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Assessment of the Socioeconomic Vulnerability to Seismic Hazards in the National Capital Region of India Using Factor Analysis

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Abstract: The seismicity of the National Capital Region (NCR) of India increased significantly over the last decade. Communities in the NCR face significant exposure to damaging seismic events, and the seismic risk arises not only from the region's proximity to the Himalayan mountains, but also from the socioeconomic vulnerabilities in its communities and the current capacities of different localities to respond to and recover from any unforeseen large seismic event. GIS-based spatial distribution of exposure to seismic hazards (SH) can help decision-makers and authorities identify locations with populations at high seismic risk, and to prepare risk-mitigation plans. Socioeconomic vulnerability (SeV) studies serve as a basis for quantifying qualitative measures. For this purpose, in the present study, the hazard of place (HoP) model is used to assess SeV to seismic hazards in the NCR. Social indicators like age, gender, literacy, family size, built environment, etc., comprising a total of 36 variables, are used to assess a socioeconomic vulnerability index (*SeVI*) based on factor and principal component (PCA) analyses. Based on PCA, 20 variables were retained and grouped into four factors: socioeconomic status, employment status, building typology, and family size. Ground-motion parameters, estimated from probabilistic seismic hazard assessment, are integrated with the socioeconomic vulnerability index to quantify exposure to seismic hazards. The spatial distributions in the produced socioeconomic-vulnerability index and seismic–hazard–exposure maps highlight the critical areas. The results reveal that areas of low literacy, high unemployment, and poor housing condition show moderate-to-high vulnerability. The south-eastern region of the study area is assessed as a high-risk zone by an integrated SeV–SH risk matrix. The results of this study emphasize the importance of the socioeconomic vulnerability component of disaster risk–reduction programs, from a holistic perspective, for the areas with high seismicity.

Keywords: socioeconomic vulnerability; seismic hazard parameters; principal component analysis; NCR of India; exposure; GIS

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1. Introduction

Different regions around the globe have experienced an increase in the frequency and intensity of seismic hazards over the past few decades. The high probability of occurrence of seismic events, paired with their high potential for overall damage and loss, poses a high seismic risk to society. It is estimated that earthquakes represent, annually, a major portion of the loss caused by natural hazards [1,2]. This loss is not limited to monetary damages but also causes devastation in terms of human life. The extent of the loss and damage caused by an earthquake or any kind of large-scale hazard depends on several factors, such as resilience, awareness, and the preparedness of the community for the occurrence of any undesirable event [3,4]. The loss due to earthquakes can be higher in developing nations, as compared with developed nations, due to uncontrolled population growth, poor infrastructure, and a lack of mitigation and management policies. India is one of the most densely populated countries in the world; is diverse in terms of geographical, cultural, and economic factors; and is prone to multi-hazard scenarios. The

Himalayan region of India, and its adjoining areas, are characterized by high seismicity [5] and experiences earthquakes of high magnitude, as in the 2015 Nepal earthquake (M_w 7.8), the 2005 Kashmir earthquake (M_w 7.6), the 2001 Bhuj earthquake (M_w 7.7), and many more. Due to uncontrolled population growth and its unplanned development of infrastructure, the northern region of India is becoming vulnerable to seismic hazards, posing a high risk to life and property. In 2020, several earthquakes of low-to-moderate magnitude shook the National Capital Region (NCR) of India, which lies in the vicinity of the Himalayan regions. Housing the capital of India and being a major centre of economic activity, the population density of the area has been increasing, resulting in a drastic change in land-use and land-cover patterns in the region, which may intensify the impact of a hazardous event in the future. The consequences of earthquakes cannot be avoided, but with the help of proper seismic risk assessment and the implementation of mitigation strategies, such damage can be minimized to a significant extent. Therefore, the identification and evaluation of hazards, and their associated risk, are key to developing efficient disaster-mitigation and management plans for the region.

According to UNISDR [6], the risk is defined as the combination of the probability of the occurrence of an event with its negative consequences. Risk can also be defined as the product of hazard, vulnerability, and elements at exposure [7]. The risk elements of an area can include human settlement, the natural and built environment, and those socioeconomic activities of the region threatened by natural hazards. The quantification of hazard and vulnerability is a precondition for assessing an area's risk; seismic hazard assessment may be carried out for a region by following a probabilistic approach, and the results are represented in terms of ground-motion parameters, such as peak ground acceleration or peak ground velocity [8]. For seismic risk assessment, two components play a vital role: exposure and vulnerability assessment [9,10]. Vulnerability is defined as the conditions of physical, social, economic, and environmental factors that could increase the susceptibility of a community to hazard [11]. Vulnerability can be expressed in terms of the physical built environment or socioeconomically [12–14]. Socioeconomic vulnerability assessment includes various factors or indicators, such as age, gender, ethnicity, socioeconomic status, unemployment, population density, quality and density of the built environment, type of land use, the immigration status of the area, household status, family structure, and the availability of other resources [15–17]. Socioeconomic vulnerability highlights the sensitivity of society to the impact of a hazard by determining the potential factors involved, and by estimating the magnitude of the loss of exposed elements. The devastating effect of natural hazards mainly depends upon vulnerability, which, in turn, depends upon the location and socioeconomic condition of the exposed population.

The main challenge in socioeconomic vulnerability assessment is the consideration of diverse factors with inadequate data. Considering this, different frameworks, such as the Pressure and Release (PaR) model [18], Cutter's Hazard of Place (HoP) model [19], the vulnerability framework of Turner [20], the BBC model [21], and the Disaster of Resilience of Place (DROP) model [22] have been developed. Among them, the HoP and DROP models are widely used for the estimation of social vulnerability due to various natural hazards [23]. Zhang et al. [23] assessed social vulnerability to earthquake hazards for Sichuan province using a catastrophe progression method. Frigerio et al. [17] developed a qualitative social-vulnerability-exposure map for Italy combining the social vulnerability index (SVI) and seismic hazard (SH) maps. Derakhshan et al. [24] identified the spatial vulnerability to seismic hazards for the Oklahoma region integrating loss scenarios, social vulnerability metrics, and potential physical damage in a geographic information system (GIS) environment. Cerchiello et al. [25] assessed social vulnerability for Nablus city using a scorecard approach, based on the information derived at the population and local administration level. Ebert et al. [26] assessed social vulnerability for the Tegucigalpa region and determined the SVI with the help of proxy variables derived from high-resolution optical and laser scanning data. Gautam [27] selected 13 variables and quantified the SVI of Nepal at the district scale by using the available census data, and the final index was mapped using GIS. Siagian et al. [28] quantified the SVI for the districts of Indonesia selecting socioeconomic status, gender, age and population growth, and family structure. Armas and Gavris [29] selected the SVI and *SeVI* to assess the social vulnerability of Bucharest using the multi-criteria approach.

For the construction of composite SVI, which is a scientific and rational method for the assessment of *SeVI*, various approaches such as additive model, principal component analysis (PCA) or factor analysis, multiplicative model and data envelop analysis are used in many studies [30–43]. It involves some challenges, namely, it is based on subjective experiences and the assignment of weights to the *SeVI*. Several methods are used in the previous studies, such as the analytic hierarchy process (AHP) and the assignment of weightage to different indicators based on expert opinions, and these methods may also have some errors leading to incorrect results. In the studies on the Indian subcontinent, the vulnerability studies are mostly limited to climate change vulnerability and flood hazard vulnerability [43–48]; for the seismic hazard vulnerability, most of the studies are focused on the built or physical environment [49–51].

For the NCR of India, a densely populated and seismic hazard-prone region, a socioeconomic vulnerability assessment is an urgent need for a better understanding of the critical areas, for sustainable development and urban planning, and appropriate decision making by the authorities and stakeholders. For this purpose, in the present study, the PCA is utilized for factor selection and the HoP model is employed to generate the socioeconomic vulnerability. This is the first attempt to assess the socioeconomic vulnerability to seismic hazards for the NCR.

The impact and consequences of the natural hazards can be reduced by proper emergency planning and disaster mitigating strategies [52]. Therefore, this research aims at integrating the bedrock level peak ground acceleration with a 10% probability of exceedance in 50 years based on the seismic hazard microzonation of the study area, socioeconomic vulnerability index, and vulnerability exposure in the NCR. This can help the concerned authorities and city planners to identify the critical areas and plan for sustainable development and disaster risk mitigation strategies.

2. Description of the Study Area

The NCR is one of the fastest-growing regions in India and home to 4.71% of India's population. It consists of the National Capital Territory (NCT) of Delhi; Alwar, and Bharatpur districts of Rajasthan; Baghpat, Bulandshahar, Gautam Buddha Nagar, Ghaziabad, Hapur, Meerut, Muzaffarnagar, and Shamli districts of Uttar Pradesh; and Bhiwani, Charkhi Dadri, Faridabad, Gurugram, Jhajjar, Sonipat, Jind, Karnal, Mahendragarh, Nuh, Palwal, Panipat, Rewari, and Rohtak districts of Haryana [53], covering a total area of about 55083 km^2 (Figure 1). The region has a mixed culture of the rural and urban population. Due to the presence of many large industries and public sector units and better employment opportunities in and around the NCT of Delhi, the population has increased rapidly. Delhi is one of the most populated cities in the world and its density increased by 20.95% in a decade from 2001 to 2011, whereas the national average increased by 17.54% in the same period [54].

The NCR lies in the foothills of the Shivalik ranges of the Himalayas and Aravalli hills. It has a population of about 58.15 million, with 55.4% in urban and 44.6% in rural areas [44]. Among the total population in Delhi, 97.5% are in the urban area, and in contrast, among the total population in two districts of Rajasthan 81.5% live in the rural areas. The districts of Uttar Pradesh and Haryana, which are part of NCR, accommodate a fair mix of the rural and urban populations. As the NCR lies in the vicinity of the young Himalayan fold mountains and due to the presence of numerous tectonic features, this region is highly vulnerable to seismic hazards. The seismotectonic setting of the region shows the presence of major faults and ridges that increases the seismic risk [55,56].

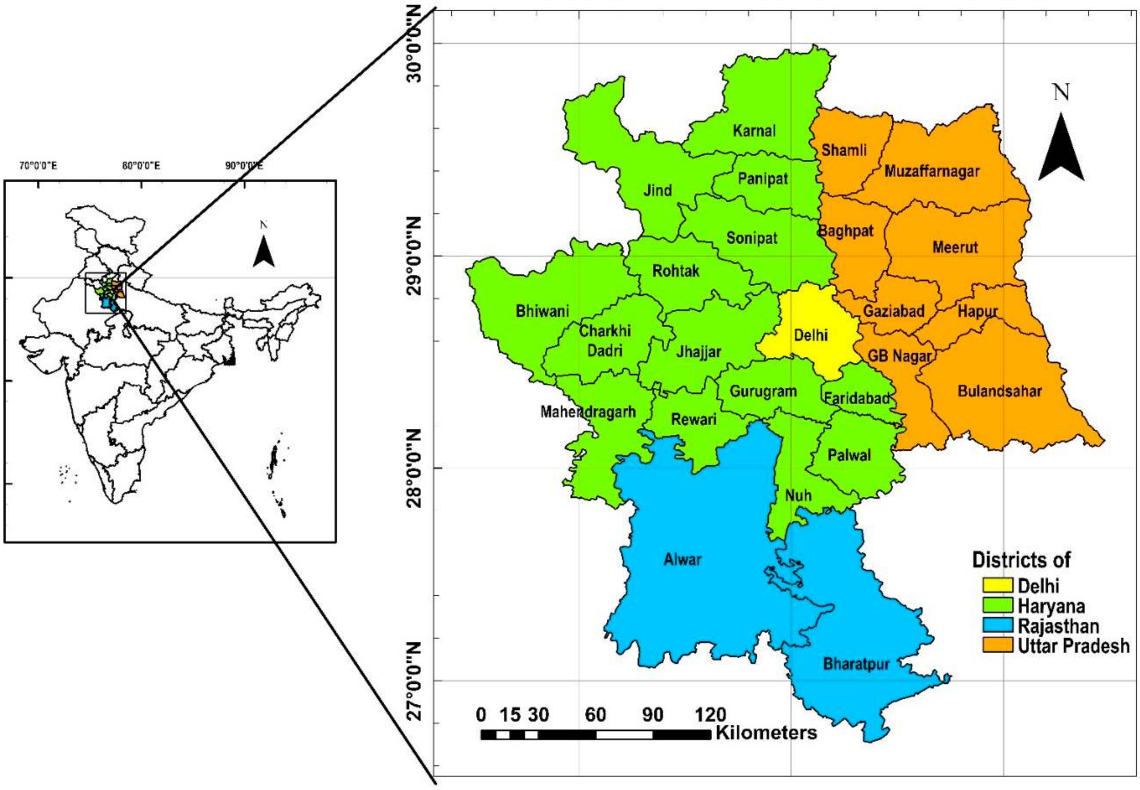


Figure 1. The study area (National Capital Region of India).

The tectonic belt of the young Himalayan mountains is located in the north-eastern part of the study area, while the Proterozoic Delhi fold belt and gneisses batholithic complex are predominant in the southern portion of the area [57]. The Great Boundary fault (GBF), the Moradabad fault (MF), the Mahendragarh–Dehradun fault (MDF), the Main Boundary thrust (MBT), the Main Central thrust, the Mathura fault line, and the Sohna fault are some of the important faults in and around the region, influencing the seismicity of the area (Figure 2). The past historical earthquakes associated with the faults of these fold belts in the region support the possible seismic risk of the region. The NCR falls under seismic zone-IV, a severe intensity zone having a zone factor of 0.24 [58]. Some of the historically significant earthquakes in the region are the 1720 Sohna earthquake (M 6.5), whose aftermath effect was felt for approximately 40 days with four to five aftershocks per day [55,57]; 1803 Mathura earthquake (M 6.8) that caused damage to Qutub Minar [59,60]; and 1960 Gurgaon earthquake (M 6.0) that caused injuries to people and minor damage to properties [61]. The effects of far seismic sources and events such as the 1999 Chamoli earthquake (M_w 6.8) [57], 2011 Pakistan earthquake (M_w 7.4), 2011 Sikkim earthquake (M_w 6.9), and 2015 Nepal earthquake (M_w 7.8) were also experienced at NCR. In recent times, from 2019 to 2020, this region has experienced more than 10 earthquakes of magnitude greater than 3.5. Figure 2 presents the seismicity of the study area in terms of the number of past earthquakes.

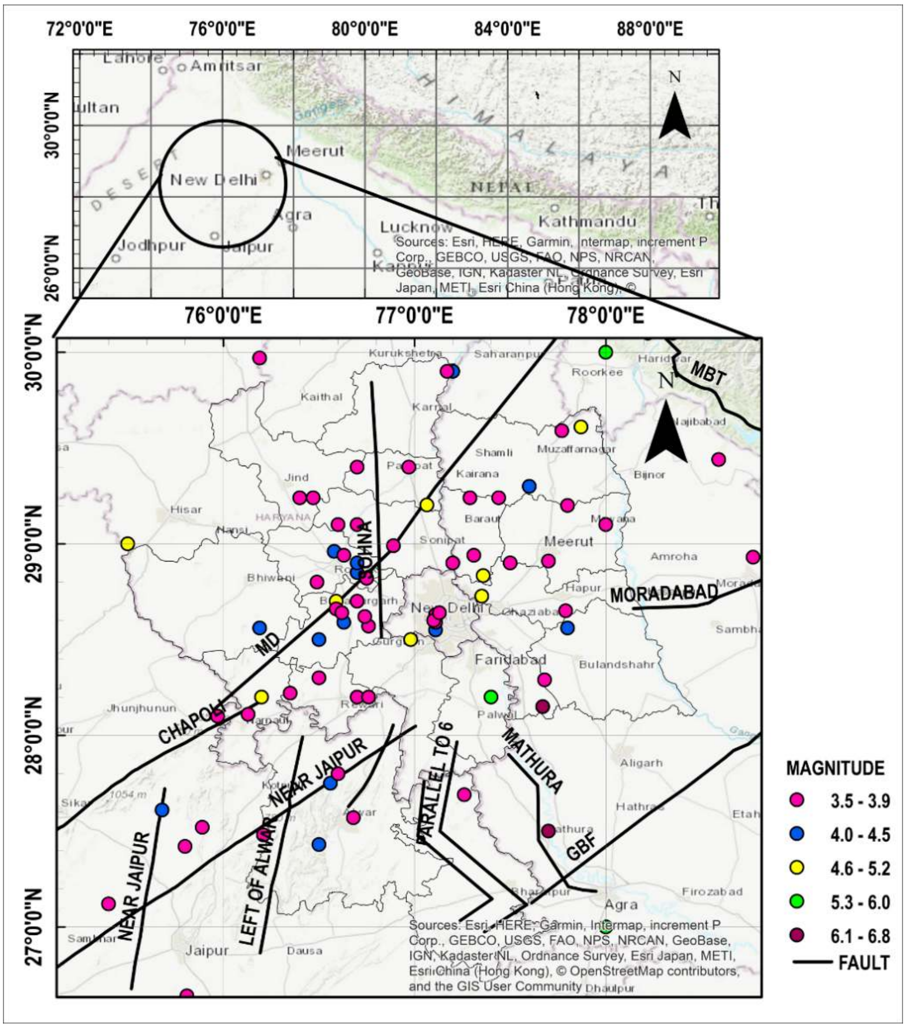


Figure 2. Seismotectonic setting and seismicity of the region.

3. Methodology

In the present study, the hazard-of-place (HoP) model of vulnerability is adopted for assessing the socioeconomic vulnerability index (*SeVI*) and exposure to seismic hazard [22,30]. This model allows a holistic approach to combining the social and biophysical vulnerability to produce overall place vulnerability [30]. The level of vulnerability of a specific geographical region can be explained as this model is geographically inherent and represents the overall scenarios and components that contribute to the vulnerability [22]. Various uncertainties involved in seismic hazard modelling and forecasting make seismic risk modelling complicated [24]. The probabilistic seismic hazard assessment is adopted in this study to incorporate the spatial, temporal, and magnitude uncertainties. Seismic hazard parameters and *SeVI* are integrated to identify vulnerable communities. The overall framework can be summarized in the three main steps: (a) selection of major social indicators using factor analysis, (b) estimation and mapping of *SeVI*, and (c) identification of areas with a high level of exposure to seismic hazard.

3.1. Selection of Major Socioeconomic Indicators Using Factor Analysis

The present study is based on the data of the 15th Housing and Population Census of India [54], which describes the socioeconomic structure and population distribution of India. The socioeconomic data for all 120 sub-districts (Tehsils) of the NCR is collected. Literature shows that socioeconomic vulnerability analysis revolves around these common socioeconomic indicators such as age, gender, employment, literacy, population density, stock of built structures, the fragility of the built environment, and density of various infrastructures and lifelines of the region [24,25,30,32,62–64]. In the present study, eight major indicators namely, population density, age, gender, built-in-environment, house condition, employment status and service opportunities, family size, and education, comprising a total of 36 variables that are considered, as described in Table 1. The indicators are selected based on their influence on the SeV of a region and the variables of the indicators explain both positive and negative impacts on SeV. After multi-collinearity analysis of 36 variables, a subset of 21 variables is derived and used in the statistical analysis

Table 1. Socioeconomic variables and their description.

S. No.	Variables	
1	TP	Total population
2	PD	Population density
3	PF	Percentage of female population
4	PSC	Percentage of the population belongs to socially backward class
5	PST	Percentage of the population belongs to tribal background
6	P06	Percentage of the population of children age less than 7
7	P07	Percentage of the population belongs to age group equal to or greater than 7
8	ELR	Effective Literacy Rate
9	Pill	Percentage of the illiterate population
10	PMW	Percentage of the population belongs to MW [1] class (agricultural laborer, cultivators, and household workers)
11	PMMW	Percentage of the male population belongs to MW [1] class (agricultural laborer, cultivators, and household workers)
12	PFMW	Percentage of the female population belongs to MW [1] class (agricultural laborer, cultivators, and household workers)
13	POMW	Percentage of the population belongs to the OMW [2] class
14	PMOMW	Percentage of the male population belongs to the OMW [2] class
15	PFOMW	Percentage of the female population belongs to the OMW [2] class
16	PMrW	Percentage of the population belongs to MrW [3] class (agricultural laborer, cultivators, and household workers)
17	PMMrW	Percentage of the male population belongs to MrW [3] class (agricultural laborer, cultivators, and household workers)
18	PFMrW	Percentage of the female population belongs to MrW [3] class (agricultural laborer, cultivators, and household workers)
19	POMrW	Percentage of the population belongs to the OMrW [4] class
20	PMOMrW	Percentage of the male population belongs to the OMrW [4] class
21	PFOMrW	Percentage of the female population belongs to the OMrW [4] class
22	PNW	Percentage of non-working population
23	PMNW	Percentage of the non-working male population
24	PFNW	Percentage of non-working female population
25	RM11	Percentage of buildings with RCC roof
26	RM12	Percentage of buildings with brick or stone roof
27	RM13	Percentage of buildings with kutcha roof
28	WL01	Percentage of buildings with pucca wall
29	WL02	Percentage of buildings with kutcha wall
30	HC11	Percentage of residential houses in good living condition
31	HC12	Percentage of residential houses in dilapidated condition
32	HC21	Percentage of residential cum other houses in good living condition
33	HC22	Percentage of residential cum other houses in dilapidated condition
34	HH1	Percentage of houses with 1–3 households
35	HH2	Percentage of houses with 4–5 households
36	HH3	Percentage of houses with 6 or more households

[1] MW: Main Workers—workers who worked for more than six months in the reference period; OW: Other Workers—workers other than cultivators, agricultural laborers, or household workers., e.g., government servants, municipal employees, teachers, bankers, trade and commerce, etc.; [2] OMW: Other Main Workers—main workers falling under OW; [3] MrW: Marginal Workers—workers who worked for less than six months; [4] OMrW: Other Marginal Workers—marginal worker falling under OW.

Following the Cutter et al. [30] framework, factor analysis (FA), specifically principal component analysis (PCA) is employed to confirm the selection of variables and to reduce the number of variables to a set of components that explains the socioeconomic characteristics of the study area. In factor analysis, KMO (Kaiser–Meyer–Olkin) and Bartlett's test are employed to check the sample adequacy. KMO value indicates the adequacy of a dataset of variables for the factor analysis. If the value of KMO is greater than 0.5, then the dataset is considered adequate and FA is appropriate for the selected variables. The selection of variables is again confirmed by Bartlett's test of sphericity. If the test results show a small value of significance level, i.e., less than 0.05, then the FA can be used with the selected variables. These tests are performed before proceeding for PCA. In this study, a KMO value of 0.75 and a significance level of 0 are obtained, which indicates that the selected dataset is adequate. These 21 variables are then standardized to z-sores (μ = 0, variance (λ) = 1) and entered into the principal component analysis (PCA). The factors having an eigenvalue more than 1.0 are extracted and rotated using a rotation method of varimax with Kaiser normalization and confirmed by tracking the changes in the slope of the scree plot shown in Figure 3. Out of these 21 variables, a single variable forming a factor is found to be explaining the very least amount of variance in the data set and it is not considered in this study to eliminate the problem associated with factor interpretation and further calculations. Based on this approach, four factors explaining 78.84% of the variance in the entire dataset are extracted from PCA. These four factors, presented in Table 2, are interpreted as socioeconomic status, employment status, building typology, and family size.

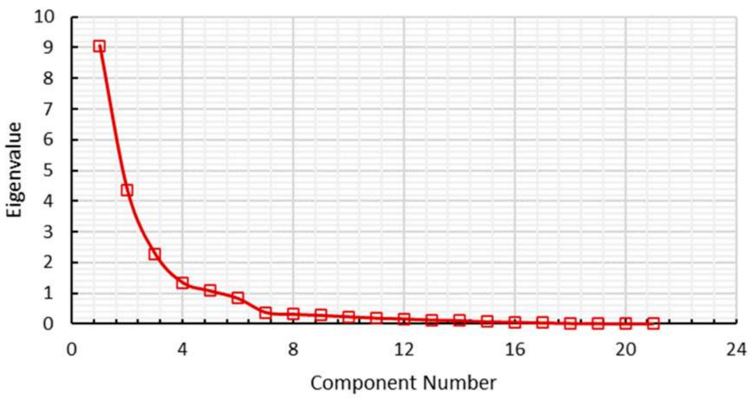


Figure 3. Scree plot.

Table 2. Extracted socioeconomic factors, the eigenvalues, and percent of variance explained by each factor.

S. No.	Factors	Variables (Descriptive)	Eigenvalue	Percentage of Variance Explained
1.	Socioeconomic status	Percentage of the illiterate population Effective Literacy Rate Percentage of the population of children age less than 7 Percentage of buildings with kutcha wall Percentage of the male population belongs to MW class Percentage of the female population belongs to the OMW class Percentage of buildings with RCC roof	5.27	25.08
2.	Employment status	Percentage of non-working female population Percentage of the female population belongs to MrW class Percentage of the female population belongs to MW class Percentage of non-working population Percentage of the male population belongs to OMrW class Percentage of the male population belongs to OMrW class	4.63	22.07

Table 2. *Cont.*

S. No.	Factors	Variables (Descriptive)	Eigenvalue	Percentage of Variance Explained
3.	Building typology	Percentage of residential cum other houses in dilapidated condition Percentage of residential cum other houses in good living condition Percentage of residential houses in good living condition Percentage of buildings with kutcha roof	4.46	21.22
4.	Family size	Percentage of houses with 4–5 households Percentage of houses with 1–3 households Percentage of houses with 6 or more households	2.20	10.47

3.2. Estimation of Socioeconomic Vulnerability Index

After extracting the factors, it is necessary to add the scores of each factor to assess the overall *SeVI* of the region. It is necessary to analyse each factor to determine whether the factor is positively impacting the vulnerability or negatively. Positive loading indicates that the factor is increasing SeV and vice versa. The aggregation method, suggested by Ge et al. [34] is adopted to generate a composite index. Each factor's influence on the overall SeV is not the same, as each factor is explaining a different percentage of variance in the entire dataset, e.g., socioeconomic status is explaining 25.08% of the variance, while the family size is explaining only 21.22% of variance out of a total of 78.84% explained by all the factors. Due to this reason, the construction of a weighted composite *SeVI* is recommended [62]. Different weighting schemes, namely equal weight scheme, Pareto-ranking scheme, and weighting according to the contribution to the total variance explained are recommended and adopted in previous studies [28,30,34,65]. In the present study, weights are assigned according to the contribution to the total variance explained and the values are obtained using Equation (1):

$$w_i = \frac{\lambda_i}{\lambda_t} \tag{1}$$

where, w_i weight of individual factor, λ_i is the variance of ith factor, and λ_t is the total variance explained by all the factors.

These weighting factors are then multiplied by the corresponding factors and summed up to get the *SeVI* score for the sub-districts using Equation (2).

$$SeVI = \sum_{i=1}^{4} w_i \times Factor(i) \tag{2}$$

The next step is to classify the scores and map the overall *SeVI* scores to compare the places visually and to get the spatial distribution of socioeconomic vulnerability using ArcGIS software. The obtained scores are normalized to a scale of 0–1 using Equation (3).

$$\delta_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

where, δ_i is the normalized score of ith sub-district, x_i is the original score of ith sub-district, and x_{max} and x_{min} are the maximum and minimum values of the dataset score.

The normalized scores are then grouped into four classes using a classification scheme based on standard deviation. Additionally, based on the classification of normalized *SeVI* scores, a thematic map is created to display spatial variation in socioeconomic vulnerability.

3.3. Estimation of Ground Motion Parameters Using Probabilistic Seismic Hazard Assessment

An earthquake is regarded as a disastrous event when it leads to the collapse of structures and causes damage and disruption to social life. The extent of the damage may vary with the ground shaking intensity, local site conditions, available infrastructures, and density and quality of the built environment. The assessment of seismic hazard helps in quantifying the probability of experiencing a certain level of earthquake shaking and its consequent effects such as landslides, liquefaction, etc. in a region within a particular period. It can be quantified in terms of ground motion parameters, namely peak ground acceleration (PGA), peak ground velocity (PGV), or spectral acceleration (SA) [8,66]. Estimation of seismic hazard parameters helps to assess the building performance, and the sustainability and resilience of the built environment and the communities facing seismic hazards. Ground motion parameters in terms of peak ground acceleration (PGA) are evaluated for NCR based on the detailed probabilistic seismic hazard assessment shown in the flowchart in Figure 4 [8,66–68]. The seismic hazard map for the study area is prepared for the PGA having a 10% probability of exceedance in 50 years using ArcGIS software. Figure 5a shows the peak ground acceleration varying from 0.06 g to 0.38 g, which shows the lowest PGA in the north-western part and the highest in the south-eastern part of the NCR. The study area is further divided into four seismic hazard classes shown in Figure 5b according to the PGA values explained in Table 3.

Table 3. Seismic hazard class according to the PGA values.

Hazard Class	Peak Ground Acceleration with 10% Probability of Exceedance in 50 Years
Very low	Less than 0.14 g
Low	0.14 to 0.20 g
Moderate	0.21 to 0.26 g
High	Greater than 0.26 g

A seismic risk matrix is created in Figure 6, and the ground motion parameters and seismic hazard classes are then integrated with the *SeVI* scores to quantify the exposure to seismic hazard in the region. Then, the risk matrix values are reclassified into four groups of very low, low, moderate, and high. The *SeVI* classes and seismic hazard classes are assigned the values of 1 to 4. The class referred to as very low is assigned 1 and the class referred to as high is assigned 4. On integration, the seismic risk matrix values range from 1 (lowest) to 16 (highest), which are then mapped into four seismic risk classes representing places with the lowest risk (lowest socioeconomic vulnerability and least exposed to potential loss) to highest risk (socioeconomically most vulnerable and most exposed) [24,62].

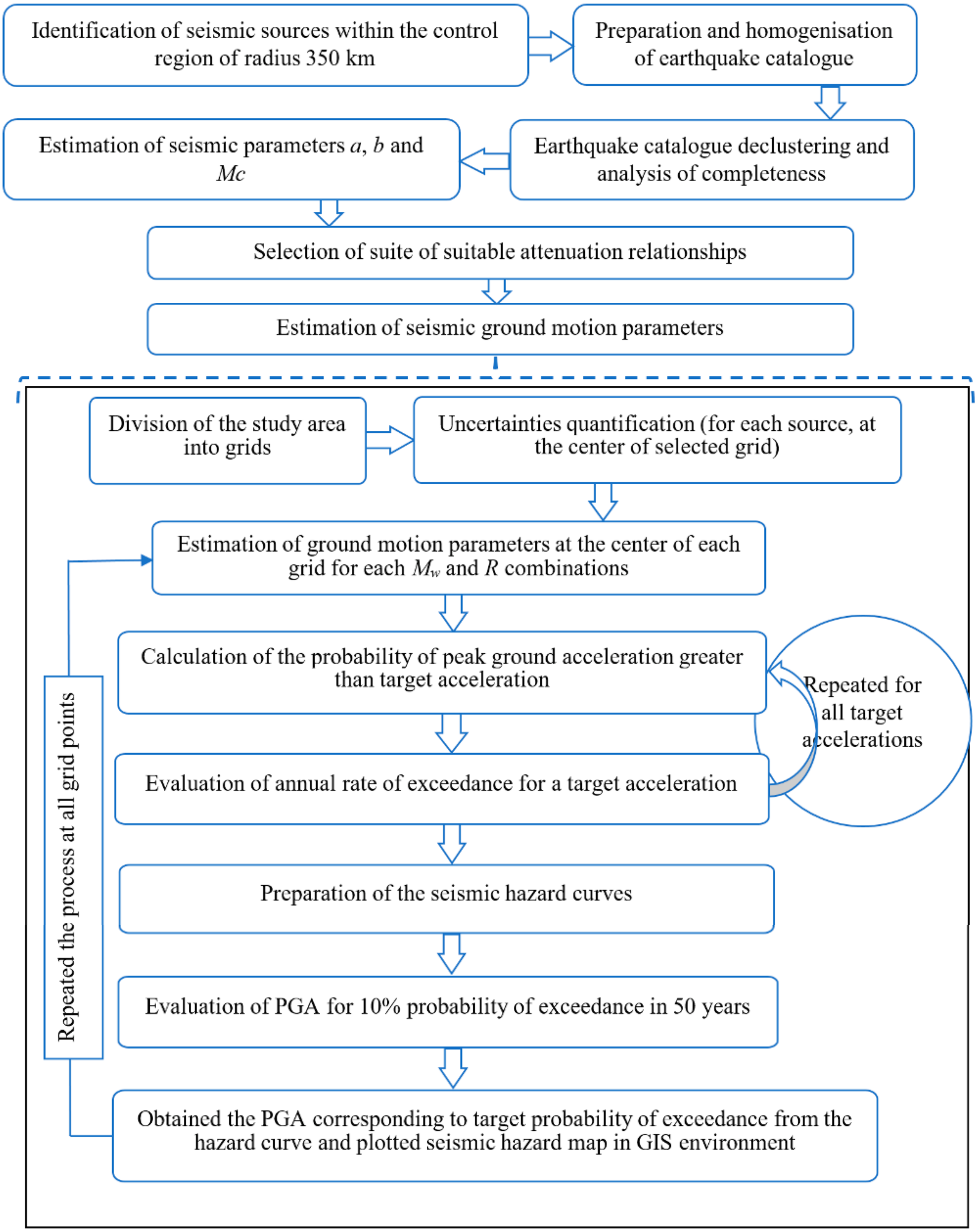


Figure 4. Detailed flowchart for evaluation of PGA using probabilistic seismic hazard assessment.

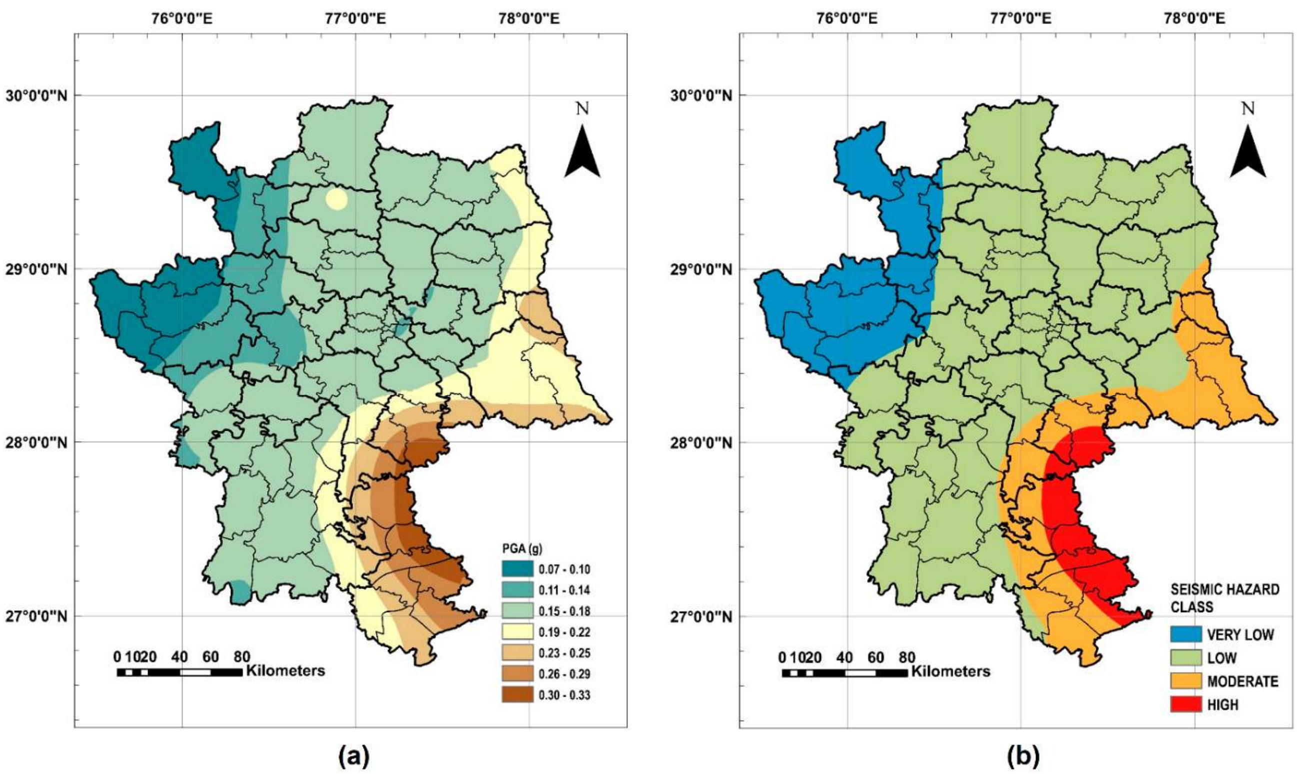


Figure 5. (**a**) PGA at bedrock level for 10% probability of exceedance in 50 years; (**b**) seismic hazard class.

		Hazard Class			
		Very Low (1)	Low (2)	Moderate (3)	High (4)
Social Vulnerability	Very low(1)	1	2	3	4
	Low(2)	2	4	6	8
	Medium(3)	3	6	9	12
	High(4)	4	8	12	16
Risk Classes		Very Low	Low	Moderate	High

Figure 6. Risk matrix.

4. Results and Discussion

Based on the PCA of 20 variables, using Kaiser criterion of factor retention, four main factors with eigenvalues >1.0 are retained that explain the percentage of total cumulative variance, as in Table 2. The selection of these four factors is also confirmed by observing the scree plot in Figure 3 [69]. These factors are named as socioeconomic status, employment status, building typology, and family size. A detailed discussion of each factor is given in the following subsections.

4.1. Factor 1: Socioeconomic Status

The combined factors of literacy, age, type of work, and building material represent the socioeconomic factor of the study area. It explains the 25.08% of the variance in the dataset, the highest among all factors. Figure 7a presents the spatial distribution of vulnerability in terms of factor 1. The eastern and south-eastern parts of the NCR are most affected by this factor, i.e., these sub-districts of NCR have a higher percentage of illiterate people and children younger than 7. As the population's literacy rate is lower, it constrains people's ability to understand the warning information and job opportunities during and after the disaster [30]. The children are dependent upon the elderly population and those younger than 7 may also have mobility constraints. Thus, the communities with a high percentage of such populations become more socioeconomically vulnerable in case of seismic events [62]. The type of population such as MW or OMW and the type of material used for the dwellings also increases the vulnerability. In a locality, the working population and the type of service they provide reflects the economic status and governs the literacy rate, education standard, and type of houses (Kutcha or pucca), which eventually governs the community resilience. The poor people with non-permanent jobs are seen to have poor-quality housing (kutcha house) and they may not afford to buy emergency supplies and may take a longer time to recover from the impact of seismic hazards [28,66,70]. The combination of such variables reflects the socioeconomic status. In the spatial distribution of factor 1 in Figure 7a, it is observed that the sub-districts with the least industrial activity and high dependency on agriculture and related works are the most vulnerable.

4.2. Factor 2: Employment Status

Factor 2, i.e., employment status, explains 22.07% of the variance, the second-highest among all factors. It comprises of six variables, namely the non-working female population, female population belonging to the MrW class, female population belonging to the MW class, the non-working population, the male population belonging to OMrW class, and the male population belonging to the OMrW class. These six variables mainly define the employment status of the population and the type of work they are involved in. The nature of employment and the number of days for which the employment opportunities are available are the critical factors, which influences the coping capacity of the people from the effects of the disastrous event and determine the SeV of the region. Figure 7b shows the spatial distribution of SeV in terms of employment status in the NCR. The variables PFMrW, PFMW, and PFNW have the highest loading. These factors are concentrated on the Alwar districts and distributed in the western and south-western parts of the region. In the rural areas, women in a family are mostly the primary caretakers and have a lower income and fewer financial resources. In case of any disaster, their responsibility as the primary caretaker of the family may not allow them to continue their jobs and they are more likely to lose their low-paying jobs. Further, the non-permanent employees (marginal workers), mostly in agriculture and small-scale industries are more likely to lose their jobs due to the post-disaster disruption in the daily activities and businesses [66,70]. Therefore, the sub-districts with a higher percentage of such female populations show higher vulnerability. The higher percentage of the non-working population and the male population in the marginal working-class increases the factor loading, whereas the weightage remains quite low compared to the variables related to the female working class. The male population belonging to the other main working class is found to decrease the vulnerability as they have better job security. Overall, the combination of these variables makes this indicator increase the SeV at the sub-district level.

4.3. Factor 3: Building Typology

Factor 3 is led by the conditions of dwellings and buildings for residential as well as other purposes. Figure 7c shows the spatial distribution of this factor in the study region and this is also an important factor explaining 21.22% of the variance. The eastern, western, and northern regions of the study area fall under low to high vulnerability; the central and southern regions are characterized as very low vulnerable. A poor-quality house is most likely to get damaged and it increases the vulnerability in case of any disastrous event. Houses used for other purposes, namely shops, small business units, or small-scale industry can also positively impact the vulnerability. On the other hand, good quality buildings undergo the least amount of structural damage and help to recover faster from the impact of the hazard and decrease the vulnerability.

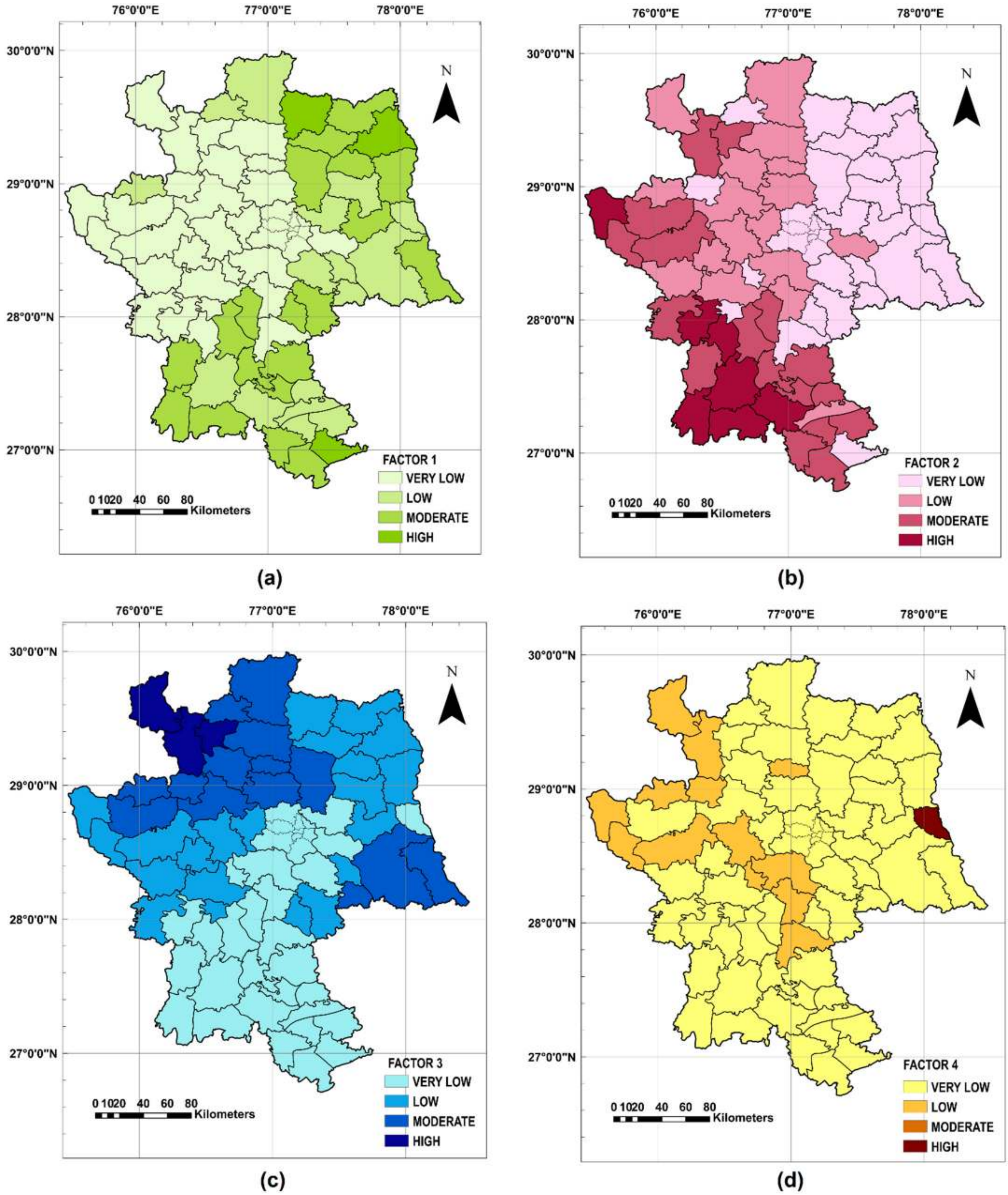


Figure 7. (**a**) Factor 1; (**b**) Factor 2; (**c**) Factor 3; (**d**) Factor 4.

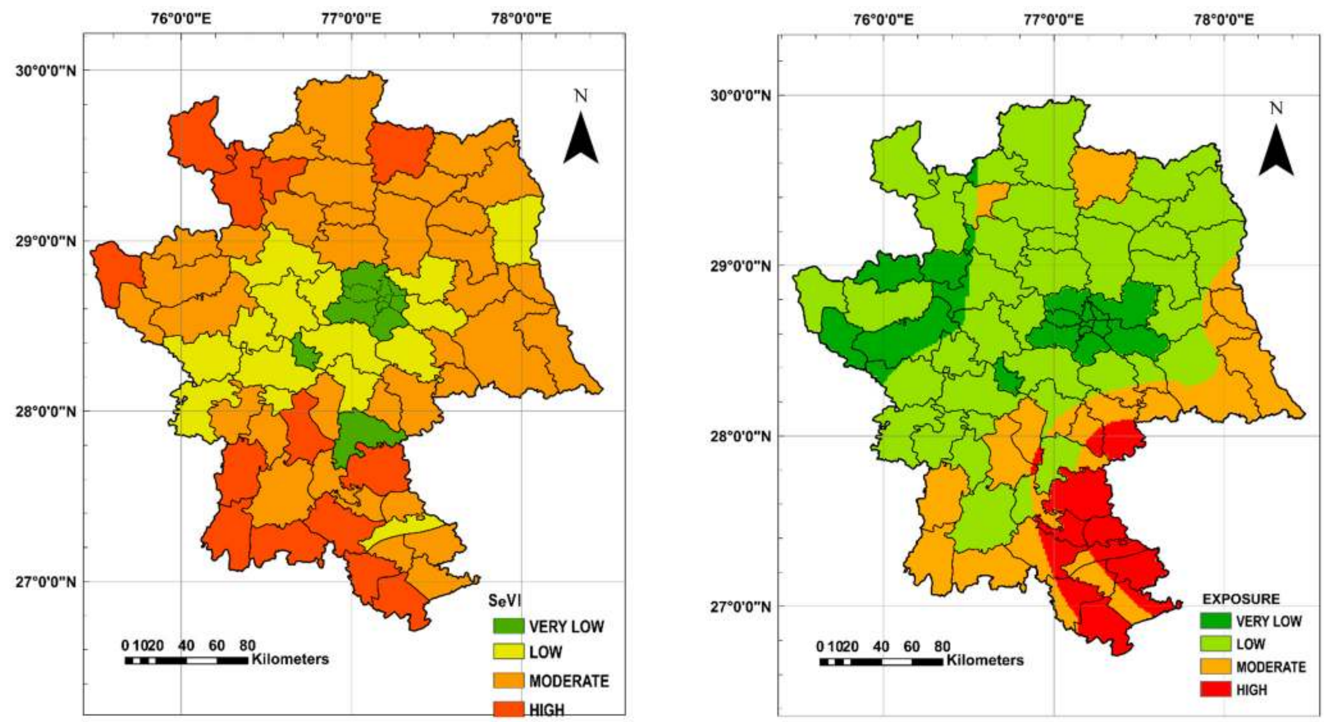
4.4. Factor 4: Family Size

Factor 4 represents the family size and it explains the least amount of variance among all factors in Table 2. The variables in this factor highlight the sub-districts with bigger family sizes. Figure 7d shows the spatial distribution of this factor, which indicates that the loading remains very low in most of the sub-districts and a very few sub-districts fall into the moderate category. A small portion in the eastern region shows a high vulnerability loading factor in terms of family size. The bigger family size with many dependents may have limited resources. Single-parent households may find it difficult to juggle job duties and care for family members. The family size governs the resilience capacity of the society and the capacity to recover from the hazard [18,30].

No other study on socioeconomic vulnerability due to seismic hazard for the present study area is available. Therefore, a comparison is made with the studies conducted in different study areas to analyse the adopted methodology and to find the suitability of the selection of indicators. The study carried out by Armas and Gavris [30] for the social vulnerability assessment of Bucharest indicates that high vulnerability is significant in the outskirts of the city with low income and poor housing conditions. Similarly, Rezaie and Panahi [14] noted that the vulnerability of the Tehran region due to seismic hazard is high in the districts having poor economic conditions, high population density, and poor living standards. Low socioeconomic vulnerability is identified in the districts with high income, lower population density, and well-built housing structures. Derakhshan et al. [24] conducted similar studies for the Oklahoma region and they found that gender, social status, and employment condition play a major role in vulnerability assessment due to seismic hazards. The results of the present study also reveal similar observations. The regions of the study area with poor housing facilities, lack of income source, and low literacy rate fall under moderate to high vulnerability class.

4.5. Socioeconomic Vulnerability Index

Socioeconomic vulnerability is dependent on individual factors like socioeconomic condition, family size, employment status, and building typology, as shown in Figure 7. The combined influence of all these factors on socioeconomic vulnerability is obtained as a single *SeVI* score using Equation (2). The spatial distribution of the *SeVI* based on the sub-district level census data is mapped in the GIS environment and it is shown in Figure 8a. This map allows us to quickly visualize the most critical areas and provides a useful tool to decision-makers for emergency management and sustainable planning. The sub-districts with high illiteracy rates, a large number of unemployed populations, and poor housing conditions show higher vulnerability. The heterogeneity in the *SeVI* values and relevant influence of the factors on each other is observed in Table 4. It reveals that 29.39% of the area exhibits high socioeconomic vulnerability and only 3.31% of the area exhibits very low vulnerability. Delhi is a very densely populated city and it is expected to fall under moderate to high socioeconomically vulnerable class, but the Delhi region falls into the very low category, as shown in Figure 8a. This may be due to a higher effective literacy rate, better employment opportunities, and better dwelling conditions increasing the resilience capacity of the sub-districts of Delhi as compared to other sub-districts, which are dominated by low-paying jobs and low-quality dwelling conditions. A total of 23.75% of the area falls into the low vulnerability class. Most of the new urban clusters in NCR such as Gurugram, Faridabad, Ghaziabad, and Noida exhibit low vulnerability class, which is again due to better infrastructure, pucca houses, and better employment status. The rest of the sub-districts (43.72% of total area) exhibit a moderate vulnerability index.



(**a**) (**b**)

Figure 8. (**a**) Socioeconomic vulnerability index; (**b**) exposure to seismic hazard.

Table 4. Percentage of the total area falling into different socioeconomic vulnerability classes.

SeVI (Based on Standard Deviation)	Vulnerability Class	Percentage of the Total Area
<−2.5	Very low	3.31
−2.5 to −5.0	Low	23.75
−5.0 to 0.50	Moderate	43.72
0.50 to 2.5	High	29.39

4.6. Exposure to Seismic Hazard

Finally, the spatial distribution of exposure to the seismic hazard is derived through the integration of seismic hazard and socioeconomic vulnerability using the risk matrix in Figure 6. According to the probabilistic seismic hazard map in Figure 5, approximately 19 sub-districts fall into moderate to high seismic hazard classes. Upon integration of seismic hazard with *SeVI*, 10 sub-districts are labelled as highly exposed to seismic hazard with a standard deviation value of +0.50 and more. These sub-districts are concentrated in the eastern and south-eastern regions. Most of the sub-districts of the NCR fall under the moderate category, and the remaining fall into the low or very low category, except for a few sub-districts in the northern region. The risk matrix and the exposure map help in identifying the spatial variations in terms of the integrated effect of the seismic hazard and socioeconomic vulnerability. The south-eastern region, characterized by high seismicity and moderate socioeconomic vulnerability, represents a high exposure value as shown in Figure 8b. The eastern region lies in a moderate seismic hazard class and has a moderate socioeconomic vulnerability class and it falls under the moderate exposure class. The southern region falls under high social vulnerability and low seismic hazard class, and it is found to be moderately exposed. The central region comes under a low seismic zone and very low socioeconomic vulnerability class and has a very low exposure value. The north and western regions lie in a very low to low seismic zone and exhibit moderate socioeconomic vulnerability values; therefore, those are classified as moderately exposed.

5. Conclusions

SeVI map is a tool that updates the decision-makers about the vulnerability of the natural hazard scenarios and helps to adapt the policies and mitigation measures in response to the hazards. In the present study, four factors socioeconomic condition, employment status, building condition, and family size are combined to explain the socioeconomic vulnerability due to the seismic hazards in the NCR of India. Socioeconomic indicators are properly selected and a multivariate statistical approach is applied, which illustrates that four factors explained 78.84% of the variance and can be used for the reduction of the dataset as well as for the final selection of the variables. The socioeconomic vulnerability index and its spatial distribution are developed at the regional scale by the integration of these four selected factors.

The results show that 3.31, 23.75, 43.72, and 29.39% of the area fall under very low, low, moderate, and high socioeconomic vulnerability classes, respectively. In terms of exposure, the south-eastern region reveals a high exposure class, the eastern and southern regions fall under the moderate exposure class and the central part falls under the very low exposure class. The results present a significant relationship between seismic hazard and socioeconomic vulnerability for the implementation of appropriate risk reduction measures at the regional level for this study area. The integrated map can help in the identification of areas that are highly vulnerable and require detailed investigation and mitigation measures for sustainable and resilient planning. The non-technical stakeholders can also benefit from this study because these maps can be easily analysed and interpreted for better management, comprehensive mitigation, emergency response planning, and allocation of resources during pre- and post-disaster situations.

The present study provides the importance of the socioeconomic vulnerability component in the disaster risk reduction programs for the areas with high seismicity as well as for other hazards. The areas having high *SeVI* can be analysed further for vulnerability due to multi-hazards considering geotechnical, hydrogeological, biophysical, and structural parameters. This study has its inherent limitations in terms of the lack of real-time data. There is a scope for further research aimed at the geospatial and temporal relationship between socioeconomic vulnerability and other natural and human-made disasters in the NCR of India.

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