

Constructing a social vulnerability index to earthquake hazards using a hybrid factor analysis and analytic network process (F'ANP) model

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Abstract Iran is a seismic prone country and has been host to a long series of devastating earthquakes which have resulted in heavy casualties and damages. In order to assess social vulnerability (SV) to earthquake hazards, this paper presents the development of a hybrid factor analysis and analytic network process model for aggregating vulnerability indicators into a composite index of SV to earthquake hazards. The proposed model is then applied in Iran as a case study. The proposed model uses factor analysis (FA) to extract the underlying dimensions of SV. The identified dimensions of SV and their primary variables are then entered into a network model in Analytic Network Process (ANP). The ANP is used to calculate the relative importance of different SV variables, taking into consideration the results obtained from FA and the possible interdependence between variables of the individual dimensions of SV. These weights are then used to compute the factor scores for the individual dimensions of SV and also the composite social vulnerability index (SOVI). The application of the proposed model to a real world case study and its validation show that it is a robust approach for constructing a composite SOVI. Its application to counties in Iran indicates that there exist severe regional differences in terms of SV to earthquake hazards. The pronounced regional variations in SV warrant special attention by both local authorities and the national government to reconsider current natural disaster management strategies.

Keywords Social vulnerability · Social vulnerability index · Composite indicators · Factor analysis · Analytic network process · Iran

1 Introduction

Iran is one of the most seismically active areas in the world and has experienced many destructive earthquakes in the past and continues to be one the most vulnerable countries

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to major earthquake disasters. “Based on the database of the earthquakes with more than 1,000 fatalities over the past 105 years (since 1900), the worst case for country vulnerability index is Iran” (Asef 2008, p. 491). These earthquakes have resulted in the death of thousands of people and destruction of many villages and cities in the country. The Bam earthquake of 26 December 2003 destroyed the entire ancient city of Bam, with a population of around 150,000. Total number of fatalities of this earthquake is reported to be more than 30,000 people (Shakib et al. 2011, p. 140). In the long and terrible earthquake history of Iran events of this nature are not rare. The Rudbar-Manjil earthquake of 1990 had resulted in the death of about 40,000 people (Jackson et al. 2006).

Disaster planning research and management in Iran has focused on physical aspects of vulnerability, concentrating on the damage and economic loss estimates for buildings and infrastructure (JICA 2000; Bahrainy 2003; Shakib et al. 2011), thus neglecting the social vulnerability component. This study aims to fill this gap by studying the spatial variability of social vulnerability to earthquake hazards among the different counties of Iran and also to introduce a new hybrid factor analysis and analytic network process (F’ANP) model for constructing a composite social vulnerability index (SOVI).

Constructing composite indicators is usually accompanied by some difficulties. Adger et al. (2004) believe that the question of weighing individual indicators is a major challenge for constructing a composite indicator for vulnerability. According to Rygel et al. (2006) one of the most pressing problems in developing composite vulnerability indices is the method of aggregation. The way the component variables or indices should be weighed and, if some sort of weighting scheme is applied, the way they should be determined either by expert judgment or by quantitative methods, is the problem that should be taken into consideration. Cutter and Finch (2008, 2305) also ascertain the difficulty in obtaining a single composite index for social vulnerability by stating that “there is no theoretical justification for assuming the relative importance of one factor over another in the construction of the (composite) index”. Clark et al. (1998) also have raised the difficulty in combining factors to get a composite index which is usually done by giving weights to factors and “the way in which the weights are obtained, which often requires subjective assessments of importance” (p. 71). Development of a new hybrid F’ANP model for social vulnerability index construction is aimed to avoid these difficulties in aggregation of social vulnerability component variables or indices.

The purpose of this paper is therefore to develop a hybrid model to aggregate vulnerability indicators and to construct a social vulnerability index which combines F’ANP and applies it to a real world case study in a developing country. This is done by assessing the social vulnerability of counties in Iran to earthquake hazards.

This article is organized as follows. After the introduction, the next section introduces the social vulnerability concept, its indicators and methods of creating SOVI. Then the study area is introduced. Thereafter, the proposed F’ANP model which combines factor analysis (FA) and analytic network process (ANP) to determine the relative weights for SV variables in arriving at SOVI scores is discussed. The results and discussion section contains results from the application of the proposed hybrid F’ANP model to counties in Iran and maps that plot the resulting scores for the different SV components as well as the composite SOVI to study the regional differences in social vulnerability. In this section the model validation is also presented. The conclusion highlights the main findings and contributions of the study to the current vulnerability research.

2 Social vulnerability, its indicators and social vulnerability index creation

Vulnerability refers to “the likelihood that an individual or group will be exposed to and adversely affected by a hazard” (Cutter 1996, p. 532), the susceptibility of human society to hazards and disaster impacts (Smit and Wandel 2006), and their ability to “anticipate, cope with, resist and recover from the impact of a natural hazard” (Wisner et al. 2004, p. 11). The level of vulnerability of a place to hazards is composed of social, physical, and built environment characteristics which determines its susceptibility to risks and hazards and influence its ability to recover from them (Borden et al. 2007).

Although there seems to be no consensus on the definition of social vulnerability (Ebert et al. 2009, p. 277), Wisner and Uitto (2009, 215) define it as “the characteristics of a person or a group that affect their capacity to anticipate, cope with, resist and recover from the impacts of a disaster”. The concept of social vulnerability to environmental hazards recognizes that vulnerability involves socioeconomic and demographic factors that affect community resilience. It identifies sensitive populations that may be less likely to respond to, cope with, and recover from a natural disaster. Social vulnerability is a multidimensional construct that could not easily be captured by a single variable. It is complex and dynamic, changing over space and through time (Cutter and Finch 2008). The spatial dimension of social vulnerability is due to the fact that people and groups of similar characteristic tend to occupy the same or similar areas and the time dimension refers to the fact that people’s degree of vulnerability may vary depending on her or his age, life situation, and also seasonality (Wisner and Uitto 2009).

Although there has been a real progress in the theoretical underpinnings of vulnerability science over the past two decades, there has not been as much advancement in developing methods for measuring vulnerability, resulting in disagreements on the appropriate methods for creating social vulnerability indices (Cutter et al. 2009, p. 22).

Cutter et al. (2000) operationalized the hazard-of-place model to identify the vulnerability of populations living in Georgetown County, USA. The hazard-of-place approach to vulnerability, according to Cutter et al. “describes the place-based interaction between biophysical vulnerability (exposure) and social vulnerability in an overall determination of the differential social burdens of hazards and how this relationship changes over time and across space” (Cutter et al. 2009, p. 4). They conceive that disasters are not caused by external events (such as natural hazards), but by social systems that make people vulnerable. In other words, social vulnerability is a pre-existing condition or an inherent property of existing communities, independent of the hazard type or threat source (Cutter et al. 2009). In the Georgetown study, Cutter et al. (2000) used nine indicators, extracted from literature review that depicted social vulnerability. In order to create a comparative proportion for each social variable in each block, each indicator was standardized by dividing the value of that indicator to the total value of the said indicator at the county level. These standardized variables were summed for each block to obtain an aggregate value for social vulnerability at block level.

In 2003, Cutter et al. using hazards-of-place approach developed the Social Vulnerability Index (SoVI) that measured differences in social vulnerability between counties in the USA. In their SoVI model 42 socio-economic, demographic and built environment variables at county level that contributed to a community’s vulnerability were selected from the literature review and post disaster research. They applied a principal component analysis (PCA) to these selected variables and produced eleven components that explained about 76 % of the total variance. SoVI scores for the counties ($n = 3,141$) were calculated

by adding the individual component scores for each county, where higher SoVI score indicated higher social vulnerability. Cutter et al.'s (2003) SoVI model, which equally weighted component scores, has since been extensively used in the USA (Borden et al. 2007; Burton and Cutter 2008; Cutter and Finch 2008; Wood et al. 2010; Burton 2010) and other developed countries (Boruff and Cutter 2007; Oliveira Mendes 2009). A sensitivity analysis conducted on Cutter et al.'s (2003) SoVI model suggests that it is both scalable and transportable throughout the U.S. (Schmidtlein et al. 2008).

In 2005, Chakraborty et al. developed the Social Vulnerability for Evacuation Assistance Index (SVEAI) for block groups in Hillsborough County, Florida. Following Cutter et al. (2000), they used ten indicators to reveal the social vulnerability to evacuation in Hillsborough County. To obtain a composite SVEAI, however instead of summing, they averaged the standardized variables and the aggregate vulnerability index was then normalized between zero to one.

In 2006, Rygel et al. developed a method for aggregating vulnerability indicators to obtain a composite social vulnerability index. They identified indicators of social vulnerability to storm surges associated with hurricanes by reviewing the vulnerability assessment literature. They chose 57 variables from the 2000 United States Census at block-group level for the metropolitan region of Hampton Roads which consists of ten cities and six counties in southern Virginia. They applied PCA to these 57 variables and using a Varimax rotation identified thirteen components of which the first three components explaining about 51 % of the variance were chosen for further analysis. To create an overall vulnerability index, they used Pareto ranking to organize the block groups into a series of ranks. As a result, the regions 1,027 block groups were sorted into 19 ranks. The social vulnerability score of each block group was defined based on its Pareto rank. The Pareto ranks for the block groups were then rescaled from zero to one for easier interpretation purposes.

In 2009, Collins et al. to study the environmental hazards vulnerability in the Ciudad Juarez (Mexico) and El Paso (USA) metropolis used the method proposed by Cutter et al. (2000) to obtain a social vulnerability index. The social indicators selected in this study were first standardized by dividing the value of each variable in each neighborhood by maximum block value for that variable. Then the standardized values for the variables were summed to obtain a composite social vulnerability index. The index was rescaled from zero to one, with higher values indicating higher social vulnerability.

In 2010, Wood et al. studying community variations in social vulnerability to Cascadia related tsunamis in the U.S. Pacific Northwest, adapted Cutter et al.'s (2003) SoVI at the census-block level. They selected 29 variables from the original 42 variables used by Cutter et al. (2003), which were considered to be appropriate at the block-level. They used PCA for the selected 29 variables at 2,083 census block level that produced 11 components that explained 64.6 % of the data variance. To obtain a composite SoVI score, extracted components were given weights equal to the percentage of variance that they explained, respectively.

In 2011, Bjarnadottir et al. developed a coastal community social vulnerability index (CCSVI) for hurricane prone areas and applied it to Miami-Dade County, Florida, as a case study. To create CCSVI, first both the social and hazard indicators are scaled to dimensionless values and then a PCA is used to identify dominant social factors. Then Analytic Hierarchy Process (AHP) is used to obtain the relative weight for an individual social indicator within a dominant social factor and also the factor weights of the dominant social factors. A weighted sum method is used to obtain the dominant social factors and the CCSVI is then calculated by multiplying the hazard factors by the weighted dominant social factors.

From the above literature review it could be seen that existing methods for creating a composite social vulnerability index have evolved from standardizing SV variables and summing them (Cutter et al. 2000; Chakraborty et al. 2005; Collins et al. 2009) to using PCA to indicators of SV and to extract SV components and summing their scores (Cutter et al. 2003), to giving weights to PCA derived SV components and summing them (Rygel et al. 2006; Wood et al. 2010) and to giving weights to both the social indicators and also the dominant social factors through AHP (Bjarnadottir et al. 2011).

In this article a hybrid F'ANP approach for constructing SOVI is presented which takes into consideration not only the relative importance of individual dimensions of SV but also the interdependence of SV variables in computing their relative weights and thus obtaining a SOVI score. The proposed model is applied to a real world case study in a developing country, by assessing the social vulnerability of counties in Iran to earthquake hazards.

3 Study area

Iran (Coordinates: 32°N 53°E), a Middle Eastern country (Fig. 1) with an area of 1,648,195 km². is divided into thirty provinces (Ostans) and each province is divided into several counties (Shahrestans). In 2006 the country had 335 Counties. The country is located in the Alpine-Himalayan seismic belt, which is one of the most earthquake-prone areas in the world. The country has a history of more than 20 major earthquakes and has faced a number of other calamities within the last 100 years, causing large-scale physical damages and human casualties (Shakib et al. 2011). “Based on the database of the earthquakes with more than 1,000 fatalities over the past 105 years (since 1900), the worst case for country vulnerability index is Iran” (Asef 2008, p. 491). In terms of the number of lives lost due to earthquakes in the twentieth century, Iran is ranked fourth in the world, following China, Japan, and Italy. Of the 153 most catastrophic earthquakes in the world, about 17.6 % have occurred in Iran as compared to 15.7 % in China and 7.1 % in Japan. Economic losses due to earthquakes during the period 1979–1992 constituted about 1.5 % of GNP in China, 2.0 % in the United States and about 7.2 % in Iran (Bahrainy 2003, p. 141).

During the past five decades, the population of Iran has increased tremendously from 18.9 million people in 1956 to about 70.5 million in 2006. The number urban population also has increased tremendously from 6 million in 1956 to about 48.2 million in 2006. During this period the number of cities has increased from 200 in 1956 to 1,012 cities in 2006. In other words, during the last 50 years the urban population of the country has grown by eight folds and the number of cities has grown more than five times (SCI 2007). This accelerated urbanization has concentrated many of the population in cities and towns, many of which are highly vulnerable to earthquake hazards.

4 Methods

The proposed F'ANP model is composed of three main phases as shown in Fig. 2.

4.1 Phase 1: Factor analysis

In the first stage indicators depicting social vulnerability for earthquake hazards are extracted from the literature review. The identified social vulnerability variables are standardized and transformed in such a way that an increase in the variable value would



Fig. 1 Iran in the Middle East

correspond to an increase in social vulnerability. A FA is applied to the identified SV indicators to extract the underlying dimensions of social vulnerability and their primary variables.

FA is a widely utilized and broadly applied multivariate analytical technique used to uncover the latent structure of a set of intercorrelated variables. It groups highly correlated variables that may be explaining the same concept into primary components or factors. It is used to derive a subset of uncorrelated variables called factors that explain the variance observed in the original dataset (Everitt and Dun 1991). FA was used here as an exploratory tool to extract different dimensions of social vulnerability and to identify the key variables associated with these dimensions.

4.2 Phase 2: Analytic network process (ANP)

In the second phase, ANP is used to construct a network model for the results obtained from the FA (phase one) in order to calculate the relative weights of the social vulnerability indicators.

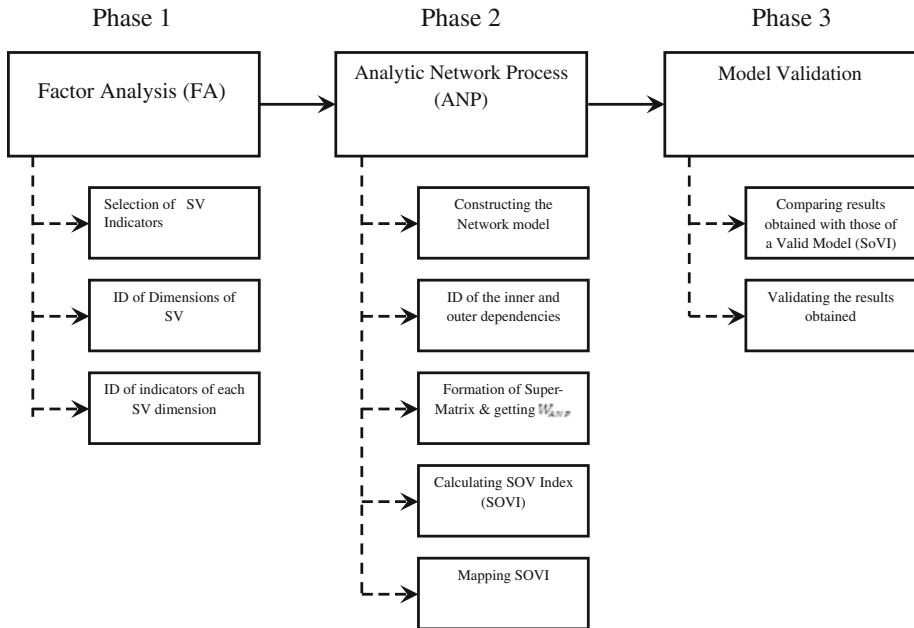


Fig. 2 Flowchart of the proposed hybrid F'ANP model

ANP introduced by Saaty (1996) is a comprehensive decision-making technique appropriate for both quantitative and qualitative data types and is capable of handling the problem of interdependence and feedback among criteria. ANP models are composed of two parts. The first part is a control hierarchy or network of objectives and criteria that control the interactions in the system under study and the second is a network of influences among the elements and clusters (Saaty 2001; Yuksel and Dagdeviren 2007).

The process of ANP comprises the following three major steps:

- Step 1: Model construction and problem structuring: The problem should be clearly stated and decomposed into a rational system like a network
- Step 2: Pair-wise comparisons matrices and priority vectors: In this step the decision elements at each cluster are compared pair-wise with respect to their importance towards their control criterion, and the clusters themselves are also compared pair-wise with respect to their contribution to the main goal. If there are interdependencies among elements of a cluster, pair-wise comparisons also need to be created, and an eigenvector be obtained for each element to show the influence of other elements on it. Usually the ANP derives ratio scale priorities for elements and clusters of elements by making paired comparisons of elements on a common property or criterion. A 9 point scale defined by Saaty (2001) is used as the basis for the pair-wise comparisons
- Step 3: Supermatrix formation: In order to obtain global priorities in a system with interdependencies, the local priority vectors are entered in the appropriate columns of a supermatrix and it is transformed into a weighted supermatrix. The weighted supermatrix is raised to the power of an arbitrarily large

number, to achieve a convergence on the importance weights and this new matrix is called the “limit supermatrix”. The final priorities of all the elements in the matrix can now be obtained by normalizing each block of this limit supermatrix (Saaty 2001). Fundamentals of the ANP could be found in Saaty (2001)

In our proposed model after constructing the network, an initial Supermatrix for the proposed network is formed wherein the priority vectors and matrices are identified. Then to carry out pair-wise comparison between the decision elements of the network and to form the supermatrix, instead of expert judgments, absolute measurements obtained through the FA part of the model are used for obtaining the priorities of decision elements in the following manner:

- The amount of variance explained by each extracted factor in the FA part is used as the degree of importance of each extracted factor in the construction of their pair-wise comparison matrix. After completion of corresponding comparison matrices, the local priority vector for the extracted factors is computed. It should be noted that in the usual ANP process the consistency of each pair-wise comparisons needs to be checked. In our proposed model, the inconsistency problem is diminished, if not eliminated at all, because of the use of absolute measurements instead of the usual subjective expert judgments.
- The absolute values of loadings of the indicators of each dimension, obtained through FA, are used as their degree of importance in constructing the corresponding pair-wise comparison matrix and thus obtaining the corresponding local priority matrix.
- For determining the interdependency between the variables of each social vulnerability dimension or factor, first correlation analysis among the variables of each dimension is done separately. Those variables in each dimension that are significantly related to one another ($p = 0.01$), are considered to be interdependent. Then the absolute values of coefficients of correlation for these interdependent variables are used as their degree of importance in constructing their respective pair-wise comparison matrices. After completion of the pair-wise comparison matrices, its local priority matrix is obtained.
- These priority matrices are entered into an unweighted-priority supermatrix. The supermatrix is actually a partitioned matrix, where each matrix segment represents a relationship between two clusters or components in a system (Saaty 1996). After constructing the supermatrix, the limit supermatrix is calculated by raising the weighted supermatrix to a power of an arbitrary large number. The goal column of this limit supermatrix displays the absolute value of relative weights of individual SV variables. These weights are first normalized and then a negative sign is inserted for those variables that had a negative factor loading in the FA part of the model.

After determining the relative weights of the social vulnerability indicators as explained, a weighted sum method is used to calculate the SOVI scores. The mean and standard deviation for the SOVI scores and also for the scores of the seven individual dimensions of SV are calculated at the national level and counties are classified in units of standard deviation from the mean. The results are then mapped using Arc GIS. It should be noted that mapping using standard deviation shows a relative representation of which counties deviate more from national mean and does not provide an absolute representation of SV.

4.3 Phase 3: Model validation

In the final stage model validation takes place. In this stage the results obtained by the proposed F’ANP model is compared with the results of a valid model to verify the adequacy of the resulting representation of social vulnerability.

5 Results and discussion

5.1 Applying factor analysis

5.1.1 Selection of social vulnerability indicators

This paper adopts the hazards-of-place model of vulnerability (Cutter et al. 2003) as a conceptual framework for assessing social vulnerability for counties in Iran for two main reasons: (a) the social vulnerability index (SoVI) of the hazards-of-place approach has been widely used, assessed and validated, and (b) has been designed as a stand-alone assessment of social vulnerability, independent of hazard type (Cutter et al. 2009). Following Cutter et al. (2003), and taking into consideration local characteristics and data availability, 27 variables were selected to reflect the social vulnerability of counties in Iran (Table 1).

These indicators were standardized and transformed in such a way that an increase in the variable value would correspond to an increase in social vulnerability. All social vulnerability variables that were positively related to social vulnerability (see Table 1) were transformed by Eq. (1) and those that were negatively related to social vulnerability were transformed by Eq. (2) (Ying et al. 2007, p. 101):

$$TX_i = \frac{X_i - X_{iMin}}{X_{iMax} - X_{iMin}} \tag{1}$$

$$TX_i = 1 - \frac{X_i - X_{iMin}}{X_{iMax} - X_{iMin}} \tag{2}$$

where TX_i is the transformed value of the original variable X_i , X_{imax} and X_{imin} are, respectively, the maximum and minimum values of the original variable X_i .

Before applying FA to the 27 intercorrelated variables to extract the different dimensions of social vulnerability, a multicollinearity check was performed. It should be noted that mild multicollinearity is permitted in FA and does not cause a problem, but extreme multicollinearity ($R > 0.8$) should be avoided since it could cause difficulties in determining the unique contribution of the variables to the extracted factor (Field 2000, p. 444). Multicollinearity could be detected by computing the determinant of the correlation matrix of the variables. If the determinant of the correlation matrix is greater than 0.00001, then there is no multicollinearity (Field 2000, p. 445). Also, using Bartlett’s Sphere Test to assess the appropriateness of the correlation matrix for FA and the Kaiser–Meyer–Olkin (KMO) measure of overall sampling adequacy, the necessary conditions for applying a factorial analysis was first checked (Sharma 1996). The Bartlett’s Sphere Test ($\chi^2 = 6,940.94$; $df = 351$; $p < 0.0001$) and KMO value of 0.77 which is well above the accepted cutoff point of 0.50 (Sharma 1996, p. 116) indicate the suitability of the factorial analysis performed.

Table 1 Social vulnerability indicators and their direction of influence (adopted from Cutter et al. 2003)

Variables	Description	Direction of influence
PF	Percent of females	↑
FHHH	Percent of female-headed households	↑
WW	Percent of women who are divorced or widowed	↑
PIL	Percent of illiterate population	↑
UEP	Percent of unemployed population	↑
MUE	Percent men unemployed	↑
HHHU	Households per housing unit	↑
PO65	Percent of population over 65 years old	↑
PO6	Percent of population under 6 years old	↑
PD	Percent of population with disability	↑
PM	Percent of population who are migrants	↑
RP	Percent of rural population	↑
EMA	Percent employed in agriculture	↑
PPL	Percent population participating in labor force	↓
FPL	Percent females participating in labor force	↓
SL	Percent simple laborer to total employed	↑
IKCSS	IKC social security recipients per 100,000 population	↑
PSSR	Permanent social security recipients per 100,000 population	↑
HU50	Percent housing units less than 50 m ² in area	↑
HUNM	Housing units built with non-durable materials	↑
HUB	Percent of housing units with bathroom	↓
HUK	Percent of housing units with kitchen	↓
HUT	Percent of housing units with telephone	↓
HSB	Hospital beds per 100,000 population	↓
GP	General practitioner physician per 100,000 population	↓
DEN	Dentist per 100,000 population	↓
SP	Specialist physician per 100,000 population	↓

The symbol ↑ indicates that the variable has a positive relationship with social vulnerability, indicating that an increase in the variable value corresponds to an increase in the social vulnerability. The symbol ↓ indicates that the variable has a negative relationship with social vulnerability

5.1.2 Identifying dimensions of social vulnerability

To determine the total number of factors to be extracted for the dataset in this analysis, the Kaiser (1960) criterion was applied. Under this criterion, only factors with eigenvalues greater than or equal to 1 are accepted as possible sources of variance in the data, with the highest priority ascribed to the factor that has the highest eigenvector sum. Seven factors satisfied this criterion. Using Varimax rotation showed that the seven extracted factors yielded a clear factor structure depicting the various social vulnerability dimensions that explained 72.16 % of the variance among all the 335 counties of the country (Table 2). A variable was assigned to a specific factor where it had the highest loading with that factor. Therefore, based on the results of FA, the initial set of 27 social vulnerability

variables were reduced to seven underlying factors. The variables in each factor provide a heuristic suggestion of a label signifying a different dimension of social vulnerability. The titles of the factors, presented in the first column of Table 2, were given based on the descriptive approach reflecting the nature of the items that belong to them.

These extracted factors: housing deprivation (F1), unemployment (F2), dependent population (F3), less development (F4), income deprivation (F5), females and migration (F6), and health infrastructure deprivation (F7) reflect different dimensions of social vulnerability to earthquake hazards in Iran. These seven factors and their primary variables are used in the ANP part of the model to construct the network hierarchy.

5.2 Applying the analytic network process (ANP)

5.2.1 Constructing the network model

At this stage, the results obtained through FA are entered into a network model (Fig. 3). In the established network, the first cluster depicts the overall objective of the study that is the social vulnerability index (SOVI) creation. The second cluster elements are the seven dimensions of SV extracted from the FA. The third level clusters are the primary variables of the seven extracted dimensions of the SV. The variables in each dimension are interdependent and this interdependency is shown through an arc in the model.

5.2.2 Formation of the supermatrix and obtaining weights for individual SV variables

The next step after constructing the network is to carry out pair-wise comparison between the decision elements of the network and to form the supermatrix. The initial supermatrix for the proposed network (a 35×35 matrix) with three levels is as follows:

$$\begin{array}{l}
 \text{Goal} \\
 \text{SV Dimensions} \\
 \text{Variables of SV}
 \end{array}
 \left(
 \begin{array}{c|c|c}
 0 & 0 & 0 \\
 \hline
 [w_{21}]_{7 \times 1} & 0 & 0 \\
 \hline
 0 & [W_{32}]_{27 \times 7} & [W_{33}]_{27 \times 27}
 \end{array}
 \right)$$

where w_{21} is a vector which represents the impact of the goal on SV dimensions, W_{32} is a matrix that denotes the impact of SV dimensions on the variables of SV, and W_{33} is the matrix that represents the inner dependence (interdependence) among the SV variables.

As was explained in the methodology, the pair-wise comparison matrix for SV dimensions, that is $[A_{21}]$, will be constructed based on the amount of variance that each factor (SV dimension) explains. Once the pair-wise comparisons are completed $[A_{21}]$, the corresponding local priority vector, or $[w_{21}]$ is computed (see Table 3).

The pair-wise comparison matrix for the variables of each extracted SV dimension $[A_{32}]$, is constructed using the absolute values of loadings of the variables of each dimension (obtained through FA—see Table 2), and then the corresponding local priority matrix $[W_{32}]$ is calculated (see Table 8 in “Appendix”).

To determine the inner dependence or interdependency among SV variables, a correlation analysis among the variables of each SV dimension was done separately. Variables that were significantly related to one another ($p = 0.01$), were considered to be interdependent. The pair-wise comparison matrix for interdependent variables of each extracted

Table 2 County level social vulnerability dimensions, their explained variance and the primary variables of each dimension

Factors	Variance (%)	Primary variables	Abbreviation	Factor loading
1. Housing deprivation	12.50	Percent of illiterate population	PIL	0.56
		Percent housing units less than 50 m ² in area	HU50	0.82
		Households per housing unit	HHHU	0.60
		Percent of housing units with telephone	HUT	0.75
		Percent of housing units with kitchen	HUK	0.71
		Percent of housing units with bathroom	HUB	0.73
		Housing units built with non-durable materials	HUNM	0.52
2. Unemployment	12.06	Percent of unemployed population	UEP	0.89
		Percent men unemployed	MUE	0.92
		Percent females participating in labor force	FPL	0.59
		Percent population participating in labor force	PPL	0.80
3. Dependent population	10.63	Percent of female-headed households	FHHH	0.72
		Percent of population over 65 years old	PO65	0.83
		Percent of population under 6 years old	PO6	0.60
		Percent of women who are divorced or widowed	WW	0.89
4. Less Development	9.98	Percent of rural population	RP	0.64
		Percent employed in agriculture	EMA	0.55
		Hospital beds per 100,000 population	HSB	0.77
		Specialist physician per 100,000 population	SP	0.75
5. Income deprivation	8.17	Percent simple laborer to total employed	SL	0.76
		Percent of population with disability	PD	0.66
		IKC social security recipients per 100,000 population	IKCSS	0.51
		Permanent social security recipients per 100,000 population	PSSR	0.60
6. Females and migration	7.22	Percent of females	PF	0.68
		Percent of population who are migrants	PM	0.81
7. Health and infrastructure deprivation	6.95	General practitioner physician per 100,000 population	GP	0.79
		Dentist per 100,000 population	DEN	0.71
Cumulative variance (%)	72.16			

$n = 27$ primary variables

SV dimension $[A_{33}]$, is constructed using the absolute values of coefficients of correlation for these interdependent variables, and then the corresponding local priority matrix $[W_{33}]$ is calculated (see Table 8 in “Appendix”).

The calculated priority matrices are then entered into a supermatrix. After constructing the supermatrix (Table 8 in “Appendix”), the limit supermatrix is calculated (see Table 9 in “Appendix”). All the calculations and analysis are done using MS Excel, MATLAB and the Super Decisions software (www.superdecisions.com).

The limit supermatrix provides a meaningful weight of influence for each of the 27 social vulnerability variables selected for the study. These weights, or W_{ANP_j} , are the

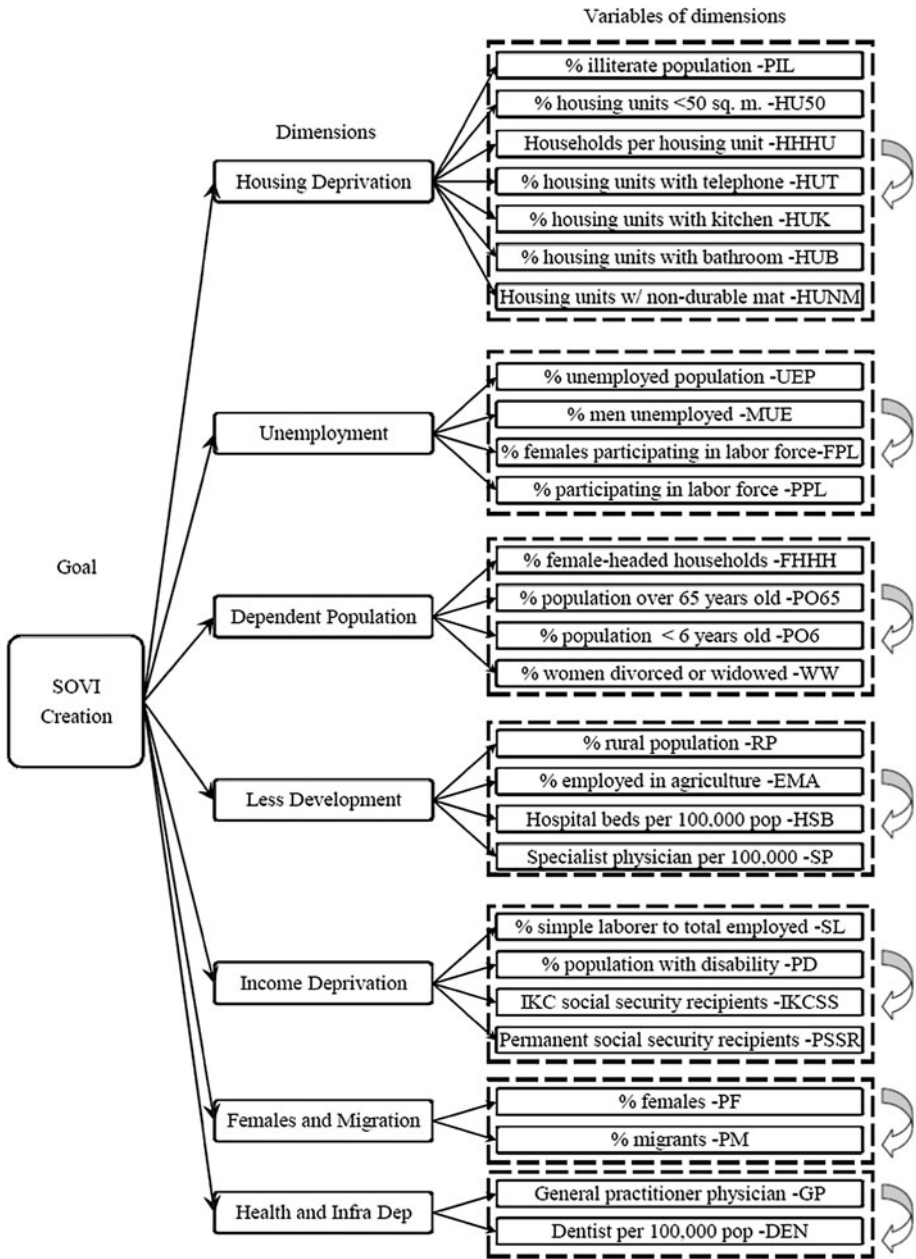


Fig. 3 The ANP model for constructing social vulnerability index

elements of the goal column of the limit supermatrix (see goal column in Table 9 in “Appendix”), which are normalized and for convenience of processing, are magnified 10 times (“see Table 4).

Table 3 The pair-wise comparison matrix for extracted factors (SV dimensional) $[A_{21}]$ and their weights or priority vector $[w_{21}]$

Variance (%)	Factors	F1	F2	F3	F4	F5	F6	F7	$[w_{21}]$	
17.1473	$[A_{21}]$	F1	1	1.42	1.61	1.72	2.10	2.38	2.47	0.238
12.0639		F2	0.70	1	1.13	1.21	1.48	1.67	1.74	0.167
10.6293		F3	0.62	0.88	1	1.07	1.30	1.47	1.53	0.147
9.97978		F4	0.58	0.83	0.94	1	1.22	1.38	1.44	0.138
8.16888		F5	0.48	0.68	0.77	0.82	1	1.13	1.18	0.113
7.21709		F6	0.42	0.60	0.68	0.72	0.88	1	1.04	0.100
6.9515		F7	0.41	0.58	0.65	0.70	0.85	0.96	1	0.096

Table 4 The relative importance of social vulnerability variables W_{ANP_j}

SV dimensions	Variables	W_{ANP_j}	W_{ANP_j} Normalized	Final W_{ANP_j} (magnified $10\times$)
1. Housing deprivation	PIL	0.0375	0.037059	0.37059
	HU50	0.0379	0.0374543	0.374543
	HHHU	0.0303	0.0299437	0.299437
	HUT	0.0387	0.0382449	0.382449
	HUK	0.0397	0.0392331	0.392331
	HUB	0.039	0.0385414	0.385414
	HUNM	0.0287	0.0283625	0.283625
2. Unemployment	UEP	0.0437	0.0431861	0.431861
	MUE	0.0463	0.0457555	0.457555
	FPL	0.0345	0.0340943	0.340943
	PPL	0.0458	0.0452614	0.452614
3. Dependent population	FHHH	0.0294	0.0290543	0.290543
	PO65	0.0405	0.0400237	0.400237
	PO6	0.0316	0.0312284	0.312284
	WW	0.0416	0.0411108	0.411108
4. Less development	RP	0.0347	0.0342919	0.342919
	EMA	0.031	0.0306354	0.306354
	HSB	0.0346	0.0341931	0.341931
	SP	0.0339	0.0335013	0.335013
5. Income deprivation	SL	0.0248	0.0245084	0.245084
	PD	0.0297	0.0293507	0.293507
	IKCSS	0.0315	0.0311296	0.311296
	PSSR	0.0305	0.0301413	0.301413
6. Females & migration	PF	0.05	0.049412	0.49412
	PM	0.05	0.049412	0.49412
7. Health infrastructure deprivation	GP	0.048	0.0474355	0.474355
	DEN	0.048	0.0474355	0.474355

5.2.3 Calculating social vulnerability index (SOVI) score

These weights are then used to compute SOVI scores by a weighted sum method of the type, as shown in Eq. (3):

$$\text{SOVI}_i = \sum_{j=1}^J W_{\text{ANP}_j} \text{SVI}_{ij} \quad (3)$$

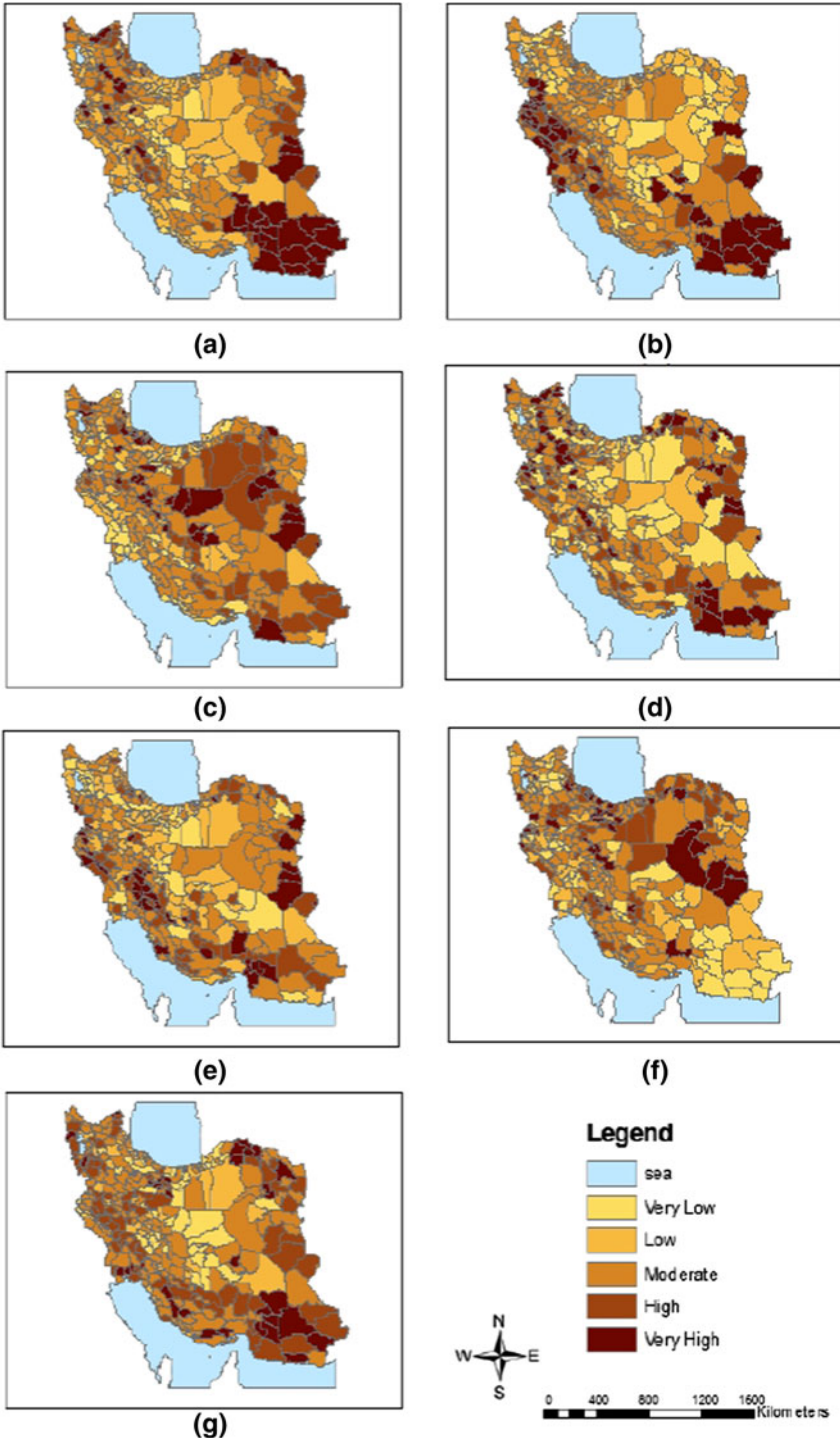
where, SOVI_i is the social vulnerability index score for county “ i ”, W_{ANP_j} is the weight of the social vulnerability variable “ j ” obtained from the ANP limit super-matrix as explained earlier (see $\text{Final}W_{\text{ANP}_j}$ column in Table 4) and SVI_{ij} is the standardized value of social vulnerability variable “ j ” in county “ i ”. It should be noted that the application of ANP has made it possible to take into consideration the relative importance of individual SV dimensions as well as the interdependency among their primary variables in the calculation of the relative weights for SV variables.

Using the relative weights obtained for the SV variables (final W_{ANP_j}), the scores for the seven extracted dimensions of SV are also calculated in a similar manner (weighted sum method) by multiplying the corresponding weights of the primary variables in each dimension to their standardized values.

5.2.4 Mapping social vulnerability index (SOVI) scores

After computing the scores for the seven extracted dimensions of SV and also the composite SOVI, for visualization purposes and also for determining the spatial patterns of vulnerability for different counties in Iran, the scores of the seven dimensions of SV and also the composite SOVI were displayed as a five-category choropleth map (using ArcGIS 9.3 software), with classes defined in terms of standard deviations above or below the mean for each component (Fig. 4) and for the composite SOVI (Fig. 5). The five categories were defined as follows: Very high vulnerability (>1 standard deviation); high vulnerability (0.5–1 standard deviation); moderate vulnerability (from –0.5 to 0.5 standard deviation); low vulnerability (from –1 to –0.5 standard deviation); and very low vulnerability (less than –1 standard deviation). It should be noted that these maps give a relative representation of how SV and its different components vary across space (because the results are deviations from the mean index value) showing which places are more or less vulnerable than others.

Figure 4 reveals different spatial patterns regarding various dimensions of social vulnerability. For example while the south eastern part of the country is highly vulnerable in terms of housing deprivation (Fig. 4a) and unemployment (Fig. 4b) dimensions of social vulnerability, they are less vulnerable in terms of females and migration (Fig. 4f) component. Counties in the periphery of the country are generally less developed (Fig. 4d) and this makes them socially more vulnerable to earthquakes. Income deprivation (Fig. 4e) and dependent population (Fig. 4c) dimensions of social vulnerability seem to be evenly distributed throughout the country. Counties in the western half of the country have relatively better position in terms of health infrastructure and facilities (Fig. 4g) than those in the eastern half of the country, making these counties less vulnerable to earthquake hazards than the eastern counties of the country.



◀ **Fig. 4** Dimensions of social vulnerability for Iran: **a** housing deprivation, **b** unemployment, **c** dependent population, **d** less development, **e** income deprivation, **f** females and migration, **g** health infrastructure deprivation

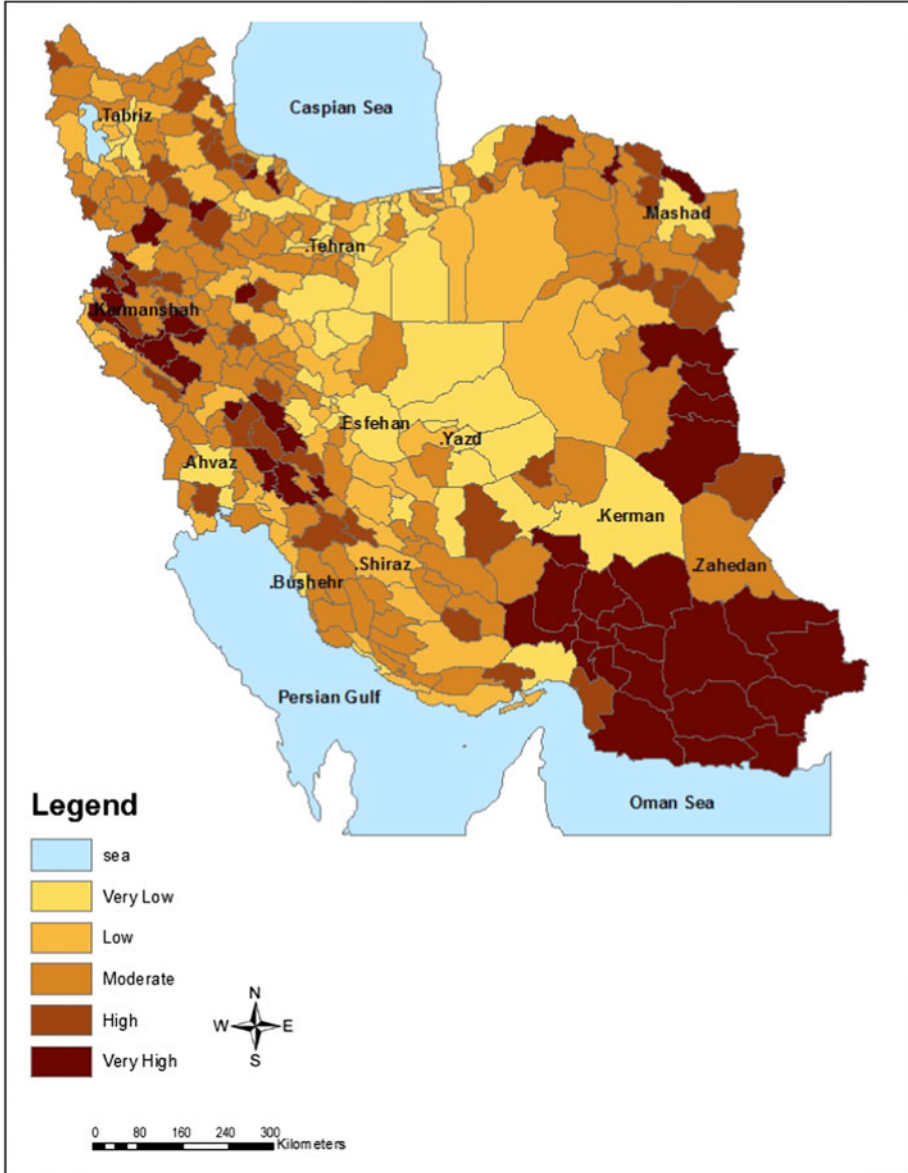


Fig. 5 Spatial distribution of levels of SOVI to earthquake hazards in Iran at county level

Figure 5 shows the comparative social vulnerability of the counties in Iran based on the SOVI scores. The most socially vulnerable counties in the country are clustered in the east, south-east and western part of the country. The SOVI score in the country

Table 5 Number and percentage of counties by levels of social vulnerability in Iran

Social vulnerability	Number	Percentage (%)
Very high	49	14.6
High	43	12.8
Moderate	132	39.4
Low	67	20
Very low	44	13.3
Total	335	100

Table 6 Most and least socially vulnerable counties in Iran

Least socially vulnerable			Most socially vulnerable		
Rank	County	F'ANP SOVI	Rank	County	F'ANP SOVI
1	Gorgan	1.959	1	Qale Ganj	6.526
2	Yazd	2.153	2	Southern Rudbar	5.956
3	Bushehr	2.305	3	Anbar Abad	5.938
4	Tehran	2.341	4	Sarbaz	5.816
5	Kashan	2.406	5	Nehbandan	5.340
6	Kangan	2.439	6	Salas Babajani	5.298
7	Sari	2.459	7	Sarbishe	5.281
8	Esfahan	2.479	8	Sarawan	5.272
9	Semnan	2.532	9	Monojan	5.224
10	Aran & Bidgol	2.541	10	Bahmaei	5.155

ranges from 1.96 (low social vulnerability) to 6.53 (high social vulnerability) with mean vulnerability score of 3.61 and standard deviation of 0.68 for all counties of Iran. The distribution of the counties by the social vulnerability levels (Table 5) indicates that 132 counties (39.4 % of the total) exhibit moderate levels of social vulnerability. A total of 49 counties (14.6 % of the total) are classified in the very high social vulnerability category and 43 (12.8 % of the total) of them are categorized as highly vulnerable.

The rest of the counties are classified as less vulnerable (67 counties or 20 % of the total) and least vulnerable (44 counties or 13.3 % of total) in terms of social vulnerability. The ranking of the 10 most and least socially vulnerable counties are presented in Table 6. The most socially vulnerable county in the nation is Qale Ganj County (Table 6) in the Kerman province, followed by Southern Rudbar and Anbar Abad Counties, also in the Kerman province. Their higher social vulnerability is largely due to the housing deprivation, unemployment, less development, and health infrastructure deprivation.

Of the ten most socially vulnerable counties, four are located in Kerman province, three in the neighboring Sistan and Baluchestan province, and two in the Southern Khorasan province. These three neighboring provinces are located in the east and south eastern part of the country and are the most socially vulnerable provinces of the country (Fig. 5). Of the ten least socially vulnerable counties seven are the counties where the regional capital cities are located in them, and three of them (Kashan, Esfahan, and Aran and Bidgol) are

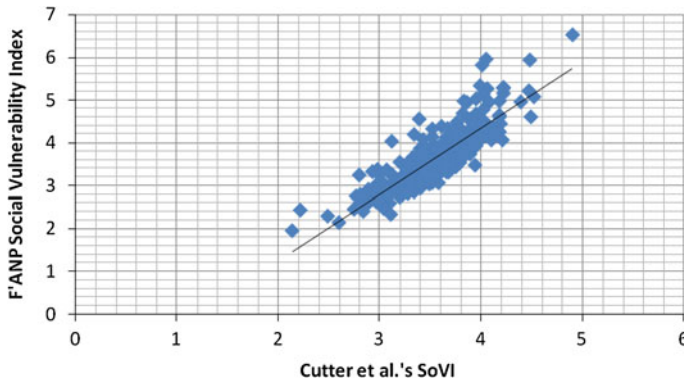


Fig. 6 The scatter-plot between the proposed F'ANP SOVI and Cutter et al.'s (2003) SoVI

located in one province, the central province of Esfahan. On the contrary, none of the ten most socially vulnerable counties are regional capital counties.

These findings indicate that regional variations in social vulnerability to earthquake hazards are pronounced in the country and since almost the entire earthquake hazard management strategies are based on bio-physical component of place vulnerability (Bahrainy 2003), this calls for a serious reconsideration of these strategies and incorporation of social vulnerability component in these strategies.

5.3 Model validation

In order to examine the validity of the proposed social vulnerability index and be assured that it provides a suitable measure that captures the overall social vulnerability of the country at county level, model validation is performed. Model validation has been defined as “a comparison of the model’s predictions with the real world to determine whether the model is suitable for its intended purpose” (Mayer and Butler 1993, p. 21). Several techniques are proposed for model validation and verifications. One of these techniques is to compare the proposed model results with the results of other models that have been validated (Sargent 1998, p. 123). Babbie (1995, 174) contends that, if different items are indeed indicators of the same measure, then they should be empirically related to each other. Cutter et al. (2003), using a factor analytic approach to 42 variables that measure vulnerability associated with the built environment, local economic activity, and availability of emergency services and lifelines, developed the Social Vulnerability Index (SoVI) that measured differences in social vulnerability between counties in the USA. The SoVI model has since been extensively applied in the USA (Borden et al. 2007; Burton and Cutter 2008; Cutter and Finch 2008; Wood et al. 2010) and other developed countries (Boruff and Cutter 2007; Oliveira Mendes 2009) and its validity also has been tested in the USA (Schmidtlein et al. 2008). To validate our proposed model findings, its results are compared with the results obtained by applying Cutter et al.’s (2003) SoVI model. First Cutter et al.’s (2003) SoVI model was applied using the same data set and the results for the seven extracted dimensions of social vulnerability and also the social vulnerability index (SoVI) were obtained. A scatter-plot was applied for the results obtained by both models (Fig. 6). This scatter-plot indicates that there is a strong positive relationship

Table 7 Correlation between the proposed F'ANP SOVI and Cutter et al.'s (2003) SoVI

F'ANP Model	Correlation	Cutter et al.'s SoVI
Social vulnerability index (SOVI)	0.868	SoVI
F'ANP FS1—housing deprivation	0.882	FS1
F'ANP FS2—unemployment	0.859	FS2
F'ANP FS3—dependent population	0.845	FS3
F'ANP FS4—less development	0.844	FS4
F'ANP FS5—income deprivation	0.838	FS5
F'ANP FS6—females and migration	0.896	FS6
F'ANP FS7—health infrastructure deprivation	0.875	FS7

All correlations are significant at the 0.01 level (2-tailed)

between the results obtained by the proposed F'ANP model and Cutter et al.'s (2003) SoVI model.

Additionally, spearman's correlation coefficients between the proposed model (F'ANP) and Cutter et al.'s (2003) SoVI results were calculated (Table 7). A correlation coefficient of 0.868 (statistically significant at 0.01 level) between the results of the two mentioned models for social vulnerability index indicates that both methodologies address the same underlying phenomena. These findings validate the results obtained by the proposed F'ANP model. All the correlation coefficients for the different dimensions of social vulnerability for both models are also highly correlated. It should be noted that the Cutter et al.'s (2003) SoVI assigns equal weights for the extracted dimensions of social vulnerability whereas in the proposed F'ANP model, variables composing the different dimensions of social vulnerability and also the composite SOVI are given unequal weights that have been obtained through the ANP part of the model. Otherwise, the results of both models would have been the same.

6 Conclusion

The objective of this study was to construct a hybrid FA and ANP (F'ANP) model for social vulnerability assessment and apply it at county level in Iran. The way the component variables or indices should be weighed and, if some sort of weighting scheme is applied, the way they should be determined either by expert judgment or by quantitative methods has always been a difficulty in composite indicator construction. Assigning weights to variables and computing composite social vulnerability index scores through the proposed F'ANP model avoids these difficulties. In the proposed model, a FA on the selected and standardized variables of social vulnerability was conducted to extract the different dimensions of SV. The seven dimensions of SV were found to be: (a) housing deprivation, (b) unemployment, (c) dependent population, (d) less development, (e) income deprivation, (f) females and migration, and (g) health infrastructure deprivation. These extracted dimensions of SV and their primary variables are then entered into a network model using ANP to determine the relative weights for each SV variable. Using the obtained relative weights for SV variables, scores for individual SV dimensions and the composite social vulnerability index was calculated by a weighted sum method. This was made possible by taking into

consideration the combined strengths of two widely used statistical and multi-criteria decision methods, FA and ANP:

- The use of FA made it possible to find the underlying dimensions of social vulnerability and to identify the variables that compose these SV dimensions.
- The ANP provided the framework to take into consideration the hierarchical as well as network structure (interdependencies of variables) of the complex problem at hand, through which the relative and appropriate weights for the different variables selected to depict social vulnerability were calculated.
- The use of absolute measurements (derived from FA) instead of the usual subjective pair-wise comparison in ANP, made the process of calculations much simpler than the ordinary ANP process. One of the inherent limitations of the ANP is that since the values of the pair-wise comparison matrices are determined by the judgments of the experts, different results may be obtained for the same problem by different experts (Yuksel and Dagdeviren 2007). Using the absolute measurements in this proposed hybrid model, instead of the ratio-scale expert judgments, has overcome this limitation and the results of the problems solved by the proposed hybrid F'ANP model would be the same at all times.
- The model validation showed that the proposed F'ANP model results are similar to those of an earlier validated model (Cutter et al.'s (2003) SoVI).

The application of the new F'ANP model to a real world case study shows that the proposed model is a robust approach for constructing a composite social vulnerability index. Its application to counties in Iran shows that there exist severe regional differences in terms of social vulnerability to earthquake hazards in the country. The SOVI scores translated into maps show how social vulnerability varies spatially. These maps provide a foundation for analyzing spatial variation and identifying the hot-spots of social vulnerability and pointing out areas that need more in-depth attention. They show that the most socially vulnerable counties in the country are clustered in the east, south-east and western part of the country. Other counties in the rest of the country exhibit relatively low to moderate levels of social vulnerability. These regional differences are largely due to the housing deprivation, unemployment, less development and health infrastructure deprivation components of social vulnerability in these areas.

The pronounced regional variations in social vulnerability to earthquake hazards in the Iran, warrants special attention by both local authorities and the national government to reconsider current natural disaster management strategies. Incorporation of social vulnerability component of hazards- of- place in these strategies seems to be inevitable in the wake of the country's very high vulnerability to earthquake hazards. This calls for incorporation of serious national policies for the structural reduction of social vulnerability. These public policies should take into consideration the different dimensions of social vulnerability and their spatial differentiation across the country.

Appendix

See Tables 8 and 9.

Table 8 The supermatrix

	Goal	HO	EM	DP	RU	IN	MI	HE	PIL	HU50	HHHU	HUT	HUK	HUB	HUNM
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HO	0.238	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EM	0.167	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DP	0.147	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RU	0.138	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IN	0.113	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MI	0.100	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HE	0.096	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PIL	0	0.120	0	0	0	0	0	0	0.243	0.124	0.133	0.141	0.133	0.117	0.153
HU50	0	0.175	0	0	0	0	0	0	0.125	0.240	0.148	0.157	0.129	0.136	0.109
HHHU	0	0.128	0	0	0	0	0	0	0.108	0.119	0.299	0.122	0.085	0.101	0.024
HUT	0	0.160	0	0	0	0	0	0	0.145	0.160	0.156	0.235	0.136	0.126	0.107
HUK	0	0.152	0	0	0	0	0	0	0.140	0.135	0.111	0.140	0.230	0.183	0.149
HUB	0	0.154	0	0	0	0	0	0	0.122	0.140	0.130	0.127	0.180	0.233	0.142
HUNM	0	0.111	0	0	0	0	0	0	0.117	0.083	0.023	0.079	0.108	0.104	0.317
UEP	0	0	0.279	0	0	0	0	0	0	0	0	0	0	0	0
MUE	0	0	0.286	0	0	0	0	0	0	0	0	0	0	0	0
FPL	0	0	0.185	0	0	0	0	0	0	0	0	0	0	0	0
PPL	0	0	0.250	0	0	0	0	0	0	0	0	0	0	0	0
FHHH	0	0	0	0.236	0	0	0	0	0	0	0	0	0	0	0
PO65	0	0	0	0.271	0	0	0	0	0	0	0	0	0	0	0
PO6	0	0	0	0.199	0	0	0	0	0	0	0	0	0	0	0
WW	0	0	0	0.294	0	0	0	0	0	0	0	0	0	0	0
RP	0	0	0	0	0.238	0	0	0	0	0	0	0	0	0	0
EMA	0	0	0	0	0.202	0	0	0	0	0	0	0	0	0	0
HSB	0	0	0	0	0.285	0	0	0	0	0	0	0	0	0	0

Table 8 continued

Goal	HO	EM	DP	RU	IN	MI	HE	PIL	HU50	HHHU	HUT	HUK	HUB	GP	DEN
SP	0	0	0	0.275	0	0	0	0	0	0	0	0	0	0	0
SL	0	0	0	0	0.301	0	0	0	0	0	0	0	0	0	0
PD	0	0	0	0	0.261	0	0	0	0	0	0	0	0	0	0
IKCSS	0	0	0	0	0.202	0	0	0	0	0	0	0	0	0	0
PSSR	0	0	0	0	0.236	0	0	0	0	0	0	0	0	0	0
PF	0	0	0	0	0	0.458	0	0	0	0	0	0	0	0	0
PM	0	0	0	0	0	0.542	0	0	0	0	0	0	0	0	0
GP	0	0	0	0	0	0	0.527	0	0	0	0	0	0	0	0
DEN	0	0	0	0	0	0	0.473	0	0	0	0	0	0	0	0

Goal	UEP	MUE	FPL	PPL	FHHH	PO	PO6	WW	RP	EMA	HSB	SP	SL	PD	IK	PSSR	PF	PM	GP	DEN
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HO	0.238	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EM	0.167	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DP	0.147	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RU	0.138	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IN	0.113	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MI	0.100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HE	0.096	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PIL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HU50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HHHU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HUT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HUK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HUB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 8 continued

	Goal	UEP	MUE	FPL	PPL	FHHH	PO	PO6	WW	RP	EMA	HSB	SP	SL	PD	IK	PSSR	PF	PM	GP	DEN	
							65									CSS						
HUNM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UEP	0	0.344	0.309	0.128	0.217	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MUE	0	0.328	0.325	0.162	0.248	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FPL	0	0.101	0.120	0.436	0.207	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PPL	0	0.227	0.246	0.275	0.328	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FHHH	0	0	0	0	0	0.473	0.171	0.018	0.192	0	0	0	0	0	0	0	0	0	0	0	0	0
PO65	0	0	0	0	0	0.236	0.343	0.269	0.268	0	0	0	0	0	0	0	0	0	0	0	0	0
PO6	0	0	0	0	0	0.020	0.210	0.441	0.206	0	0	0	0	0	0	0	0	0	0	0	0	0
WW	0	0	0	0	0	0.271	0.275	0.272	0.334	0	0	0	0	0	0	0	0	0	0	0	0	0
RP	0	0	0	0	0	0	0	0	0	0.384	0.269	0.189	0.192	0	0	0	0	0	0	0	0	0
EMA	0	0	0	0	0	0	0	0	0	0.240	0.431	0.144	0.127	0	0	0	0	0	0	0	0	0
HSB	0	0	0	0	0	0	0	0	0	0.188	0.161	0.385	0.287	0	0	0	0	0	0	0	0	0
SP	0	0	0	0	0	0	0	0	0	0.188	0.140	0.281	0.393	0	0	0	0	0	0	0	0	0
SL	0	0	0	0	0	0	0	0	0	0	0	0	0	0.566	0.140	0.102	0.112	0	0	0	0	0
PD	0	0	0	0	0	0	0	0	0	0	0	0	0	0.167	0.473	0.202	0.170	0	0	0	0	0
IKCSS	0	0	0	0	0	0	0	0	0	0	0	0	0	0.129	0.213	0.447	0.258	0	0	0	0	0
PSSR	0	0	0	0	0	0	0	0	0	0	0	0	0	0.137	0.174	0.250	0.461	0	0	0	0	0
PF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.721	0.279	0	0	0
PM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.279	0.721	0	0	0
GP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.676	0.324
DEN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.324	0.676	0.676

Table 9 The limit supermatrix after convergence

	Goal	HO	EM	DP	RU	IN	MI	HE	PIL	HU50	HHHU	HUT	HUK	HUB	HUNM
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PIL	0.0375	0.1577	0	0	0	0	0	0	0.1577	0.1579	0.1577	0.1579	0.1579	0.1577	0.1579
HU50	0.0379	0.1592	0	0	0	0	0	0	0.1592	0.1594	0.1592	0.1594	0.1594	0.1592	0.1594
HHHU	0.0303	0.1275	0	0	0	0	0	0	0.1275	0.1277	0.1275	0.1276	0.1276	0.1275	0.1277
HUT	0.0387	0.1626	0	0	0	0	0	0	0.1626	0.1628	0.1626	0.1628	0.1628	0.1626	0.1628
HUK	0.0397	0.1668	0	0	0	0	0	0	0.1668	0.1669	0.1667	0.1669	0.1669	0.1668	0.167
HUB	0.039	0.1641	0	0	0	0	0	0	0.164	0.1642	0.164	0.1642	0.1642	0.164	0.1642
HUNM	0.0287	0.1207	0	0	0	0	0	0	0.1207	0.1208	0.1207	0.1208	0.1208	0.1207	0.1209
UEP	0.0437	0	0.2617	0	0	0	0	0	0	0	0	0	0	0	0
MUE	0.0463	0	0.2775	0	0	0	0	0	0	0	0	0	0	0	0
FPL	0.0345	0	0.2066	0	0	0	0	0	0	0	0	0	0	0	0
PPL	0.0458	0	0.2744	0	0	0	0	0	0	0	0	0	0	0	0
FHHH	0.0294	0	0	0.1997	0	0	0	0	0	0	0	0	0	0	0
PO65	0.0405	0	0	0.2751	0	0	0	0	0	0	0	0	0	0	0
PO6	0.0316	0	0	0.2148	0	0	0	0	0	0	0	0	0	0	0
WW	0.0416	0	0	0.2827	0	0	0	0	0	0	0	0	0	0	0
RP	0.0347	0	0	0	0.2517	0	0	0	0	0	0	0	0	0	0
EMA	0.031	0	0	0	0.2245	0	0	0	0	0	0	0	0	0	0
HSB	0.0346	0	0	0	0.2505	0	0	0	0	0	0	0	0	0	0
SP	0.0339	0	0	0	0.2458	0	0	0	0	0	0	0	0	0	0

Table 9 continued

Goal	HO	EM	DP	RU	IN	MI	HE	PIL	HU50	HHHU	HUT	HUK	HUB	HUNM
SL	0.0248	0	0	0	0.2199	0	0	0	0	0	0	0	0	0
PD	0.0297	0	0	0	0.2633	0	0	0	0	0	0	0	0	0
IKCSS	0.0315	0	0	0	0.2785	0	0	0	0	0	0	0	0	0
PSSR	0.0305	0	0	0	0.2699	0	0	0	0	0	0	0	0	0
PF	0.05	0	0	0	0	0.5	0	0	0	0	0	0	0	0
PM	0.05	0	0	0	0	0.5	0	0	0	0	0	0	0	0
GP	0.048	0	0	0	0	0	0.5	0	0	0	0	0	0	0
DEN	0.048	0	0	0	0	0	0.5	0	0	0	0	0	0	0

Goal	UEP	MUE	FPL	PPL	FHHH	PO65	PO6	WW	RP	EMA	HSB	SP	SL	PD	IKCSS	PSSR	PF	PM	GP	DEN
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PIL	0.0375	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HU50	0.0379	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HHHU	0.0303	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HUT	0.0387	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HUK	0.0397	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HUB	0.039	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HUNM	0.0287	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UEP	0.0437	0.2617	0.2621	0.2617	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MUE	0.0463	0.2775	0.2779	0.2775	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 9 continued

Goal	UEP	MUE	FPL	PPL	FHHH	PO65	PO6	WW	RP	EMA	HSB	SP	SL	PD	IKCSS	PSSR	PF	PM	GP	DEN
FPL	0.0345	0.2065	0.2068	0.2066	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PPL	0.0458	0.2744	0.2748	0.2745	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FHHH	0.0294	0	0	0	0.1997	0.1995	0.1997	0.1997	0	0	0	0	0	0	0	0	0	0	0	0
PO65	0.0405	0	0	0	0.2752	0.2748	0.2751	0.2751	0	0	0	0	0	0	0	0	0	0	0	0
PO6	0.0316	0	0	0	0.2148	0.2146	0.2148	0.2148	0	0	0	0	0	0	0	0	0	0	0	0
WW	0.0416	0	0	0	0.2827	0.2824	0.2827	0.2827	0	0	0	0	0	0	0	0	0	0	0	0
RP	0.0347	0	0	0	0	0	0	0	0.251	0.252	0.251	0.251	0	0	0	0	0	0	0	0
EMA	0.031	0	0	0	0	0	0	0	0.224	0.224	0.224	0.224	0	0	0	0	0	0	0	0
HSB	0.0346	0	0	0	0	0	0	0	0.250	0.251	0.250	0.250	0	0	0	0	0	0	0	0
SP	0.0339	0	0	0	0	0	0	0	0.245	0.2463	0.245	0.245	0	0	0	0	0	0	0	0
SL	0.0248	0	0	0	0	0	0	0	0	0	0	0	0.219	0.22	0.220	0.220	0	0	0	0
PD	0.0297	0	0	0	0	0	0	0	0	0	0	0	0.262	0.263	0.263	0.263	0	0	0	0
IKCSS	0.0315	0	0	0	0	0	0	0	0	0	0	0	0.278	0.278	0.279	0.279	0	0	0	0
PSSR	0.0305	0	0	0	0	0	0	0	0	0	0	0	0.269	0.27	0.270	0.270	0	0	0	0
PF	0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.5	0	0
PM	0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.5	0	0
GP	0.048	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.5
DEN	0.048	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.5

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