ASSESSMENT OF URBAN VULNERABILITY TO EARTHQUAKE HAZARD FOR TABRIZ CITY, NW IRAN USING ANP-ANN MODEL

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ABSTRACT: Tabriz city is a seismic-prone province in the northwestern part of Iran with recurring devastating earthquakes which have resulted in heavy casualties and damages. This research developed a new computational framework to investigate four main dimensions of vulnerability such as environmental, social, economic and physical in Tabriz City. The Analytic Network Process (ANP) and Artificial Neural Network (ANN) Model were applied to achieve the objectives of this investigation. Firstly, a literature survey was performed to explore indicators with significant impact on the dimensions of vulnerability to the earthquake in the study area. In the next stage, twenty indicators were identified and analyzed using geographic information system (GIS) software package (ARC GIS 10.3) to generate earthquake vulnerability maps. The classified and standardized indicators were subsequently weighed and ranked using ANP model to construct the training database. Then, standardized maps along with the training site maps were presented as input to a Multilayer Perceptron (MLP) and Self-Organizing Map (SOM) neural network. The resulting Earthquake Vulnerability Maps (EVMs) were categorized into five classes, namely very high, high, moderate, low and very low. Additionally, the impact of the vulnerability of Tabriz city on population during an earthquake was included in this analysis for accurate risk forecasting. The comparison of data provided by Earthquake Vulnerability Map (EVM) with the Population Vulnerability (PV) of Tabriz city approved the validity of the results. The findings of this research are useful for decision-makers and government authorities to obtain a better knowledge of a city's vulnerability dimensions and to adopt better preparedness strategies in the future.

1. INTRODUCTION

Urban vulnerability to earthquakes has increased over the years due to rising complications in urban areas. The main causes of high vulnerability of cities to earthquakes are uncontrolled urban growth in highly seismic areas, improper disaster management, high exposure to indicators of risk, vulnerable buildings and infrastructures, rising urbanization and population growth, incising wealth measures, and the high vulnerability of modern communities and technologies (Duzgun et al. 2011). Mainly, the earthquake vulnerability assessment methods focus on magnitude prediction (Yousefi and Taghikhany 2014) and structural and geological engineering (Karimzadeh et al. 2014).

The comprehension and preparation of urban earthquake vulnerability take into account a wide scale of vulnerability aspects that could be managed by developing an integrated approach. Many representations of urban vulnerability were suggested to discuss the several methods where the community becomes exposed to hazard (Menoni 2001). Due to uncertainty being an inherent nature of earthquake phenomena, Artificial Neural Networks (ANN) can provide computational models to assess earthquake vulnerability. It provides good predictions even on noisy and uncertain data (Garcia-Rodriguez and Malpica 2010). ANN has the capacity to produce classified vulnerability maps arising from complex interactions with high accuracy.

Tabriz city located in the northwestern part of Iran (Fig. 1) is a seismic-prone province with recurring devastating earthquakes which have resulted in heavy casualties and damages. It is one of the high-risk zones for future earthquakes in Iran due to its geographical location and geological structural features. Historical studies have shown

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that Tabriz has been devastated by several destructive earthquakes and the need exists to generate a local and national assessment framework at the municipal scale. According to the probabilistic and deterministic assessment, believe that a strong earthquake might occur in Tabriz in the near future. Therefore, hazard mitigation studies for decreasing the damage severity from a most probable earthquake in future are urgent and inevitable. For that reason, Tabriz city was selected as a case study in this investigation.

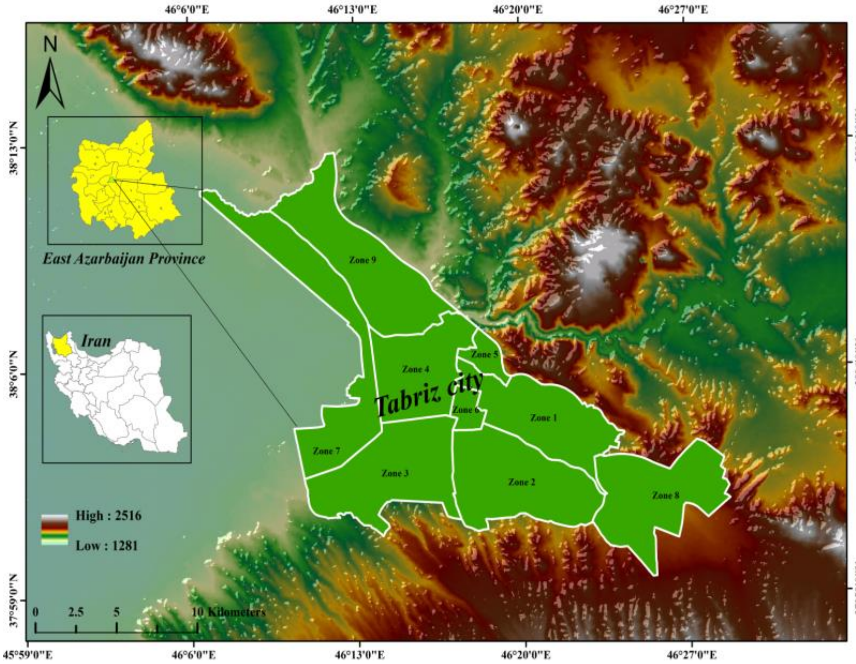

Figure 1. The geographic location of Tabriz city in the northwestern of Iran.

2. MATERIALS AND METHODS

2.1 Study area

Tabriz City with a population more than 1.5 million people consists of 9 regions (Fig. 1). It is the second largest city of Iran in terms of land area. It encompasses about 25km2 area of old texture. The tectonic features in the west of Iran and the east of Turkey are caused by the interaction between Arabian and Eurasian plates (Jackson 1992). An important feature here is the North Tabriz Fault (NTF), which encircles an area of extreme deformation and seismicity situated between a couple of fold-and-thrust belts of the Caucasus to the north and the Zagros Mountains to the south, covering a distance of 150 km in Northwest-Southeast direction in the Northwest of Iran. NTF is the most noticeable tectonic structure in the nearby surrounding area of Tabriz City (Jackson 1992).

2.2 Data acquisition and analysis

Several criteria were determined for the evaluation of urban vulnerability (Table 1). Indicators were chosen according to previous research and data accessibility in the study area. The manual classifier method has been applied in this research to reclassify the values into five different vulnerability classes. For this purpose, at first, classification of all the required layers is based on the density of buildings, residential building, buildings floors, materials, quality of buildings, age of buildings, commercial buildings, literate people, employed people, unemployed people, population, household and size of building blocks. The logics in these factors are similar to a bigger density leads to a greater vulnerability. The other metric of classification is distance to the area such as road network, faults, danger centres, relief centres and open spaces. With the exception of the slope that is represented in percent and geology, all the features of the layers were divided into five classes. To calculate density, kernel density function (ARC GIS, 10.3) was used. To calculate distance, Euclidean function with a cell size of 10 was applied in the ARC GIS (version 10.3) environment. However, to calculate slope, Digital Elevation Model (DEM) (generated from contours on 1:50,000 topographical maps) of Tabriz was applied to raster surface as an input, and the classification was based on the percentage. The next map is the geology that was evaluated by expert judgment and based on the features of texture,

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stone type, stone material, soil type, water permeability and also the presence of faults and fractures. Fig. 2 shows the research flow using the GIS procedure. Several indicators were used, each holding a definite range scale value, needing standardization. Standardization is a procedure to determine membership value according to the usage of each criterion.

Criteria	Indicators- Description	Abbreviation	Scale	Source
Physical	Building Density Residential Density Distance to road network Distance to open space Size of building block density Building's floor density Quality of buildings density Distance to relief centers Distance to Danger centers Buildings' Materials density Age of building density Commercial building density	BD RD DRN DOS SBBD BFD QBD DRC DDC BMD ABD CBD	1.2500 1.2500 1.2500 1.2500 1.2500 1.2500 1.2500 1.2500 1.2500 1.2500 1.2500 1.2500	4 4 1 1 4 4 5 1 1 4 4 4
Environmental	Percent of Slope	PS	-	6
	Features of geology	PG	1.100000	2
	Distance to fault	DF	1.100000	1
Social	Population density	PD	1.10000	3
	Household density	HD	1.10000	3
	Literate People density	LPD	1.10000	3
Economic	Employed People density	EPD	1.2500	3
	Unemployed people density	UPD	1.2500	3

Table 1. Selected Criteria and indicators for Vulnerability assessment in this study.

In this step, all the layers under the study which had been standardized in the previous stage were transferred to IDRISI environment. The most important point in this stage is to consider the similar extent of all layers. For this purpose, raster calculator was used and the similar display is considered for all the layers. Then all of the maps with the identical extent were entered into IDRISI software with ENVI format. Analytical Network Process (ANP) is a more general form and extension of Analytical Hierarchy Process (AHP) (Saaty, 1996). The ANP analysis can be represented by steps A to D as follows:
Step A: ANP model construction and Problem structuring
Step B: Paired comparisons
Step C: Super matrix calculation
Step D: Selection

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The Artificial Neural Network (ANN), a computational model, has the ability to conclude non-linear associations among variables in input and output datasets. It is founded on a learning route (training; calibration) and is able to provide estimated values of output variables for input data (Nedic et al. 2014). The architecture of a multi-layered ANN is shown in Figure 3.

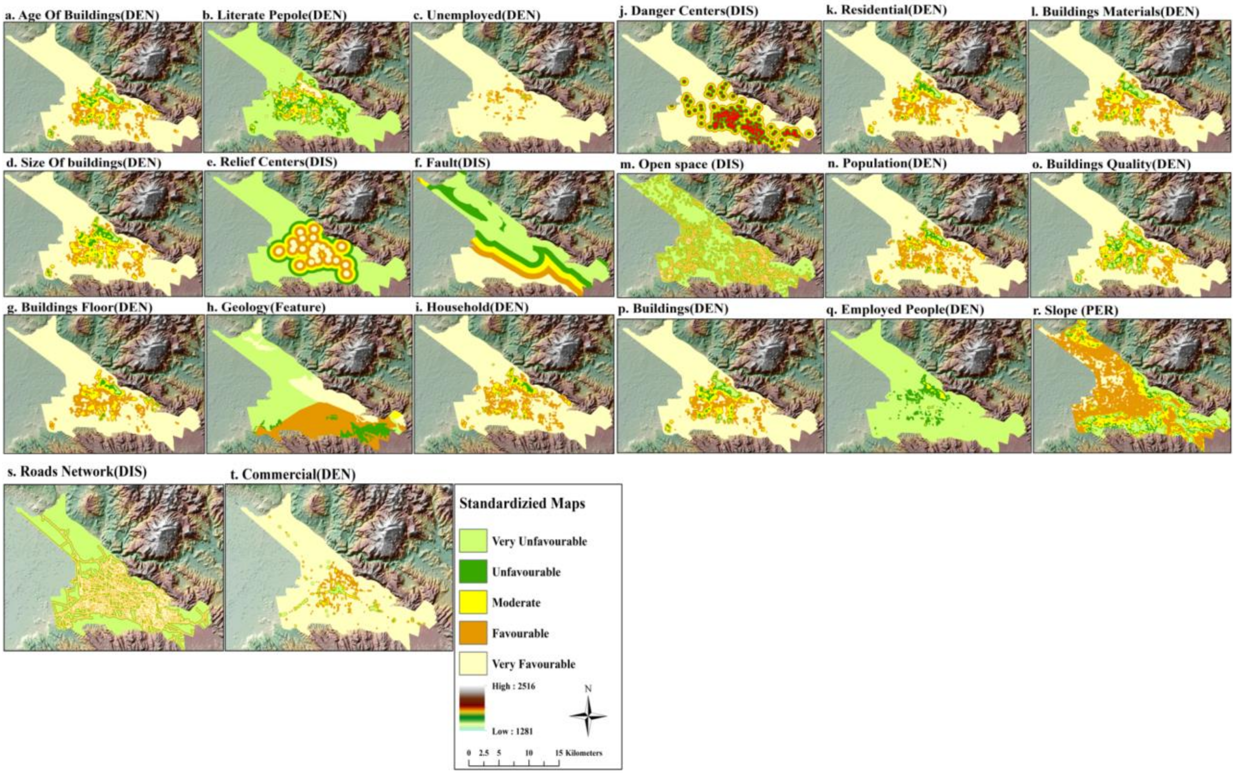

Figure 2. Standardization of input layers into with respect to resilience as shown in legend; (a) Age of buildings Density; (b) Literate Density (c) Unemployed Density; (d) Size of buildings Density; (e) Distance to relief centers; (f) Distance to fault; (g) Buildings floors Density; (h) Features of Geology; (i) Household Density; (j) Distance to Danger centers; (k) Residential Density; (l) Buildings material Density; (m) Distance to open spaces; (n) Population Density; (o) Buildings quality Density; (p) Buildings Density; (q) Employee Density; (r) Percentage of Slope; (s) Distance to Roads network; (t) Commercial Density.

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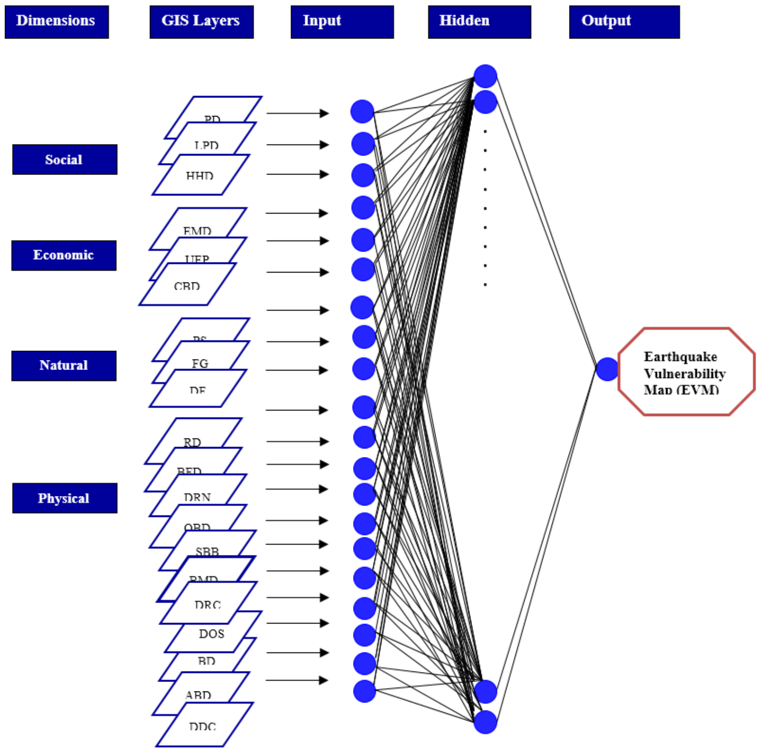

Figure 2. The architecture of a multi-layered ANN.

3. RESULTS AND DISCUSSION

MLP classifies the remotely sensed imagery using the back propagation (BP) algorithm. The calculation is based on information from training data. MLP performs a non-parametric regression analysis between input variables and one dependent variable, which is represented by one output neuron in the network (Atkinson and Tatnall 1997). To model the assessment of urban vulnerability to earthquake hazard in Tabriz city, the Multi-Layer Perceptron (MLP) was run in hard classification mode (threshold transfer function for output neurons), using IDRISI selva (Version 17.1) software (Clark Labs). According to the research goal we used classification option for the output. The 20 input layers were then specified and their names entered in the grid. The mask image contains Boolean values containing 1s in all cells to be considered and 0s elsewhere. For training data the raster file containing the weights of the selected (14 indicators) in ANP was entered. The training process reduces the error between ANN output and the real data by adjusting the weights according to the BP algorithm (Pradhan and Lee 2010). For each class in the training data, the number of training and testing sample sizes are randomly divided. The actual number of pixels used for training and testing is also determined by the ratio between the numbers specified for the maximum training and testing pixels. Using the same values for each entry will divide the pixels at a 1 to 1 ratio. In general, it is specified as hundreds to thousands rather than a large number of pixels per category. In this study, an average of 500 pixels per class was used for training and testing in Tabriz. The training pixels are used in the training and the testing pixels are used to validate the results. The network topology included 1 hidden layer with 7 nodes, 20 input layer nodes and 5 output layer nodes (Table 2).

Group	Parameter	value
Input specifications	Avrg. training pixels per class	500
	Avrg. testing pixels per class	500
Network topology	Hidden layers	1
	Nodes	10
	Input Layers Node	20
	Output Layer Nodes	5
	Automatic training	Yes
	Dynamic learning rate	Yes
Training parameter	Start Learning rate	0.001
	End learning rate	0.0006

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	Momentum factor	0.5
Stopping criteria	RMS	0.1534
	Iterations	10000
	Accuracy rate	90.00

Table 2. Network, data, and training parameters used for ANP-ANN for vulnerability map in IDRISI selva software.

The number of input layers is identified through the number of images and the number of outputs is the training data categories in the training file. The next several steps deal with training parameters, and the critical part is the learning rate which is a positive constant that controls adjustment done to the connection weights. Automatic training and dynamic learning rate were used; automatic training adjusts the learning rate during training. With the use of dynamic learning, starting and ending learning rates must be entered. Entered learning rates and momentum factor are (0.001), (0.0001), and (0.5) respectively. Small learning rates tend to increase the time in the training phase and large training rates produce poor results with fluctuating adjustments. The momentum factor is used in this study to speed up the convergence procedure. Adjustments can be made with the criteria to terminate the procedure. The acceptable error is measured through root mean square (RMS) associated with the learning of the network. The extracted RMS in this study is (0.1534) that is acceptable with regard to IDRISI default which is (0.5). When acceptable error is defined as very small, the convergence is hard to obtain. Thus additional iterations may lead to over-training. Specified iterations were (10000) at which the training procedure was terminated. Lastly, the sampling specifications of the training and testing data determine the accuracy rate per category. According to this analysis, ANN recorded 90.01% overall accuracy with testing data. In the final step of ANN analysis, the earthquake vulnerability map (EVM) was prepared by using the trained and tested ANN model and applying it to the derivative data sets and subsequently, the EVM of the study area was produced. After producing the EVM from ANP-ANN method, the resultant map was transferred to GIS environment. After this, raster map was converted to vector format and Dissolve function was processed to calculate the vulnerability of whole city (Table 3). The results indicate that 1.19% of the total area is found to be very highly vulnerable. High, moderate and low vulnerable zones represent 5.60%, 34.11%, and 52.74% of the area, respectively. The very low vulnerability is recorded for 6.35% of the total study area. South and Southeast regions of Tabriz city are in good condition regarding vulnerability whereas some parts of zone 1, Zone 4, and Zone 5 are under critical vulnerability condition. By adding municipality zones map to EVM of Tabriz city, the Level of vulnerability in various zones was obtained (Fig. 4).

vulnerability	Area (Km^2)	Hectares	Percentage (%)
Very High	3.05	305.35	1.19
High	14.33	1433.05	5.60
Moderate	87.29	8729.49	34.11
Low	134.96	13496.37	52.74
Very Low	16.25	1625.14	6.35
Total	255.894	25589.40	100.00

Table 3. The level of Vulnerability in Tabriz city according to ANP-ANN model.

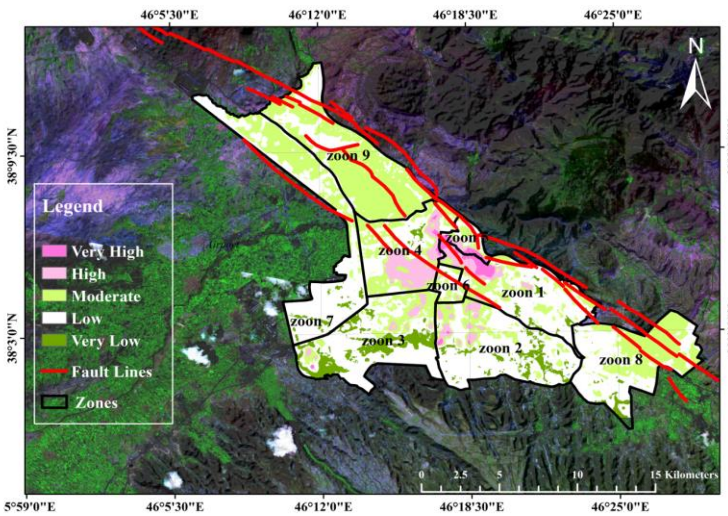

Figure 3. Final earthquake vulnerability map extracted from ANP-ANN model.

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Based on the data provided by EVM, 35.99% and 26.05% of zone 5 is classified in the very high and high vulnerability categories, respectively. Zone 4 is the second most vulnerable zone with 3.3% and 58.06% in very high and high vulnerability categories, respectively. Finally, zone 1 with 5.74% and 9.80% respectively in very high and high vulnerability categories is third most critical area in Tabriz city (see Fig. 4). On the other hand, zone 7 with 67.55% and 3.65% in low and very low vulnerability categories, respectively, exhibit the lowest vulnerability. Then, zone 3 with 58.20% and 22.10% in low and very low vulnerability categories, respectively, is the second least vulnerable zone among the zones. Thereafter, zone 2 with 68.30% and 10.14% in low and very low vulnerability categories, respectively, is categorized as third least vulnerable zone (see Fig. 4).

4. CONCLUSIONS

The results show that the most vulnerable zones in Tabriz City are zones 1, 4, and 5 that are located in unfavorable and critical positions. Reviews of the Development Plans and Master Plan of study area indicate that the expansion of Tabriz city was toward North Tabriz Fault (NTF) and a huge volume of marginal areas and informal settlements are located in the vicinity of the fault. Unplanned construction in the form of mass-housing and lack of monitoring of constructions in informal settlements point to the lack of attention being paid to the fault risk and its consequences. Furthermore, analysis of residential buildings and population implies that the NTF has never played a determined role in the physical development of Tabriz city. Moreover, the existence of the narrow passages and their irregularity in zones 1, 4, and 5, compaction of urban fabric in these zones, poor quality of buildings materials, lack of open spaces and lack of access to relief centers have added to the criticality of the situation.

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