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Earthquake Vulnerability in the Himalaya by Integrated Multi-Criteria Decision Models

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Abstract

Himalaya is one of the most seismo-tectonically active mountain on the surface of the earth. Recurring moderate and high magnitude earthquakes are not uncommon in this region. This paper maps the earthquake vulnerability in the Himalayan seismo-tectonic zone using integrated multi-criteria decision models. Several factors influence the earthquake vulnerability in a region, such as the social, geotechnical, structural, and physical parameters. We have used the analytical hierarchy process (AHP) approach to determine the weights of various parameters, which have been further used in the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) and Grey Relational Analysis (GRA) method to develop earthquake vulnerability maps for the study area. The map generated by AHP-VIKOR reveals that 12.93% of the Himalayan region is highly vulnerable, 26.39% moderately vulnerable, and 60.67% of the area is relatively low vulnerable. On the other hand, the AHP-GRA method reveals that 9.75% of the region is high vulnerability zone, 20.26% moderate, 70% as a relatively low vulnerable zone. A high correlation between the final vulnerability maps generated from AHP-VIKOR and AHP-GRA further validates our result. The results of this paper may be useful for the various hazard mitigation and infrastructure planning agencies in the Himalayan seismicity zone.

Keywords: Himalaya, Earthquake Vulnerability, Multi-Criteria Decision Making, AHP-GRA, AHP-VIKOR, GIS.

1. Introduction

Himalaya is one of the world's most seismo-tectonically active zone on the earth. The continuous collision of Indian and Eurasian plates results in the accumulation of the strain energy (Dewey et al. 1989), which is frequently released in the form of earthquakes from time to time. The available historical database (Rahman et al. 2017) indicates that many catastrophic earthquakes have occurred in this region (Table 1). These destructive earthquakes caused substantial casualties and financial loss in the affected neighboring countries. The extreme destructive power of earthquakes endangers life and properties (Xi-wei, 2010). One of the recent and most devastating earthquakes, i.e., the Gorkha earthquake (M~7.8), occurred in the central Himalaya on 25th April 2015. This earthquake caused approximately 9000 casualties, destroying thousands of buildings and causing substantial economic losses (Bilham, 2015).

It is nearly impossible to predict earthquakes in space and time, which causes modern cities to be more exposed and vulnerable to this severe natural disaster (Asadi et al., 2019). Early warning systems, good quality infrastructure, and identifying the vulnerable areas can minimize primary and secondary damages. The underprivileged section of society is more vulnerable to earthquakes because the poor quality of their houses may not withstand even moderate-sized earthquakes (Schilderman, 2004). Furthermore, the women population may be more vulnerable than men because of pre-existing practices and norms (Ruddock, 2007).

The rapid urbanization with improper and unplanned constructions and management and high population density caused significant destruction due to earthquakes. The lack of planning and not following the government's infrastructure development codes often resulted in structural and financial damages. Because of better planning and management in developed countries, human casualties are somewhat low, while financial casualties are usually high, whereas the situation is reversed in developing countries (Ebert and Kerle, 2008). With rapid urbanization, it has become more important to study structural and social vulnerability. The development of good health care facilities with communication networks helps minimize the

casualties in pre and post-earthquake situations. A more comprehensive study is required to evaluate the urban and rural areas struck by the earthquake's impact (Merciu et al., 2018).

One of the main reasons behind the lack of availability of earthquake vulnerability maps may be due to the limited availability of datasets (Rashed and Weeks, 2003). However, data available in the public domain in recent times allows us to evaluate earthquake vulnerability on various parameters. In the recent past, several researchers have applied the MCDM methods such as analytic network process (ANP) and analytical hierarchy process (AHP) approach through geographical information system (GIS) (Alizadeh et al., 2018a). An integrated model of an artificial neural network (ANN) and analytic hierarchy process (AHP) developed by Jena et al. (2019) to develop the earthquake risk assessment map for Banda Aceh. The VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method was used to estimate the seismic vulnerability in Banda Aceh (Jena et al. 2020), whereas AHP and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was used to develop earthquake hazard and risk maps of Küçükçekmece, Istanbul (Nyimbili et al., 2018). AHP and GIS were used to assess the seismic vulnerability of the residential houses in urban areas of Tabriz city (Alizadeh et al., 2018a) and for the school buildings in Tehran city (Panahi et al., 2014). Chakraborty and Joshi, 2016 used AHP to map a multi-disaster scenario for India, whereas Nath et al. (2015) applied the AHP technique through GIS to map the socio-economic and structural vulnerability and risk index for Kolkata. Duzgun et al., 2011 used the simple additive weighting (SAW) method to assess the earthquake vulnerability for Eskisehir, Turkey. Walker et al., 2014 combined physical, social, and systemic parameters to evaluate the earthquake vulnerability in Victoria, British Columbia, using AHP. Karaman and Erden, 2014 create high-resolution earthquake hazard maps using an AHP and GIS for Istanbul. For the Himalayan region, several studies have been done to estimate the landslide and flood susceptibility mapping; however, not much has been done to map the seismic vulnerability except the earthquake hazard model for Sikkim Himalaya done through fuzzy logic AHP (Pal et al., 2008).

Considering the importance of the issues related to the impacts of the earthquake on densely populated regions, we apply an integrated MCDM model to assess the earthquake vulnerability in the Himalayan region. The historical seismicity, geological features, lithology of the area, slope, population density, quality of the infrastructure, and proper health facilities with good communication networks are the primary factors considered in mapping the earthquake risk and vulnerability. These main factors responsible for assessing the earthquake vulnerability can be broadly classified into groups, such as social, geotechnical, structural, and physical parameters. This makes it a perfect case for study using multi-criteria MCDM models. To prepare an earthquake vulnerability map for the study region, two MCDM models have been integrated with the analytical hierarchy process (AHP). The models used are the analytical hierarchy process (AHP) and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique (AHP-VIKOR), and the analytical hierarchy process (AHP), and Grey Relational Analysis (GRA) technique (AHP-GRA). The AHP method is used to evaluate the priority and criterion ranking. AHP works based on previously available literature and the experts' opinion, which may be subjective to an extent. The VIKOR technique helps to determine the compromise ranking and comprises the solution acquired through the initial weights.

The Grey Relational Analysis (GRA) evaluates the complicated uncertainty among the multi-criteria in a given system and optimizes it. We calculated the weight of the four variables using AHP and VIKOR, and GRA provides the result of the criteria/alternative. The purpose of using two integrated MCDM is to check the influence of AHP on VIKOR and GRA and determine the accuracy of both the integrated models by comparing the developed results. The vulnerability factors are classified into social, geotechnical, structural, and physical vulnerability and integrated with a GIS platform. Factors such as liquefaction, explosion, fire, landslide, and other secondary hazards caused by earthquakes have not been considered.

Accurate mapping of earthquake vulnerability is always challenging, particularly on a large scale. Specific computational methods can help in reducing the uncertainties associated with

it. The MCDM methods depend on data, which are related to their uncertainties. Therefore, we used the VIKOR and GRA method to optimize these uncertainties and provide relatively robust results.

2. Study Area

The study area, the Himalayan mountains extending from the northern to the north-eastern border of India, is probably one of the most seismo-tectonically active features. The region's prominent tectonic feature is the Himalayan Frontal Arch (HFA), stretching in NW to SE direction with destructive earthquakes occurred in this region. From west to east direction, the prominent tectonic features comprise the Main Central Thrust (MCT), Indus Tsangpo Suture (ITS), and Main Boundary Thrust (MBT), which are extending throughout the Himalaya. Active collision and subduction of Indian and Eurasian plates have resulted in a considerable accumulation of strain energy, which caused several large earthquakes of magnitude 8 or more (Dewey et al. 1989). The seismic hazard zonation map of India assigned this region under seismic zones IV and V because of high seismic activities in this region (BIS 2002). Our study area is spread in several countries such as India, China, Bangladesh, Myanmar, Pakistan, and Bhutan, with about 976661 km², and inhabited by more than 90 million people, and millions reside in nearby areas (Fig. 1). Therefore, it is essential to map the earthquake vulnerability to mitigate future potential events.

Most of the earthquakes in this region are shallow earthquakes with focal depths less than 30km; however, few deep earthquakes have also been recorded, indicating the breaking of the subducting Indian plate in the mantle. Furthermore, the stress release rate along the subduction zone is not homogeneous in space and time (Bilham, 2015), making this practically impossible to predict the Himalayan earthquakes with any practical use. Numerous earthquakes of magnitude varying from moderate to large occurred in the last 200 years. The recent historical earthquakes, such as the 1934 Bihar-Nepal earthquake (Mw~8.4) and the 1950 Assam-Tibet (Mw~8.6) earthquake, along with the 2015 Gorkha earthquake (Mw~7.8), proved extremely devastating for the region. The Gorkha earthquake of 2015, which ruptured

a segment of the Main Himalayan Thrust fault (MHT) (Rupakhety, 2018), resulted in 8790 deaths and 22300 injured persons (NPC, 2015). These earthquakes pose a significant threat to the densely populated region of northern India. Therefore, it is important to understand the associated hazard and risks in the region. In the following sections, we discuss the details of the data, methodology, and results obtained in this study.

3. Data and Methodology

This study uses several datasets available in the public domain, including geological data, historical and recent seismicity, population and infrastructure data, social and healthcare facilities data for estimating earthquake vulnerability in the study region. The datasets have been extracted from multiple public domain sources (Table 2). Since the study area is distributed in several countries, we have collected data from multiple international agencies and homogenized them. Most of the social data have been collected from the Office of the Registrar General & Census Commissioner, India (<https://censusindia.gov.in/>), the Bangladesh Bureau of Statistics (<http://www.bbs.gov.bd/>), the China National Bureau of Statistics (<http://www.stats.gov.cn/english/>), the National Statistics Bureau, the Royal Government of Bhutan (<http://www.nsb.gov.bt/main/main.php>), the Myanmar Population and Housing Census (<http://themimu.info/census-data>), the Central Bureau of Statistics Nepal (<https://cbs.gov.np/>), and the Pakistan Bureau of Statistics (<http://www.pbs.gov.pk/>). The structural and physical datasets are taken from OpenStreetMap (<https://www.openstreetmap.org/>). The earthquake data were obtained from NOAA (<https://www.noaa.gov/>), whereas the dataset for active faults is taken from the global earthquake model (<https://www.globalquakemodel.org/>). The methodology adopted in this study is discussed in the following sections.

3.1 Multi-criteria decision-making model

Multiple criteria decision-making (MCDM) is a mathematical tool for supporting the subjective assessment of decision-makers' performance criteria (Zavadskas and Turskis, 2011). This method helps examine the complexity of the problem and judge several alternatives based on specific aspects of the appropriate selection of alternatives (Malczewski and Liu, 2014). MCDM helps decision-makers store, modify, analyze, and visualize data. On the other hand, a geographic information system (GIS) is a platform where the decision-maker can analyze and realize the alternatives' desirability. An expert's opinion is required to understand the relative importance of various parameters, which sometimes leads to several uncertainties (Jankowski and Nyerges, 2001; Meng and Malczewski, 2015). We have applied MCDM models in an integrated manner, i.e., the AHP-VIKOR and AHP-GRA, to map the earthquake vulnerability in the entire Himalayan seismicity zone. The AHP is used to evaluate the priority and criterion ranking. The VIKOR and GRA help allocate rank to a social, geotechnical, structural, and physical vulnerability and produce the final earthquake vulnerability map.

3.1.1 AHP Method

Analytic Hierarchy Process (AHP) (Saaty, 1980) is a commonly used, powerful, and simple MCDM and includes objective and subjective factors that help decision-makers to manage many complex problems. A detailed description of the decision-making problem required for AHP calculation and examination of each stage (hierarchy) are briefly described in the following section.

A pairwise comparison matrix was obtained with the criterion score. Comparison between each alternative is performed with some specific criterion ($x_1, x_2 \dots x_n$). The scores' scaling between 1 and 9 is assigned for equally important and extremely important criteria (Saaty, 1980), which is based on expert's opinion and/or on the basis of available literature. A normalized pairwise matrix has been developed by dividing the elements of each column by the total column value. The criteria weight ($w_1 \dots w_n$) is then evaluated by averaging the row-wise normalized value, with the condition that $\sum_{j=1}^n W_j = 1$.

The weighted sum vector is formulated as given in Eq. (1):

$$W_i = \sum x_{ij} w_j \quad (1)$$

where x_{ij} indicates the i th class rank, which depends on the j th layer, and W_j is the weight that is normalized for the j th layer. The consistency index (CI) and consistency ratio (CR) is calculated using Eq. (2) from the principal eigenvalue (λ_{max}).

$$CI = (\lambda_{max} - n) / (n - 1); \quad \text{and} \quad CR = CI / RI \quad (2)$$

where n is the number of criteria being used, and RI is a randomness indicator that depends on the dimension of the comparison matrix. Boulos (2003) estimated the RI 's value for the matrices with a dimension between 1 and 15. For a consistent matrix, CR 's acceptable value must be less than equal to 0.10. $CR > 0.10$ indicates that the inputs obtained from the expert's opinion and/or on the basis of available literature are not reliable and need to be reviewed. After developing the comparison matrix, the priorities, consistency ratio, and rank can be estimated.

In this study, the assessment of social, physical, geotechnical, and structural vulnerabilities have been estimated with the help of AHP for the study region. The framework of the methodology used for our study is presented in the flow chart given in Fig. 2.

3.1.2 VIKOR Method

Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method (Opricovic, 1998; Mardani et al., 2016) is used to solve MCDM problems based on the aggregating LP-metric function. In case of contradictory criteria, this method chooses between sets of available alternatives (Chiu et al., 2013) and provides proper optimization of the multi-criteria complex systems (Opricovic and Tzeng, 2004).

Firstly, the best (X_i^*) and worst ($\bar{X}_i$) values for each criterion from the normalized decision matrix, $j=1, 2, \dots, m$ is computed as $X_i^* = \max [(X_{ij})]$, and $\bar{X}_i = \min [(X_{ij})]$ (3)

where $\bar{X}_i$ and X_i^* are the minimum and maximum value of X_{ij} . The value of the matrix is X_{ij} , and X_i indicates the alternative of i^{th} criteria. In the second step, the S_j and R_j , which signify the utility measure and regret the alternative (X_j) measure, are computed as per the following formulas.

$$S_j = \sum_{i=1}^n W_i \frac{X_i^* - X_{ij}}{X_i^* - \bar{X}_i} \quad \text{and} \quad R_j = \max \left[W_i \left(\frac{X_i^* - X_{ij}}{X_i^* - \bar{X}_i} \right) \right] \quad (4)$$

where W_i is a criterion weight that expresses their importance relatively, in this case, $i=1, 2, \dots, n$.

After that, values of Q_j , $j=1, 2, \dots, j$ is estimated

$$Q_j = v \left(\frac{S_j - S^*}{\bar{S} - S^*} \right) + (1-v) \left(\frac{R_j - R^*}{\bar{R} - R^*} \right) \quad (5)$$

Where $S^* = \min (S_j)$, $\bar{S} = \max (S_j)$; and $R^* = \min (R_j)$, $\bar{R} = \max (R_j)$

S^* and $\bar{S}$ indicates the minimum and maximum of measures of utility; whereas R^* and $\bar{R}$ represents the minimum and maximum measures of regret, respectively. v is known as the strategical maximum group utility weight, while $1-v$ is measured as an individual regret weight. Typically, the v value is considered to be 0.5 (Liu et al., 2013), but if $v > 0.5$, the Q_j index rank can be determined that incline toward the majority agreement. In the case of $v < 0.5$, the value of Q_j indicates the negative attitude in the majority. This approach is considered a powerful tool to address the MCDM problems, especially when the decision-maker is unaware of the system design at the foundation level.

3.1.3 Grey Relational Analysis (GRA) Method

Grey Relational Analysis (GRA) model was developed to efficiently address MCDM problems with inaccurate and inadequate information (Deng, 1982, 1988; Hamzaçebi and Pekkaya, 2011; Wu and Peng, 2016). Normalization of data is required to avoid the unit difference and make the dataset unbiased (Haq et al., 2008). In this case, the reference sequence is X_{0j} , and the original data Y_{ij} is attributed j of alternative i . Translation of Y_{ij} into the comparability

sequence X_{ij} is possible using equations 6 and 7 to maximize and minimize the response, respectively.

$$X_{ij} = \frac{Y_{ij} - \min(Y_{ij})}{\max(Y_{ij}) - \min(Y_{ij})} \quad (6)$$

$$X_{ij} = \frac{\max(Y_{ij}) - Y_{ij}}{\max(Y_{ij}) - \min(Y_{ij})} \quad (7)$$

Δ_{ij} , the deviation sequence of the reference and the comparability sequence is computed by the following formula

$$\Delta_{ij} = |X_{0j} - X_{ij}| \quad (8)$$

The grey relational coefficient is calculated as:

$$\gamma(X_{0j}, X_{ij}) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}} \quad (9)$$

where $\Delta_{\min}$ and $\Delta_{\max}$ indicate the minimum and maximum values of the deviation sequence, ζ is the distinguishing or identification coefficient, and the value of ζ belongs to 0 to 1; usually, taken as 0.5. Finally, the grey relational grade is computed using Eq. (10)

$$\Gamma(X_0, X_i) = \sum_{j=1}^n W_j \gamma(X_{0j}, X_{ij}) \quad (10)$$

Here, W_j is the attribute weight j and $\sum_{j=1}^n W_j = 1$ and $\Gamma(X_0, X_i)$ is the grey relational grade (GRG). GRG signifies the correlation level between the reference and the comparability sequence and represents overall quality characteristics (Haq et al., 2008).

This study uses two integrated MCDM methods, i.e., AHP-VIKOR and AHP-GRA. A total of 26 parameters have been selected and used to estimate four vulnerability maps. The selected factors are categorized into four types of vulnerability (Tables 3 and 4): social, geotechnical, structural, and physical vulnerability. The social, geotechnical, structural, and physical vulnerability maps were generated using AHP through experts' opinions and knowledge. The VIKOR and GRA methods with entirely different mathematical approaches were used to rank the four vulnerability layers and develop the earthquake vulnerability maps (Tables 5-8). The

weighted sum technique is used for all the layers with rank and weight values to develop the final vulnerability maps. The weighted sum approach is formulated in Eq. (11):

$$V = \sum_{i=1}^n L(AHP) \quad (11)$$

where V is the final vulnerability layer, L(AHP) is the layers acquired by the AHP approach, and i is the number of layers (Jena et al., 2020). The classification of each layer is done as suitable conditions (2 classes), medium domain (1 class), and unsuitable conditions (2 classes) to standardize the criteria. Based on this vulnerability, layers are scaled from 1-5. The scaled maps were categorized into five classes, i.e., very low, low, moderate, high, and very highly suitable. The final vulnerability maps were compared to evaluate the area, population, and the number of buildings under the vulnerable zones and their statistical relationships.

4. Results and Discussions

The Himalaya mountain covers large area spread in several countries. Estimating earthquake vulnerability is a multi-criteria problem and substantially includes a number of parameters that are likely to affect the region under investigation, such as population density and quality of buildings and infrastructure, nearness to the seismo-tectonically active geological features, historical and recent seismic activities, and availability of the health care facility, communication network, etc. Hence the multi-criteria approach is suited for the evaluation of such problems. In the following sections, we evaluate earthquake vulnerability on several parameters.

4.1 Social Vulnerability

The earthquake hazard is more multi-faceted and riskier in urban areas because of rapid urbanization without proper planning and management (Rahman et al., 2015). Unplanned population growth in cities results in the inadequate distribution of health and infrastructure facilities besides environmental issues and societal problems (Hassanzadeh et al., 2013). Increasing population enhances the risk of more casualties due to secondary effects of

earthquakes such as the collapse of buildings etc. However, an increase in the literacy rate enhances awareness among people about such disasters and their impacts on society (Rygel et al. 2006) and impacts earthquakes vulnerability (Martins et al., 2012). Information about populated sites, religious places, parks, and visiting places should be timely updated to minimize the risk factor (Wisner et al., 2003; Alizadeh et al., 2018b).

Parameters included in estimating social vulnerability are shown in Fig. 2. The social vulnerability map for the Himalayan region is non-uniform (Fig. 3), as expected. We find that the risk is higher in high population density areas of the central Himalayan region and in the westernmost part of Himalaya, where few major cities are located. Kathmandu and its surrounding region with high population density and literacy rate and several famous and religious places come under the very high vulnerability zone, which is also true for the cities such as Peshawar, Islamabad, and Rawalpindi. With a high population and low literacy rate, certain areas are relatively more vulnerable socially, whereas other areas with low population density, such as Bhutan, are relatively very low to low social vulnerability. With a chain of mountains and harsh climatic conditions, the Tibetan region makes it incapable of living. Therefore, those regions fall under the very low to low social vulnerability. The region within India is having moderate to high population density, which makes it very low to moderately vulnerable on these parameters. Bangladesh and Myanmar comprise a small fraction of the land cover of the Himalayan belt. Bangladesh, one of the densely populated countries globally, makes the region low to moderately socially vulnerable. An average population density of 83 people per square km and a literacy rate of about 90% makes Myanmar relatively very low socially vulnerable.

In total, 55.46 % of the study area falls under very low social vulnerability, 32.86% low, 7.52% moderate, 3.27% high, and the rest falls under the very high vulnerability. The social vulnerability as a function of the population comprises 15.81% of the total population under very low social vulnerability, 37.42% low, 14.71% moderate, 16.05% high, and 16.01% (Table 9). Therefore, our concern should be moderate to a very high degree of social vulnerability.

4.2 Physical Vulnerability

The earthquakes themselves are not always accountable for the loss of life, but sometimes it is because of accessibility network, communication blockage, lack of proper healthcare services during the hours of need increases the numbers. Thus, distance to healthcare services and hospitals, lack of road, rail, and air transport networks, lack of community services such as fire service, disaster management teams, etc. plays an important role in mitigating and imparting proper rescue during an earthquake event (Hosseini et al., 2009; Manshoori, 2011; Karimzadeh et al., 2014; Alizadeh et al., 2018b).

Vulnerability estimates using physical parameters (Fig. 3) discussed earlier indicate that 32.14% of the study area lies under very low physical vulnerability, 23.97% low, 18.25% moderate, 16.50% high, and 9.14% very high vulnerability. The geotechnical vulnerability in terms of the population comprises 77.35% of the total population includes under very low vulnerability, 16.05% low, 5.71% moderate, and a negligible amount of population falls under high to very high vulnerability (Table 9). A remarkable observation is that more than 90% of the total population lies under very low to low vulnerability, which indicates that developing countries in the region are trying their best to develop proper medical facilities and spreading the communication networks, which is suitable for disaster mitigation.

4.3 Geotechnical Vulnerability

The seismicity data indicates the possible earthquake zones in a particular region (Soe et al., 2009). Thus, distance from active fault plays a significant role, and closeness to the fault intensifies risk due to seismic hazard and vice-versa (Alizadeh et al., 2018a Soe et al., 2009). Lithology, topography, cracks, and fractures are the major control over probable earthquake locations (Hosseini et al., 2009; Alizadeh et al., 2018b).

Several active faults and high mountain peaks make the Himalayan region one of the most probable zones for expecting catastrophic earthquakes, making this region geotechnical vulnerable (Fig. 4). Estimating the geotechnical vulnerability has been done using the factors

such as the proximity to the fault and earthquake epicentres, magnitude density, lithology, and elevation. Based on the geotechnical vulnerability, 7.31% of the total area falls under very low vulnerability, 20.59% low, 31.35% moderate, 29.27% high, and 11.49% under very high vulnerability. 2.14% of the total population lies under a very low geotechnical vulnerability, 14.02% low, 29.18% moderate, 32.15% high, and 22.51% very high vulnerability (Table 9). About 55% population lies under high to a very high degree of vulnerability, distributed in more than 40% of the area. Thus, a considerable percentage of people live under threat of high to very high geotechnical vulnerability.

4.4 Structural Vulnerability

Properly planned and managed land distribution and building were required to minimize the earthquake vulnerability (Aghataher et al., 2008). The damage during an earthquake will be less for well-constructed historical sites, stadiums, museums, etc. On the other hand, if the construction quality is poor, then the probable loss of life may be more during an earthquake if that happens during holidays when more people are likely to visit these places (Alizadeh et al., 2018a; Alizadeh et al., 2018b). Similarly, vulnerabilities at hotels, transport terminals, dams are multi-faceted (Brown et al., 2017). Similarly, dams are not inherently safe against seismic events (Wieland, 2016). Lack of maintenance of old structures makes them risky and prone to structural failure during earthquakes (Orchiston, 2012; Roark et al., 2000).

The structural vulnerability were computed, ignoring the variations during day and night (Martins et al., 2012). It is observed that most of the metropolitan cities in the study area fall under moderate to a very high degree of structural vulnerability (Fig. 4). Out of the total, 25.47% of the area lies under very low vulnerability, 30.98% low, 31.95% moderate, 7.46% high, and 4.14% very high structural vulnerability. On the other hand, with respect to population, 1.08% of the population in the study area is under very low vulnerability, 13.19% low, 48.55% moderate, 23.37% high, and 13.82% of the population are under very high risk due to structural vulnerability (Table 9). It is interesting to note that the very low and low structural vulnerability comprises more than 55% of the area, but the number is slightly less

than 15% in terms of population. Because of harsh climatic and geographical distribution, a large population is settled in a region where they get favorable climatic and geographical conditions. Therefore, most of the region has a significantly lower population density with low structural vulnerability.

4.5 Comparison of the AHP-VIKOR and AHP-GRA vulnerability maps

The final vulnerability maps of the region were developed using two integrated MCDM methods of AHP-VIKOR and AHP-GRA (Fig. 5). The percentage of vulnerable areas, population, and buildings were estimated by analyzing AHP-VIKOR and AHP-GRA (Table 10). The final vulnerability maps show almost the same vulnerability level as the major cities. The Pearson's correlation coefficient computed for the AHP-VIKOR with the AHP-GRA with respect to vulnerable area and population is 0.8578 and 0.9471, respectively. In contrast, the correlation coefficient for the vulnerability of buildings is 0.6673 (Fig. 6).

For example, the vulnerability for Itanagar is moderate to low, as computed by the two methods. The city of Kathmandu, the capital of Nepal, which often experiences moderate to major earthquakes, falls under a very high vulnerability region, as indicated by both methods. The three main populated and important cities of Pakistan, Peshawar, Rawalpindi, and Islamabad, are highly vulnerable. In contrast, major cities of Bhutan, i.e., Thimpu and Paro, also show a moderate degree of vulnerability. Thus, the AHP-VIKOR and AHP-GRA earthquake vulnerability maps estimated in this study show similar vulnerability patterns in the study area.

5. Conclusions

Identifying the region's vulnerability to severe damage due to earthquakes is one of the most important factors for seismic hazard mitigation. This study estimated earthquake vulnerability using integrated MCDM techniques of AHP-VIKOR and AHP-GRA for the Himalayan region. The twenty-six important parameters were classified into social, geotechnical, structural, and physical vulnerability classes. The estimated result shows that 29.4% of the total area lies under very low earthquake vulnerability, 35.94% low, 23.33% moderate, 7.73% high, and 3.62% highly vulnerable to disasters due to earthquakes. Population-wise, a considerably large percentage of the population is high vulnerability (51.46%), 8.70% high, 18.39% moderate, 13.73% low, and 7.73% of the population are very low vulnerable to risks due to earthquakes. About 8.53% of the buildings have a very low degree of vulnerability, 9.23% are under low, 35.34% moderate, 25.81% high, and 21.09% of the buildings are highly vulnerable. The vulnerability maps computed using the two methods, i.e., AHP-VIKOR and AHP-GRA, show a high correlation. Both methods identify almost the same areas as high and low vulnerable zones. The correlation coefficient between earthquake vulnerability maps computed by the two methods as a function of vulnerable populations, areas, and buildings are 0.9471, 0.8578, and 0.6673. Most of the highly populated major cities lying in this region are highly vulnerable to earthquakes and associated risks. Results obtained in this study may be useful for the hazard mitigation and planning agencies.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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Figures

Figure 1

Map showing the location of the study area (modified from Mukherjee et al., 2015). Lithology, fault, historical earthquakes, and important cities are also shown for reference.

Figure 2

Flowchart illustrating method adopted to compute various vulnerability maps for the study region.

Figure 3

Social (top panel) and physical (bottom panel) vulnerability maps for the Himalayan region. Red-zones are highly vulnerable, while the green zones are relatively low vulnerable based on the social criteria.

Figure 4

Geotechnical (top panel) and structural (bottom panel) vulnerability map for the Himalayan region. Red zones are highly vulnerable, while the green zones are relatively low vulnerable based on the geotechnical criteria.

Figure 5

Earthquake Vulnerability Map using the AHP-VIKOR (top panel) and AHP-GRA (bottom panel) techniques. Red zones are highly vulnerable, while the green zones are relatively low vulnerable to earthquake hazards.

Figure 6

(a) Correlation between AHP-VIKOR and AHP-GR w.r.to vulnerable area. (b) Correlation between AHP-VIKOR and AHP-GR w.r.to vulnerable population. (c) Correlation between AHP-VIKOR and AHP-GR w.r.to vulnerable buildings.