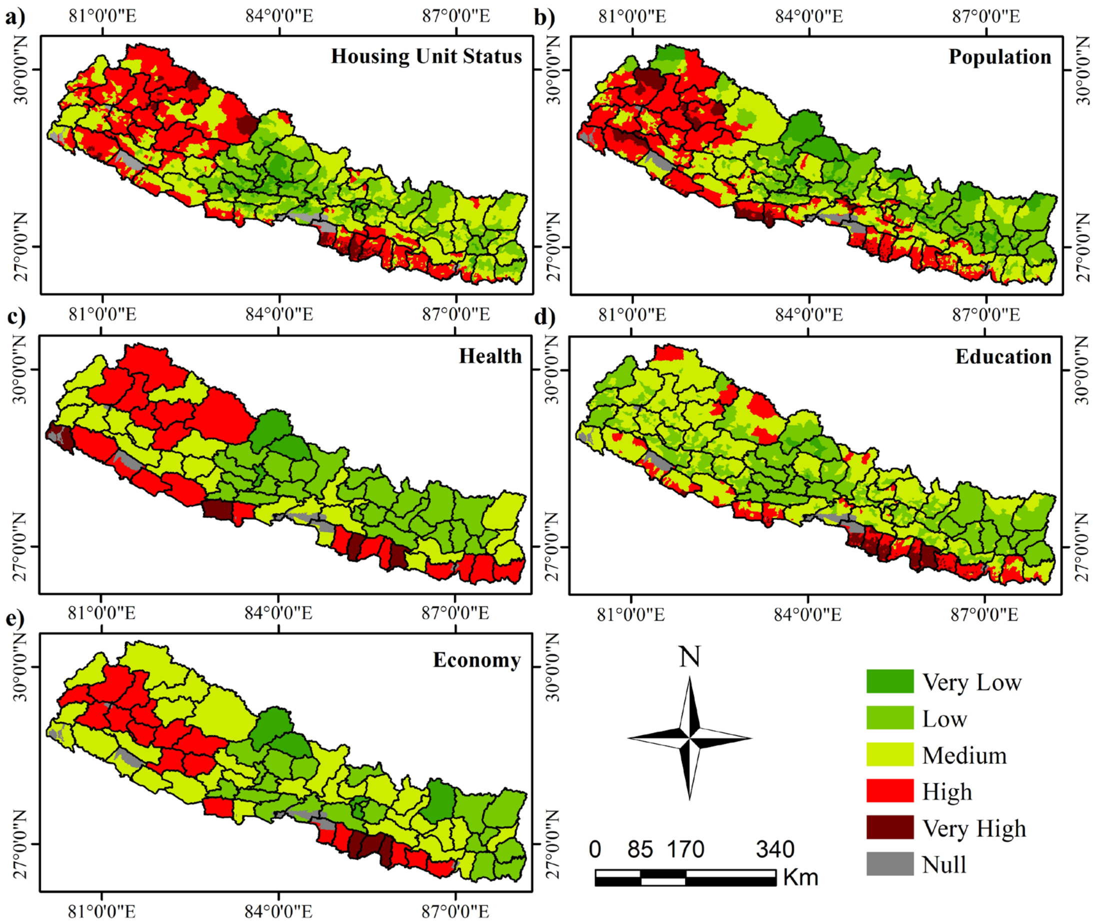


Figure 8: Spatial distribution of social vulnerability of sub-categories

4.2 Seismic Risk Assessment

The seismic risk assessment at the bedrock level for 2% and 10% of probability of exceedance in 50 years has been evaluated in this study. Like SoVI, AAL (average annual loss) index obtained from the risk analysis is also classified into five quintiles from very low (< -1.5 standard deviation) to very high (> 1.5 standard deviations) vulnerability. Figure 9 shows the distribution of AAL per capita in monetary terms and Figure 10 shows the distribution of AAL index across the country. It is observed that the Terai region, especially the western one has a higher seismic risk. Kathmandu Valley also lies in a very high-risk category. Contrary to social vulnerability, the western part of Nepal lies in the lower AAL value region. Chaulagain et al. (2015) also showed a similar result in their probabilistic seismic risk study.

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
Discussions

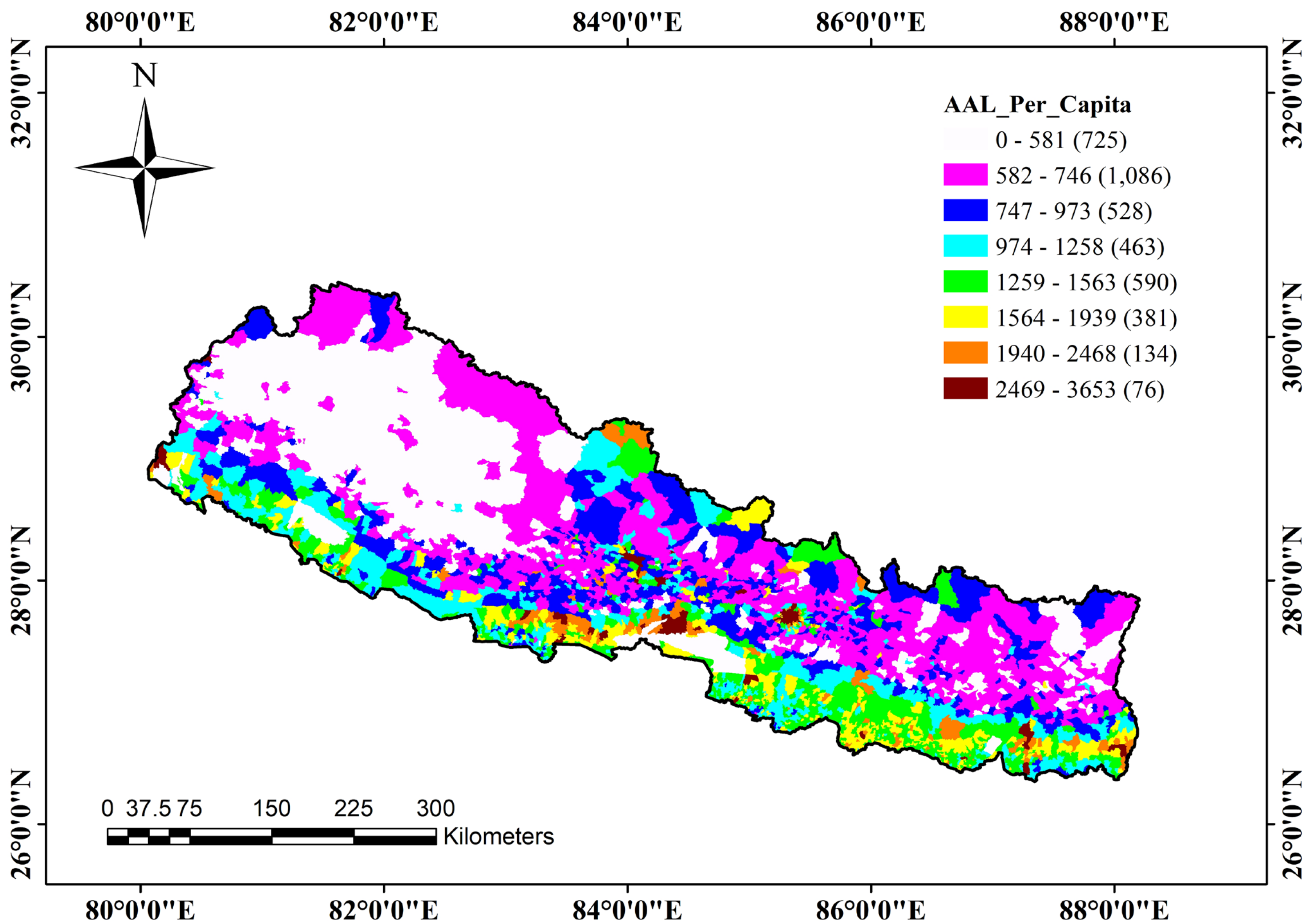


Figure 9: Average Annual Loss per capita, as calculated from OpenQuake, for Nepal.

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
Discussions

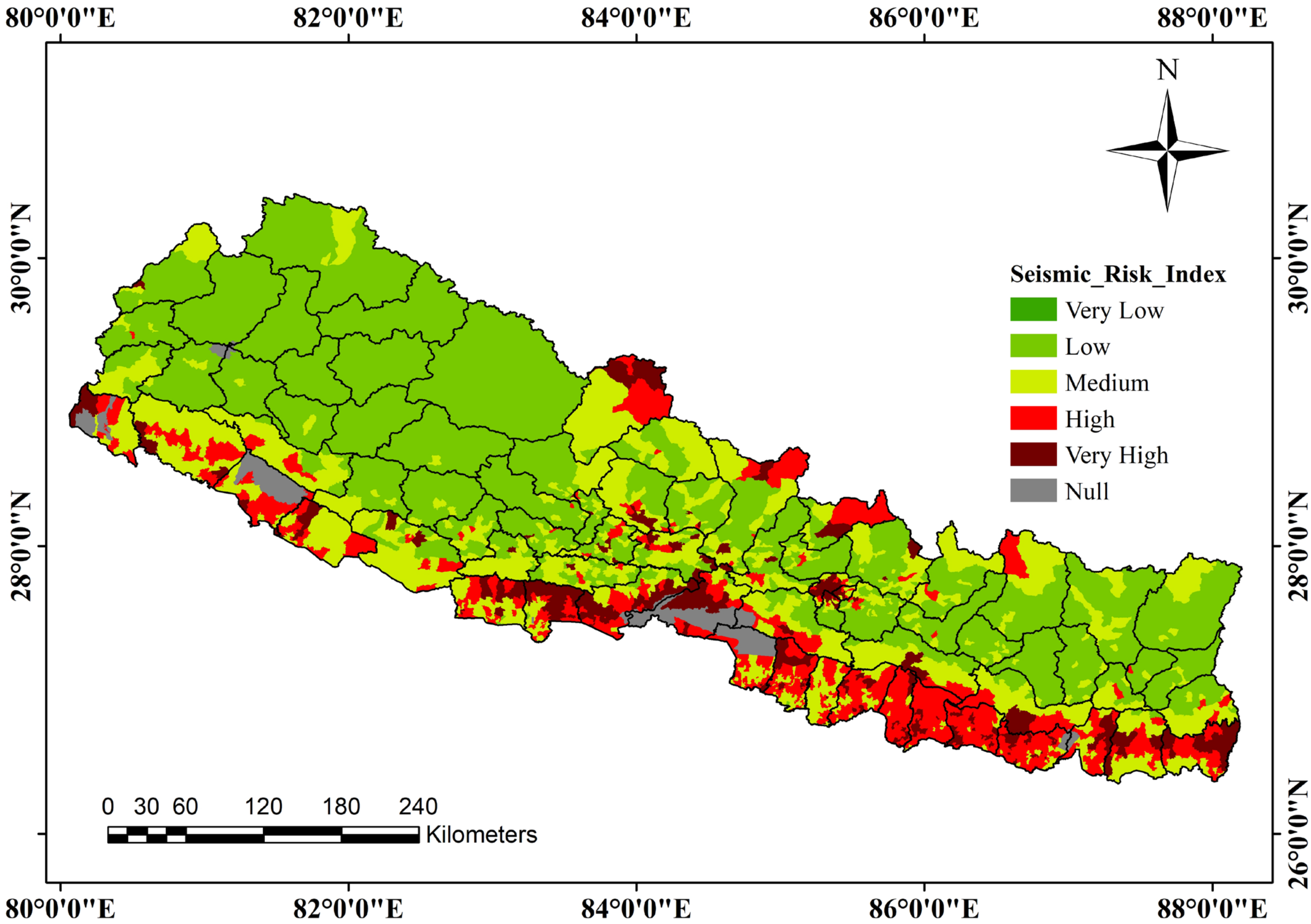


Figure 10: Spatial distribution of Average Annual Loss Index in Nepal.

335 **4.3 Integrated risk assessment**

Social vulnerability shows the intensity of impact for any disaster. When combined with the impact of seismic action, the true nature of the distribution of seismic risk becomes evident. As shown in Figure 11, the integrated risk is higher in the Terai region. Kathmandu region has a low SoVI index, but a high integrated risk index. Similarly, the western hills and mountain regions are found to be in the low risky region, even though they have a high SoVI index. However, due to their high social vulnerability, these regions should still be depicted as a concern. Despite having a low number of houses, the houses may be of lower quality, which is inclined to suffer damage to even low-magnitude earthquakes, and these regions may not have enough resources for mitigation measures. On top of that, even though they are in a low seismic risk region, the respective population may be at high risk to other disasters like a landslide, flood, glacier, and other weather conditions (Burton and Silva, 2016).

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

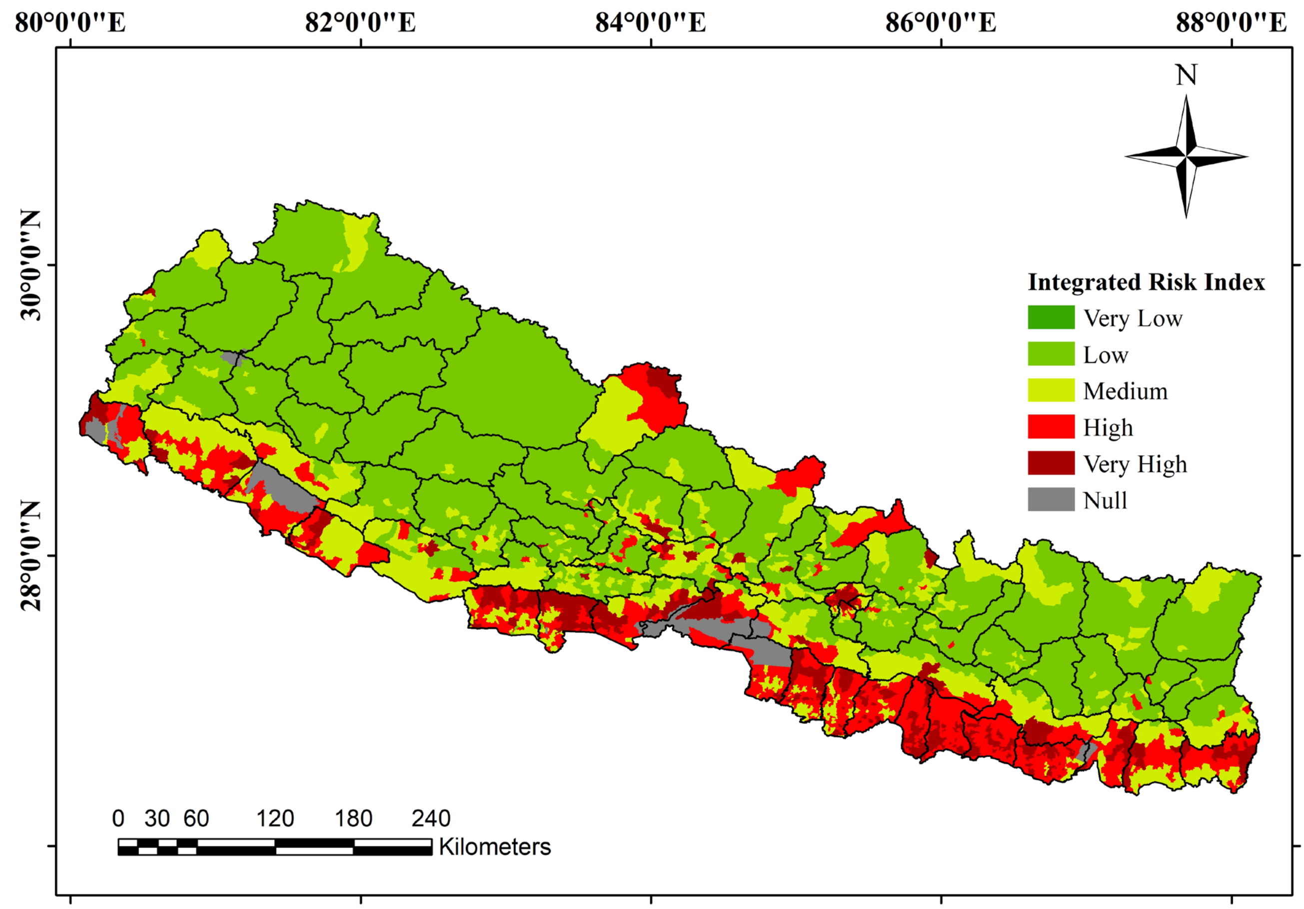


Figure 11: Spatial distribution of Integrated Risk Index in districts of Nepal.

4 Conclusion

The impacts of earthquakes cannot be defined only from the potential damages from them. Such effect also depends on the capacity of society to address and rebound from damage. Social vulnerability index depicts how society will prepare and respond to any disaster, while seismic risk index (AAL) shows how society will get affected due to earthquakes. This paper presents a method using SPSS and OpenQuake to delineate integrated seismic risk for Nepal. The integration of seismic risk with social characteristics inhibits a different outlook on seismic risk mitigation and planning, as described below:

- It combines the loss and damage (effects of earthquakes) with social characteristics such as health, poverty, education and economy (how society responds to earthquakes).
- It helps clearing up the confusion on whether to focus on loss and damage, or the population that are least likely to be able to recover from losses. For example, if only social vulnerability index is considered, western hills and mountain region seems more vulnerable than Kathmandu Valley, while considering seismic risk index, Kathmandu

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Valley is more vulnerable. Only on integrating, we can confirm that Kathmandu Valley is more vulnerable to earthquakes and need more attention than western Hills and mountain region.

- The findings reinforce the concept in the hazards and vulnerability field that analysis of socio-demographic characteristics, when taken into account along with the physical environment, brings a greater understanding of the potential impacts of hazards.
- Additionally, this study provides a method for local policymakers to integrate knowledge about the physical environment, social, and demographic composition of their region to assess their natural hazards mitigation, using a standardized tool like OpenQuake before an event occurs.

SIn this study, we assess social vulnerability characteristics to potential risks from a large earthquake on seismically active zones across the country. Since local level policymakers and municipalities have big responsibility to minimize, prepare, and respond to hazards and their impacts, a proper understanding of the social vulnerability is crucial to alleviate the risks caused by earthquakes. The distribution of potential seismic hazard-related losses across the country can be partially explained by the region's ethnicity, income, and renter population. Although previous studies have also identified the integration or relationship between natural disasters and vulnerability features, this research extended the applicability of social vulnerability by integrating it with earthquake risk estimates.

The authors are aware to the fact numerous estimations such as casualties, non-structural damage, business-interruption loss, and loss to critical infrastructure may improve the indicator of physical risk. However, only economic losses to buildings are utilized at this stage as an initiation for this type of research for Nepal. Moreover, a more recent data for SoVI will depict more exact status of society and its vulnerability to disaster. However, census is done every 10 years in Nepal, and the most recent census was held in 2011. More recent data can be used in the future study, once Nepal census 2021 is completed and published.

Author contribution

SB, and RM initiated the research; SB gathered the data; SB, and RM analysed the data; SB plotted the maps and graphs; RM wrote the manuscript draft; SB and RM reviewed and edited the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

The authors would like to express special thanks of gratitude to Department of Civil Engineering, Pulchowk Campus for noteworthy support in this project. Also, the authors would like to thanks Saman Shrestha, Sagar Gurung, and Sajesh Kuikel for interest and support in carrying the work.

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

References

Abdi, H., Williams, L.J., 2010. Principal component analysis. Wiley interdisciplinary reviews: computational statistics 2, 433–459.

Aksha, S.K., Juran, L., Resler, L.M., Zhang, Y., 2019. An analysis of social vulnerability to natural hazards in Nepal using a modified social vulnerability index. International Journal of Disaster Risk Science 10, 103–116.

Alizadeh, M., Alizadeh, E., Asadollahpour Kotenaee, S., Shahabi, H., Beiranvand Pour, A., Panahi, M., Bin Ahmad, B., Saro, L., 2018. Social vulnerability assessment using artificial neural network (ANN) model for earthquake hazard in Tabriz city, Iran. Sustainability 10, 3376.

Atkinson, G.M., Boore, D.M., 2003. Empirical ground-motion relations for subduction-zone earthquakes and their application to Cascadia and other regions. Bulletin of the Seismological Society of America 93, 1703–1729.

Boore, D.M., Atkinson, G.M., 2008. Ground-motion prediction equations for the average horizontal component of PGA, PGV, and 5%-damped PSA at spectral periods between 0.01 s and 10.0 s. Earthquake spectra 24, 99–138.

Borden, K.A., Schmidtlein, M.C., Emrich, C.T., Piegorsch, W.W., Cutter, S.L., 2007. Vulnerability of US cities to environmental hazards. Journal of Homeland Security and Emergency Management 4.

Burby, R.J., Steinberg, L.J., Basolo, V., 2003. The tenure trap: The vulnerability of renters to joint natural and technological disasters. Urban Affairs Review 39, 32–58.

Burton, C.G., Silva, V., 2016. Assessing integrated earthquake risk in OpenQuake with an application to Mainland Portugal. Earthquake Spectra 32, 1383–1403.

Campbell, K.W., Bozorgnia, Y., 2008. NGA ground motion model for the geometric mean horizontal component of PGA, PGV, PGD and 5% damped linear elastic response spectra for periods ranging from 0.01 to 10 s. Earthquake spectra 24, 139–171.

Carreño, M.L., Cardona, O.D., Barbat, A.H., 2012. New methodology for urban seismic risk assessment from a holistic perspective. Bulletin of earthquake engineering 10, 547–565.

Cattell, R.B., 1966. The scree test for the number of factors. Multivariate behavioral research 1, 245–276.

Central Bureau of Statistic (CBS), 2014a. Population Monograph of Nepal Volume I (Population Dynamics).

Central Bureau of Statistic (CBS), 2014b. Population Monograph of Nepal Volume III (Economical Demography).

Central Bureau of Statistic (CBS), 2012. National Population and Housing Census 2011 (National Report).

Chaulagain, H., Rodrigues, H., Silva, V., Spacone, E., Varum, H., 2016. Earthquake loss estimation for the Kathmandu Valley. Bulletin of Earthquake Engineering 14, 59–88.

Chaulagain, H., Rodrigues, H., Silva, V., Spacone, E., Varum, H., 2015. Seismic risk assessment and hazard mapping in Nepal. Natural Hazards 78, 583–602.

Chiou, B.-J., Youngs, R.R., 2008. An NGA model for the average horizontal component of peak ground motion and response spectra. Earthquake spectra 24, 173–215.

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

Cornell, C.A., 1968. Engineering seismic risk analysis. Bulletin of the seismological society of America 58, 1583–1606.

Cota, A.A., Longman, R.S., Holden, R.R., Fekken, G.C., Xinaris, S., 1993. Interpolating 95th percentile eigenvalues from random data: An empirical example. Educational and Psychological Measurement 53, 585–596.

Cutter, S.L., Boruff, B.J., Shirley, W.L., 2003. Social vulnerability to environmental hazards. Social science quarterly 84, 242–261.

Cutter, S.L., Finch, C., 2008. Temporal and spatial changes in social vulnerability to natural hazards. Proceedings of the national academy of sciences 105, 2301–2306.

Department of Health Services, 2013. Annual Report Department of Health Services 2070/71 (2013/2014).

Dixit, A., 2003. Floods and vulnerability: need to rethink flood management. Flood problem and management in South Asia 155–179.

Fang, C., Spencer Jr, B.F., Xu, J., Tan, P., Zhou, F., 2019. Optimization of damped outrigger systems subject to stochastic excitation. Engineering Structures 191, 280–291.

Fekete, A., 2009. Validation of a social vulnerability index in context to river-floods in Germany. Natural Hazards and Earth System Sciences 9, 393–403.

Fernandez, J., Mattingly, S., Bendimerad, F., Cardona, O.D., 2006. Application of indicators in urban and megacities disaster risk management: a case study of metro Manila. Earthquakes and Megacities Initiative (EMI).

Franklin, S., 1995. Science as culture, cultures of science. Annual review of anthropology 24, 163–184.

Frigerio, I., Ventura, S., Strigaro, D., Mattavelli, M., De Amicis, M., Mugnano, S., Boffi, M., 2016. A GIS-based approach to identify the spatial variability of social vulnerability to seismic hazard in Italy. Applied geography 74, 12–22.

Gautam, D., 2017. Assessment of social vulnerability to natural hazards in Nepal. Natural Hazards and Earth System Sciences 17, 2313–2320.

Gehrels, G.E., DeCelles, P.G., Ojha, T.P., Upreti, B.N., 2006. Geologic and U-Th-Pb geochronologic evidence for early Paleozoic tectonism in the Kathmandu thrust sheet, central Nepal Himalaya. Geological Society of America Bulletin 118, 185–198.

Glorfeld, L.W., 1995. An improvement on Horn's parallel analysis methodology for selecting the correct number of factors to retain. Educational and psychological measurement 55, 377–393.

Government of Nepal National Planning Commission, UNDP, 2014. Nepal Human Development Report 2014.

Guo, X., Kapucu, N., 2020. Assessing social vulnerability to earthquake disaster using rough analytic hierarchy process method: A case study of Hanzhong City, China. Safety science 125, 104625.

Hewitt, K., 2007. Preventable disasters. Addressing social vulnerability, institutional risk and civil ethics. Geographische Rundschau. International edition 3, 43–52.

Hodges, K. V, 2000. Tectonics of the Himalaya and southern Tibet from two perspectives. Geological Society of America Bulletin 112, 324–350.

Horn, J.L., 1965. A rationale and test for the number of factors in factor analysis. Psychometrika 30, 179–185.

https://doi.org/10.5194/nhess-2021-354
Preprint. Discussion started: 14 January 2022

Natural Hazards and Earth System Sciences
Open Access
Discussions

Humphreys, L.G., Jr, R.G.M., 1975. An investigation of the parallel analysis criterion for determining the number of common factors. Multivariate Behavioral Research 10, 193–205.

IBM Support, 2020. Kaiser-Meyer-Olkin measure for identity correlation matrix. IBM Support.

Jolliffe, I.T., 2002. Principal Component Analysis, Second. ed. Springer.

Kaiser, H.F., 1970. A second generation little jiffy. Psychometrika 35, 401–415.

Kaiser, H.F., 1960. The application of electronic computers to factor analysis. Educational and psychological measurement 20, 141–151.

Khazai, B., Merz, M., Schulz, C., Borst, D., 2013. An integrated indicator framework for spatial assessment of industrial and social vulnerability to indirect disaster losses. Natural hazards 67, 145–167.

Mainali, J., Pricope, N.G., 2019. Mapping the need for adaptation: assessing drought vulnerability using the livelihood vulnerability index approach in a mid-hill region of Nepal. Climate and Development 11, 607–622.

Malakar, Y., 2014. Community-based rainfall observation for landslide monitoring in western Nepal, in: Landslide Science for a Safer Geoenvironment. Springer, pp. 757–763.

Martins, L., Silva, V., Crowley, H., Cavalieri, F., 2021. Vulnerability Modellers Toolkit, An Open-source Platform for Vulnerability Analysis.

Mileti, D., 1999. Disasters by design: A reassessment of natural hazards in the United States. Joseph Henry Press.

Mori, T., Shigefuji, M., Bijukchhen, S., Kanno, T., Takai, N., 2020. Ground motion prediction equation for the Kathmandu Valley, Nepal based on strong motion records during the 2015 Gorkha Nepal earthquake sequence. Soil Dynamics and Earthquake Engineering 135, 106208.

Pachauri, R.K., Allen, M.R., Barros, V.R., Broome, J., Cramer, W., Christ, R., Church, J.A., Clarke, L., Dahe, Q., Dasgupta, P., 2014. Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. Ipcc.

Pagani, M., Monelli, D., Weatherill, G., Danciu, L., Crowley, H., Silva, V., Henshaw, P., Butler, L., Nastasi, M., Panzeri, L., 2014. OpenQuake engine: An open hazard (and risk) software for the global earthquake model. Seismological Research Letters 85, 692–702.

Pandey, M.R., Chitrakar, G.R., Kafle, B., Sapkota, S.N., Rajaure, S.N., Gautam, U.P., 2002. Seismic hazard map of Nepal. Kathmandu: Department of Mines and Geology.

Pandey, M.R., Tandukar, R.P., Avouac, J.P., Vergne, J., Heritier, T., 1999. Seismotectonics of the Nepal Himalaya from a local seismic network. Journal of Asian Earth Sciences 17, 703–712.

Rahman, N., Ansary, M.A., Islam, I., 2015. GIS based mapping of vulnerability to earthquake and fire hazard in Dhaka city, Bangladesh. International journal of disaster risk reduction 13, 291–300.

Schmidtlein, M.C., Shafer, J.M., Berry, M., Cutter, S.L., 2011. Modeled earthquake losses and social vulnerability in Charleston, South Carolina. Applied Geography 31, 269–281.

Sharma, P., Guha-Khasnobis, B., Khanal, D.R., 2014. Nepal human development report 2014. United Nations Development Programme: In Kathmandu.

Shrestha, A., 2005. Vulnerability assessment of weather disasters in Syangja District, Nepal: A case study in Putalibazaar Municipality. Nepal: Department of Hydrology and Meteorology.

Stevens, V.L., Shrestha, S.N., Maharjan, D.K., 2018. Probabilistic seismic hazard assessment of Nepal. Bulletin of the Seismological Society of America 108, 3488–3510.

Tate, E., 2012. Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis. Natural Hazards 63, 325–347.

Taylor, M., Yin, A., 2009. Active structures of the Himalayan-Tibetan orogen and their relationships to earthquake distribution, contemporary strain field, and Cenozoic volcanism. Geosphere 5, 199–214.

Thapa, D.R., Guoxin, W., 2013. Probabilistic seismic hazard analysis in Nepal. Earthquake Engineering and Engineering Vibration 12, 577–586.

Thompson, B., Daniel, L.G., 1996. Factor analytic evidence for the construct validity of scores: A historical overview and some guidelines.

Ulak, N., 2015. Nepal's earthquake-2015: Its impact on various sectors. The Gaze: Journal of Tourism and Hospitality 7, 58–86.

UNISDR, U., 2009. Terminology on disaster risk reduction. Geneva, Switzerland.

Upreti, B.N., Le Fort, P., 1999. Lesser Himalayan crystalline nappes of Nepal: Problems of their origin. SPECIAL PAPERS-GEOLOGICAL SOCIETY OF AMERICA 225–238.

Velicer, W.F., Eaton, C.A., Fava, J.L., 2000. Construct explication through factor or component analysis: A review and evaluation of alternative procedures for determining the number of factors or components. Problems and solutions in human assessment 41–71.

Vivek, P., Singh, S.N., Mishra, S., Donavan, D.T., 2017. Parallel Analysis Engine to Aid in Determining Number of Factors to Retain using R.

Youngs, R.R., Chiou, S.-J., Silva, W.J., Humphrey, J.R., 1997. Strong ground motion attenuation relationships for subduction zone earthquakes. Seismological Research Letters 68, 58–73.

Zwick, W.R., Velicer, W.F., 1986. Comparison of five rules for determining the number of components to retain. Psychological bulletin 99, 432.