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Earthquake risk assessment using an integrated Fuzzy Analytic Hierarchy Process with Artificial Neural Networks based on GIS: A case study of Sanandaj in Iran

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Abstract

Earthquakes are natural phenomena, which induce natural hazard that seriously threatens urban areas, despite significant advances in retrofitting urban buildings and enhancing the knowledge and ability of experts in natural disaster control. Iran is one of the most seismically active countries in the world. The purpose of this study was to evaluate and analyze the extent of earthquake vulnerability in relation to demographic, environmental, and physical criteria. An earthquake risk assessment (ERA) map was created by using a Fuzzy-Analytic Hierarchy Process coupled with an Artificial Neural Networks (FAHP-ANN) model generating five vulnerability classes. Combining the application of a FAHP-ANN with a geographic information system (GIS) enabled to assign weights to the layers of the earthquake vulnerability criteria. The model was applied to Sanandaj City in Iran, located in the seismically active Sanandaj-Sirjan zone which is frequently affected by devastating earthquakes. The Multilayer Perceptron (MLP) model was implemented in the IDRISI software and 250 points were validated for grades 0 and 1. The validation process revealed that the proposed model can produce an earthquake probability map with an accuracy of 95%. A comparison of the results attained by using a FAHP, AHP and MLP model shows that the hybrid FAHP-ANN model proved flexible and reliable when generating the ERA map. The FAHP-ANN model accurately identified the highest earthquake vulnerability in densely populated areas with dilapidated building infrastructure. The findings of this study are useful for decision makers with a scientific basis to develop earthquake risk management strategies.

Keywords

fuzzy, analytic, hierarchy, process, artificial, neural, networks, gis:, case, study, sanandaj, earthquake, iran, risk, assessment, integrated

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Earthquake risk assessment using an integrated ~~a~~ Fuzzy Analytic Hierarchy Process with Artificial Neural Networks based on GIS: A case study of Sanandaj in Iran

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Abstract: Earthquakes are ~~catastrophic natural hazard~~ natural phenomena, which induce natural hazard that seriously threatens urban areas, despite significant advances in retrofitting urban buildings and enhancing the knowledge and ability of experts in natural disaster control. Iran is one of the most seismically active countries in the world. The purpose of this study was to evaluate and analyze the extent of earthquake vulnerability in relation to demographic, environmental, and physical criteria. An earthquake risk assessment (ERA) map was created by using a Fuzzy-Analytic Hierarchy Process coupled with an Artificial Neural Networks (FAHP-ANN) model generating five vulnerability classes. Combining the application of a FAHP-ANN with a geographic information system (GIS) enabled to assign weights to the layers of the earthquake vulnerability criteria. The model was applied to Sanandaj City in Iran, located in the seismically active Sanandaj-Sirjan zone which is frequently affected by devastating earthquakes. The Multilayer Perceptron (MLP) model was implemented in the IDRISI software and 250 points were validated for grades 0 and 1. The validation process revealed that the proposed model can produce an earthquake probability map with an accuracy of 95%. A comparison of the results attained by using a FAHP, AHP and MLP model shows that the hybrid FAHP-ANN model proved flexible and reliable when generating the ERA map. The FAHP-ANN model accurately identified the highest earthquake vulnerability in densely populated areas with dilapidated building infrastructure. The findings of this study are useful for decision makers with a scientific basis to develop earthquake risk management strategies.

Keywords: Earthquake hazard, Vulnerability, Risk assessment, FAHP-ANN, GIS, Iran.

1. Introduction

In the 20th century, earthquake disasters have caused casualties of close to 2 million people worldwide (Doocy et al., 2013). The purpose of urban planning is to drastically reduce effects caused by natural disasters and enhance safety (Cruz-Milán et al., 2016). In developing countries however uncontrolled development, poor planning choices, design issues and structural failure have impeded progress to equip humanity with measures against the complex challenges posed by earthquakes (~~Ghafory-Ashtiany, 2009;~~ Xu et al., 2010; Zhang and Jia, 2010).

Earthquakes have caused considerable economic damage and loss of lives (Guha-Sapir et al., 2011). In Iran more than one million casualties have been recorded since 1900 (Asef and Kessmati, 2005; Zebardast, 2013), and more than 180 thousand individuals during the past 5 decades (Omidvar et al., 2012). Iran has one of the worst recorded earthquake vulnerability indices in the world, defined as the degree of damage inflicted upon a property at risk of earthquakes of different magnitudes (see Barbat et al., 2010; Coburn and Spence, 2006; Ghajari et al., 2017, 2018; Karashima et al., 2014; Karimzadeh et al., 2014; ~~Omidvar et al., 2012;~~ Wei et al., 2017).

Iran suffers from frequent destructive earthquakes due to its location in the active collision zone between the Eurasian and Arabian plates (Asef, 2008; Aghamohhamdi et al. 2013; Zebardast, 2013) causing severe damage (Ghodrati -Amiri et al., 2003; ~~Aghamohammadi et al., 2013~~; Ibrion et al., 2015; Moradi et al., 2015; Ranjbar et al., 2017), as captured in historical records and information from the earthquake database of the United States Geological Survey (USGS) (Zafarani et al., 2009; Asadzadeh et al., 2014; Najafi et al., 2015; Bahadori et al., 2017). According to Zamani et al. (2011) and Panahi et al. (2014), the Iranian plateau with its flanking seismic zones is characterized by different types of active faults, tectonic domains, recent volcanoes and high surface elevation following the Alpine Himalaya seismic belt. Forty-six earthquakes occurred here between 1900 and 2014 that directly caused casualties (Berberian, 2005, 2014; the ISC and IGUT databases).

The development of earthquake risk assessment (ERA) methodologies has been studied extensively but rarely have measures been studied for ERA in urban zones. Davidson and Shah (1997) for instance introduced the Earthquake Disaster Risk Index (EDRI) to estimate urban risk, accounting for seismic hazards and vulnerability. In addition to this holistic approach, there are many other studies assessing specific aspects of risk using various methods such as social fragility and lack of resilience in seismic risk in urban areas (Jaramillo et al. (2016).

So far, researchers have investigated different aspects of ERA at different scales using various approaches including GIS-based techniques (Rashed and Weeks, 2002; ~~Sun et al., 2008;~~ Alparslan et al. 2008; Hashemi and Alesheikh, 2011; Villagra et al. 2014; Rahman et al., 2015; Karimzadeh et al., 2017; Alizadeh et al., 2018 a, b; Ningthoujam and Nanda 2018), high-resolution QuickBird Imagery (Fu et al., 2007), GIS modelling using satellite remote sensing and digital elevation model (DEM) data (Liu et al., 2012; Xu, 2015), GIS-based Support vector machine modelling (SVM) (Xu et al., 2012), statistical analysis (Ghassemi, 2016), GIS-based statistical analysis (Hassanzadeh, 2019), catastrophe progression method (Zhang et al., 2017), Artificial Neural Network (ANN) Models (Tavakoli and Ghafory-Ashtiany, 1999; Panakkat and Adeli, 2007; Kulachi et al., 2009; Vicente et al. 2011; Akhoondzadeh, et al., 2019), ANN models integrated with an Analytic Network Process (ANP) (e.g., Alizadeh et al. 2018a), Analytical Hierarchy Process (AHP) (Bitarafan et al., 2013; Robat Mili et al., 2018), an integrated model of AHP in GIS (Bahadori et al., 2017), an integrated ANN–AHP model (Jena et al., 2019), fuzzy logic techniques (Lamarre & Dong, 1986; Wadia-Fascetti & Gunes, 2000; Ahumada et al., 2015), and fuzzy multi-criteria decision making (FMCDM) (Ranjbar and Nekooei, 2018). Our study is the first to ask how an integrated FAHP combined with an ANN model can improve ERA accuracy by generating a classification of vulnerability zones to improve earthquake vulnerability planning in Iran.

In the aforementioned studies, 'expert systems' have become an important tool for solve complex problem solving and decision-making. The application of expert systems extends to almost all engineering fields and uses artificial intelligent theories (e.g., Neural Network, Fuzzy Logic) to develop expertise and propose conclusions (Jackson, 1998; Liao, 2005). Because of this several researchers have considered the Fuzzy approach in ERA as effective for spatial decision making (refer to Sanchez-Silva and Garcia, 2001, Şen, 2010; Ahumada et al., 2015; Hu et al., 2018; Rezaei-Malek et al., 2019).

Here we focus, on the case of Sanandaj, the capital city of Kurdistan province in Iran that is located in a major earthquake zone near the active faults of Sanandaj-Sirjan, Morvarid, and Nahavand, with the closest fault being only 3 km away from the city. Zagros fault includes numerous cases of active faulting (refer to Mirzaei et al., 1999; Hessami et al., 2003; Bachmanov et al., 2004). These faults generate earthquake magnitudes between level 1.6 and 6.9 on the Richter scale (Ghodrati-Amiri et al., 2009). ~~Estimating the seismic site amplification of Sanandaj is required to predict the likelihood of future earthquakes (Mohajjel and Fergusson, 2000; Allen et al., 2011), and so is calculating its vulnerability and earthquake-related risks (Azami et al., 2015; Karimi and Boussauw, 2018).~~

The remainder of this paper is organized as follows: The above-mentioned contributions to knowledge and justification of the study are highlighted by conducting a comprehensive literature review in Section 2. An overview of the research methodology is presented in Sections 3. Section 4 provides the results. Finally, Section 5 presents the discussion, conclusions and future research directions.

2. Background and related works on ERA

In this section, we give a brief overview of fuzzy methods, multi-criteria decision making (MCDM) approaches and algorithms that have been applied for ERA. To better control results of vulnerability evaluations and parameters, researchers proposed MCDM (e.g., Samadi Alinia and Delavar, 2011; Moradi et al., 2015; Peng, 2015; Bahadori et al., 2017). The FAHP-ANN model is a specific type of MCDM approach that has not yet been comprehensively applied in urban vulnerability assessments for earthquakes. Studies in related fields however are summarized as follows.

Many researchers have integrated MCDM approaches in GIS environments as effective tools for spatial decision making around earthquake hazards (Erden and Karaman, 2012; Feizizadeh and Blaschke, 2012; Karimzadeh et al., 2014; Delavar et al., 2015; Rezaie and Panahi, 2015; Feizizadeh and Kienberger, 2017; Sánchez-Lozano et al., 2017; Hooshangi and Alesheikh, 2018; Nyimbili et al., 2018; Skilodimou, et al., 2019; Nazmfar, 2019).

Ranjbar and Nekooie (2018) recently adopted the improved fuzzy multi criteria decision-making (FMCDM) approach in a GIS environment to identify buildings endangered by earthquakes. They focussed on detecting buildings prone to earthquakes in Tehran, one of the most vulnerable seismic regions in Iran (JICA, 2000). Seismic vulnerability assessments are highly important for earthquake risk mitigation programmes. A similar study was conducted by Ningthoujam and Nanda (2018) who used a GIS system to perform an Earthquake Vulnerability Assessment of buildings in Imphal city, India. The authors used the GIS platform to generate and display various thematic maps. Their study identified areas under risk of great damage to structure and human beings in the case of an earthquake to inform local disaster management plans.

The advantage of using ANN in the FAHP-ANN model is that it can describe nonlinear and complex interactions among system variables and work with imprecise data. These strengths of an ANN are emerging as a powerful tool for modelling (Ramakrishnan et al., 2008). ANN can generate easy-to-use models that are accurate even for complex natural systems with large inputs (Jahnavi, 2017). It thereby allows generating computational models to evaluate earthquake vulnerability accounting for uncertainty, which is an inherent property of the 'earthquake phenomena' (Tavakoli and Ghafory-Ashtiany, 1999; Vicente et al. 2011).

In order to determine the need for an in-depth investigation of earthquake vulnerability scenarios in urban areas, Alizadeh et al. (2018a) identified and evaluated quantitative earthquake vulnerability indicators for generating a vulnerability map by constructing Artificial Neural Network (ANN) and Analytic Network Process (ANP) models. Bahadori et al. (2017) researched ERA, disaster management and seismic vulnerability assessments, while Robat Mili et al. (2018) considered AHP utilizing GIS as an integrated model to estimate the safety of urban building materials and residential buildings with earthquake risk mitigation and disaster risk reduction in mind. The results depict the safety level of different urban zones depending on their hazards and earthquake vulnerability.

Although recent works propose a large variety of indicators to measure ERA relating to demographic, environmental, physical, and economic dimensions of a city (refer to Ainuddin and Routray, 2012; Villagra et al., 2014; González et al., 2018; Atrachali et al., 2019), this is an ongoing task. Recommendations depend on the methodology and the different scales of the study (Zhou et al., 2010). Amini-Hosseini et al. (2009) for instance recommended using socio-economic and physical parameters to quantify the seismic vulnerability of Tehran, Iran. Notably, in that case effective parameters of the model and their weights were constructed by accounting for local conditions and judgments by Iranian experts (Robat Mili et al., 2018). Bahadori et al. (2017) considered physical, social, and economic aspects for vulnerability assessments and earthquake hazard assessments (EHA).

Karimzadeh et al. (2017) used a GIS-based hybrid site condition map to assess earthquake building damage in Iran. They identified a hybrid model (the Karmania Hazard Model) using the single parameter of earthquake wave velocity. For the top 30 m (Vs30) this gives a better estimation than a topography-based model. Novel GIS-based approaches to earthquake damage zone modelling using satellite remote sensing and DEM data have been addressed by Liu et al. (2012) for Wenchuan County in the Sichuan Province, China. The resulting earthquake damage map revealed potential for current and future damage (hazard).

Hassanzadeh et al. (2013) modelled earthquake scenarios interactively by focusing on the Karmania Hazard Model. This model has been applied to Kerman City, South East of Iran. The authors found GIS-based scenario development useful for earthquake disaster management during all stages of an earthquake, namely, before, during and after the occurrence. Rahman et al. (2015) addressed vulnerability to earthquakes and fire hazards using GIS for Dhaka city, Bangladesh. The major finding was that vulnerability assessments of earthquakes and fire hazards corresponded well with social aspects of vulnerability.

Alizadeh et al. (2018a) developed a Hybrid Analytic Network Process and Artificial Neural Network (ANP-ANN) Model on urban earthquake vulnerability in a case study in Tabriz city, Iran. The study identified the most vulnerable zones which are clustered in several zones in Tabriz. More recently, Jena et al. (2019) assessed environmental indicators, seismic indicators and vulnerability indicators for constructing an ERA map. An integrated model using ANN–AHP is developed for constructing the ERA map in Banda Aceh, Indonesia. The proposed hybrid model was adopted to evaluate urban population risk due to impending earthquakes.

Aghataher et al. (2005) noted some important spatial factors affecting vulnerability to earthquakes; in particular physical vulnerability of urban structures and facilities, and they identified the most vulnerable areas of Tehran, Iran using a fuzzy-AHP model to specify layer weights through a pairwise comparison. In a similar study, Silavi et al. (2006) the shortcomings of the fuzzy-AHP model were overcome by adopting intuitionist fuzzy logic when determining vulnerability, which takes the indeterminacy of membership functions into account. They also discussed mortality rates of humans to describe their vulnerability to earthquakes.

The use of fuzzy logic algebra in structural damage estimation was advocated, in particular because expert opinion can easily be integrated into this technique (Fischer et al., 2002). Allali et al. (2018) argued for a methodology based on fuzzy logic for post-earthquake assessments of building damage to correctly predict level of damage. Rezaei-Malek et al. (2019) introduced a study for prioritizing management for disaster-prone areas to prepare for large-scale earthquakes. There, the fuzzy DEMATEL was applied to specify interrelationships between influential factors, and the weights of factors were determined through fuzzy ANP. The model aimed to identify special points of demand that need to be prioritized in case of large-scale earthquakes. An integrated approach of the ANN and fuzzy model was developed by Nazmfar (2019), to evaluate urban vulnerability to earthquakes with the aim to construct a vulnerability map as a means to improve safety and to reduce casualties in Tehran, Iran.

Our literature review revealed that in spite of the numerous ERA studies; there is a clear gap on choosing the best parameters for a comprehensive ERA. To address this issue, the potential of FAHP-ANN models needs to be explored for selecting appropriate ERA measures, which is our focus. ~~Sspecifically~~ , Specifically, in this research we develop a hybrid FAHP-ANN model using GIS techniques to improve the ERA. This study also extends our perspectives on ERA by including expert knowledge on the vulnerability of a specific locale as an important reference when constructing vulnerability maps. To date, there has been little discussion about considering a combination of three key parameter groups, namely demography, environmental, and physical parameters for an ERA. In fact, no previous studies have considered these parameters together when building FAHP-ANN models. Here, we will also fill this gap.

Generally, this study makes two contributions. First and foremost, it developed a model of ERA in which critical factors (CFs) were categorized along demography, environmental, and physical dimensions. Next, it determined the earthquake vulnerability factors of ERA in Sanandaj, Iran, and revealed their level of importance using FAHP-ANN coupled with GIS analysis. This is the first time a comprehensive model has been developed for Sanandaj in a detailed ERA. Our ultimate purpose is to provide the necessary background to fully convey the requirements of these techniques and to introduce a flow diagram that outlines the fundamental steps involved in creating the FAHP-ANN model.

We propose this approach because we see the following advantages of our technique for ERA and parameter selection:

- Applying an FAHP model creates a suitable training database for the Artificial Neural Network (ANN). The major potential of ANN as a non-linear computational model lies in the high-speed processing achieved through a massive parallel implementation (Izeboudjen et al. 2014) akin to the structure and function of the human nervous system (Su et al., 2017; Luo et al., 2019).

- ~~The proposed hybrid approach allows selecting a set of key factors affecting social, environmental, and physical criteria prior to ERA in accordance with experts' opinions and then sets a weight for each criterion based on its significance.~~

- A set of key factors affecting demography, environmental, and physical criteria prior to ERA and in accordance with experts' opinions is applied based on their significance (Achu et al., 2020).

- Selecting suitable training sites is complex but made possible by creating a new FAHP-ANN model for the ERA while adequately considering all the relationships among the critical criteria.

- The utility of the methodology is demonstrated by providing a real case study that shows its positive management implications on an applied ERA problem.

- The application of our technique enables to reduce the impact of an earthquake by identifying categories of the most vulnerable zones. It allows prioritizing ERA for regional-scale earthquakes in the pre-disaster phase.

- Overall, the proposed approach underpins the vital role of ERA and considers the interrelationships among criteria.

For the Iranian case study context in particular, the combination of these techniques can accurately determine vulnerability zones and improve building an Earthquake Vulnerability Map (EVM). The GIS platform itself was used to classify risk by zones which will aid disaster management (Lepuschitz, 2015; Cai et al., 2019).

3. Methods

3.1 Study area

The region of Kurdistan in the west of Iran has experienced several majorly destructive earthquakes (Shabani and Mirzaei, 2007; Ghodrati-Amiri et al., 2009). Sanandaj City in the southern centre of the Kurdistan Province is surrounded by the Zagros Mountains. The city is located in the structural zone of Sanandaj-Sirjan and is exposed to earthquakes along the crossings of the Zagros and Marivan-Sirjan faults. ~~(see Fig. 1).~~ The historical earthquake recordings on the Surface-wave magnitude scale (MS) collected in the surrounding area of Sanandaj up till 2014 are shown in Fig 1.

Caption 1:

Please insert Figure 1 here:

The study area is a watershed located in Kurdistan Province, Iran (see Fig. 2). The watershed lies between 46° 59′ 32″ E longitude and 35° 18′ 52″ N latitude (Asadi, 2019) and covers an area of 2 906 km^2 or 10.3% of the province with a population of, 414 069 (Statistical Center of Iran, 2017; Murgante, 2017). Its elevation varies between 1368 m and 1720 m above sea level. Slope degree ranges from 0 to 50%.

Caption 2:

Please insert Figure 2 here:

3.2 Applied FAHP-ANN proposed model for ERA

The FAHP method allows determining weightings for the evaluation criteria identified by experts in the field. Mikhailov and Tsvetinov (2004) focussed on the constraints that have to be considered within the FAHP. FAHP represents reality more so than AHP (Khashei-Siuki et al., 2020).

The ANN is a computational model that captures non-linear associations among variables in input and output datasets. It relies on a learning route of training and calibration, and estimates values for output variables from input data (Antanasijevi´c et al., 2013; Nedic et al., 2014).

Our literature review confirmed that there is no study that uses FAHP-ANN for a performance assessment of an ERA and the effect of ~~11~~ 13 critical factors (derived from literature and experts' opinion) on the overall performance.

The key criterion for the selection of our experts was a high-level understanding and overview of the field. Specifically, the selection of the experts was based on their known (national, regional, municipal) status in the area of seismology in the Sanandaj district, reflecting their professional activities on seismology and in risk assessment.

As mentioned in Table 1, ~~11~~ 13 indicators associated with ERA in Sanandaj City were presented to academic staff of the department of geography, geology and urban planning (Kurdistan's University) who were chosen as experts for this study. Interviews were conducted face-to-face, via questionnaire, or by using online video tools (e.g., Skype), or by telephone. The experts were asked to rank the importance and relevance of the selected earthquake indicators associated with urban vulnerability to earthquakes affecting Sanandaj City (Kurttila et al., 2000). In total, 45 experts were interviewed to investigate their opinions regarding key factors that influence earthquake risk.

A model for ERA was developed according to a FAHP-ANN. This section describes the different components of the proposed model, in particular its architecture. The model consists of two basic steps combining the FAHP and ANN methodologies. The steps involved in this process are (1) the data acquisition and the creation of vulnerability classes; (2) transferring of layers to the IDRISI software, (3) establishing the theoretical background of the methods, (4) FAHP model development, (5) the ANN implementation for ERA and (6) the application of the results as described below. Fig. 3 presents the methodological flowchart.

Overall, the development of a hybrid FAHP-ANN model involves a number of stages. The main flowchart in Fig. 3 shows the series of fundamental steps involved in the ERA.

Caption 3:

Please insert Figure 3 here:

3.3 Data acquisition and creation of vulnerability classes

For an ERA, data can be retrieved from various sources. Freely available earthquake data can be collected from several public and private agencies. These sources are accessible from the internet and include the Advanced National Seismic System, the United States Geological Survey (USGS), and the Department of Road and Urbanity (Kurdistan Province). Further DEM 30 m Landsat data (http://www.std2800.ir/); data from the Iranian Geological organization (https://www.usgs.gov/), the municipality of Sanandaj City (https://gsi.ir; http://www.Sanandaj.ir/), and the Census Center of Iran (http://www.amar.org.ir/).

To effectively utilize a comprehensive evaluation method for an ERA, it is necessary to incorporate important vulnerability criteria (Table 1). The study area was classified based on three main criteria sets to generate five different vulnerability classes ~~by adopting the manual classifier method~~. For the classification the following criteria stored in spatial layers were used (Fig. 3): ~~social criteria~~ demographic data (population density, and family density), environmental data (distance from the runway, distance from a fault, slope, elevation, geology), and physical data (presence of buildings with quality materials, buildings with no quality materials, distance from the road network, building area, number of floors, land use). To calculate distance, a Euclidean function with a cell size of 30 m (pixel size 30*30) was applied in ArcGIS desktop 10.4. To calculate slope, a Digital Elevation Model (DEM) (generated from contours on 1:25,000 topographical maps) was used, and the classification was based on the percentage. Accordingly, all thirteen layers (including both quantitative and qualitative data) (see Table 1) were converted to a raster format in ArcGIS using the feature-to-raster, vector-to-raster and/or polygon-to-raster tools. Geographical coordinates of the project area were set in WGS 84 Datum UTM zone 38 N.

Caption 4:

Please insert Table 1 here:

3.4. Transferring Layers to the IDRISI Software

Here, the standardized layers as per previous step were transferred to the IDRISI environment. Considering the similar extent of all layers was now critical and so a raster calculator was used to display layers similarly. Using the ENVI format all the maps of identical extents were then entered into the IDRISI software.

Since the measurement units and scales of each vulnerability layer were unique, the layer values were standardized between 0 and 1, by building a matrix of pairwise comparisons based on the maximum and minimum layers method in IDRISI and by using the MAP Algebra command. Fig. 4 shows the standardized input layers derived from the GIS procedure. The layers were weighted to acknowledge their relative importance in assessing earthquake hazard vulnerability; namely, as very high, high, moderate, low or very low. Afterwards, a GIS analysis was undertaken to explore how well the system performs in terms of zoning for an ERA.

Caption 5:

Please insert Figure 4 here:

3.5. Theoretical background of methods

The AHP model is created by a mathematical language that describes the decision process (Ding, 2018). The AHP method is a reliable technique to determine the weight of criteria in multi-criteria decision making (Yang and Xu, 2016). The F-AHP model was developed to solve hierarchical problems (a weakness of the AHP) in which the decision maker can specify preferences about the importance of each criterion (Yaghoobi, 2018). The purpose of using the AHP model in this study was to weight the criteria and to map the F-AHP model.

Using ANNs can provide a way to predict the output of input data not used in the modeling process (Khawaja et al., 2018). The ANN is useful for processing input information of units by considering weight, threshold and mathematical transfer functions, and processes input units relative to other units (Gopal, 2016). Therefore, ANN is capable of displaying maps that categorize vulnerability into individual zones with high potential for forecasting. That makes the ANN successful in describing the spatial heterogeneity of the earth's surface (Gopal, 2016). We will provide more detail on ANNs in ~~chapte~~r section 3.7.

Shortcomings of ANNs for creating multi-criteria decision making models (Ebrahimi et al., 2016; Nallusamy, 2015; Alizadeh, 2018c) are overcome by using a hybrid FAHP-ANN model based on natural, physical and demographic data relevant for an ERA.

3.6 F-AHP model development

The F-AHP model for MCDM helps evaluating qualitative and quantitative attributes for ranking alternatives and finding solutions from possible alternatives. Ranking alternatives and defining weights of criteria is attempted by using crisp numbers based on expert opinions (Singh and Benyoucef, 2011). However, the issue is that human judgment is imprecise and crisp numbers in this case are not suitable for ranking alternatives and defining weights of criteria. To manage the uncertainty of human judgments, the fuzzy set theory was integrated into MCDM which was coined FMCDM. Here we discuss the theories underpinning fuzzy set theory as deployed in this study.

Fuzzy MCDM was used primarily as it overcomes some of the uncertainties relating to MCDM. Uncertainty arises in an MCDM problem around weighting evaluation criteria and subsequently, around crisp input data for decision making. The first type of uncertainty may arise during decision making because of the varying interests, expertise and backgrounds of experts (Chen and Chang, 2010). The second type may originate where data are transformed into numerical values. A fuzzy concept prevents such problems (Jun et al., 2013).

~~When applying a fuzzy concept, alternative weight decision making is determined through a set of numerical calculations.~~

Alternative weights are calculated only by the information provided in the decision matrix for each criterion by applying a fuzzy concept. The best alternative is obtained by the affected weight vector in the decision matrix (Zoraghi et al., 2013). Then each alternative is calculated by means of a double comparison matrix, and the relative weight of each element must be multiplied by the high weight elements to replace the final weight for ranking. A final score will be calculated for each alternative using the following equation:

$$Pr = \sum_{k=1}^{n} . \sum_{i=1}^{m} \mathrm{W_k} \ \mathrm{W_i} \ (\mathrm{g_{ij}}) \qquad (1)$$

W_k is a preference coefficient for the criterion W_i and k is the preference coefficient of subset i and g_{ij} is the score criterion of subset i (Zhang, 2016).

The λmax must be equal to n so consistency is met (refer to equation 2). Using the Consistency Index (CI) of the relation enables this computation (Saaty, 1980; Neaupane and Piantanakulchai, 2006; Stein and Norita, 2009; Zabihi et al., 2015):

$$CI = \frac{\gamma max - 1}{n-1} \quad (2)$$

In this way, the inconsistency ratio (CR) of CI is given by:

Where;

λmax value is an important validating parameter in ANP and is used as a reference index to screen information by calculating the Consistency Ration (CR) of the estimated vector. Additionally, λmax is the largest eignvalue of a given matrix. Our study analyzed the information from the experts' through an eigenvalue method to identify the higher risk factors. RI is the random consistency index, which depends on the matrix size. The CR should fall below 0.1, (equation 3), indicating that the degree of consistency of the pairwise comparison matrix is acceptable (Saaty 1980; Chang et al., 2007; Niu et al., 2019; Kumar et al., 2019).

$$CR = \frac{CI}{RI} \qquad \text{If} \leq 0.1 \qquad CR = 0.0021 \leq 0.1 \quad (3)$$

Fuzzy set theory was primarily introduced by Zadeh (1965) to deal with uncertainty due to imprecision and vagueness (Yuksel and Dagdeviren, 2010). The fuzzy set theory is based on the logic that the degree of the membership of each element can be calculated in such a way that the membership degree of each element in the fuzzy set is defined spectrally among the data between [0, 1] (Ayag and Ozdemir, 2009; Biswas, 2018). The basic steps of FAHP can be given as follows:

Step 1. Choose the linguistic ratings for criteria and alternatives with respect to criteria. In this step, the importance weights of the evaluation criteria and the ratings of alternatives are considered as linguistic terms to assess alternatives in a fuzzy environment (for more information refer to Zhang et al., 2018; Wątróbski et al., 2018). In addition, a fuzzy linguistic set was developed for the risk assessment of the ERA. The model can transform expert assessments into numerical values through a triangular fuzzy number.

The evaluation process involves fuzzy factors, and is therefore referred to as a fuzzy synthetic evaluation. The key to determining the fuzzy relation is to determine the degree of membership between each factor. This involves ascertaining the quantitative relationship between the evaluation factors and therefore the corresponding function to measure the degree of membership is called a membership function.

Step 2. Determine the degree of membership and development of the fuzzy evaluation matrix for a single factor.

Step 3. Determine the index weight which can be derived from the AHP. The 1–9 scale method generates a judgement matrix from the 13 selected indicators, as suggested by Saaty (1990).

Step 4. Comprehensive evaluation. Assume that the number of criteria is *n* and the count of alternatives is *m*, the fuzzy decision matrix of a single factor will be obtained with *m* rows and *n* columns. After constructing the fuzzy decision matrix, the first level of comprehensive evaluation vectors can be obtained with their corresponding weights.

Fig. 5 illustrates the triangular phase from the smallest to the most promising value with (a, b, c) and its membership function (Rodcha et al., 2019). The triangular membership function is used to demonstrate the relative strength of the fuzzy matrices' elements (Wicaksono et al., 2020). Additionally, the Triangular Fuzzy Number (TFN) is used, which can handle the fuzziness and enhance reliability (Wu et al., 2019). Fuzzy decision-making based on fuzzy sets theory is the technique of choice for decision making problems as human thought is fuzzy. Meanwhile TFN or fuzzy linguistics have been widely utilized in fuzzy decision-making (Benítez et al., 2007; Cabrerizo et al., 2009; Chen and Li, 2011).

Caption 6:

Please insert Figure 5 here:

$$\mu\,(x) = \begin{cases} 0 & x < a \\ \dfrac{(x-a\,)}{(b-a\,)} & a \le x\ \le b \\ . & \\ \dfrac{(c-x)}{(c-b)} & b \le x\ \le c \\ 0 & c\ \le x \end{cases} \tag{4}$$

$$\mu\,(x) = \begin{cases} 0 & x < a \\ \dfrac{(x-a\,)}{(b-a\,)} & a \le x\ \le b \\ & b \le\ x\ \ \le c \\ \dfrac{(d-x)}{(d-c)} & c \le x\ \le dc \\ 0 & d < x \end{cases} \qquad \cancel{(5)}$$

AHP in spite of its popularity and frequent usage in multi criteria decision analysis (MCDA) is not sufficient to eliminate uncertainty in data (Wątróbski et al., 2018; Rodcha et al., 2019). Crisp pairwise comparisons in the conventional AHP are insufficient to capture expert judgments adequately (Taha and Rostam, 2012). Moreover, F-AHP models are more powerful to handle real-world problems whereas traditional AHP does not handle such problems (Moktadir et al., 2018).

While conventional AHP is not effective for ambiguous problems, FAHP as an extension of AHP using fuzzy set theory manages uncertainty and therefore overcomes this limitation. It therefore addresses the fuzziness of decision makers' opinions (Nilashi et al., 2016). Chang's extent analysis method is more suitable for this study (Chang, 1992, 1996) because of its ease of use compared to the other FAHP approaches.

3.7 ANN implementation for ERA

Artificial Neural Networks (ANN) (Islam et al., 1995; Sözen et al., 2005) computes useful models for ERA by accounting for the uncertainty inherent to earthquake scenarios. ANN systems process information of interconnected units that respond to inputs of weights, thresholds, and mathematical transfer functions (Islam et al., 1995). ANN also has advantages over statistical methods (Zhang et al. (1998)). Each unit processes input from other units and passes on the signals. Non-linear modelling with fast processing and high accuracy can be achieved that way (Pradhan and Lee, 2010a; Yilmaz, 2009, 2010; Dou et al. 2015; Lee et al. 2016), which is useful when analysing big data with many different alternatives and to examine complicated patterns that cannot be solved otherwise (Sözen et al., 2005; Sözen, 2009). Furthermore, ANN provides reliably handles noisy, uncertain and incomplete data (Midilli et al., 2007; Sözen et al., 2007). Therefore, ANN is efficient at producing vulnerability maps arising from complex interactions with high accuracy. However; it needs training to achieve that using an appropriate choice of training ~~algorithm~~ parameters and an adequate network architecture (Safa and Samarasinghe, 2011; Sözen, 2009). These two features of the network are regrettably not well defined. Trial and error procedures may help (Karapidakis, 2007; Kankal et al., 2011). Still, the accuracy of the ANN method outcompetes other methods (Lynch et al., 2001).

ANN units are known as nodes. Information is processed along the network from input to output unit akin to neural networks (Zamani et al., 2013; Abiodun et al., 2018).

To determine the ANN model structure the number of layers, nodes in each layer and their connections need to be known (Maier et al., 2010). The general structures of ANN models is described in numerous publications (e.g., Hagan et al., 1996; Jiang, 2001) and relies upon ‘training’ the ANN so that it can precisely predict the system performance under different conditions (Najafi et al., 2009). ~~The architectures of the ANN models are shown in Fig. 6.~~

~~Caption 7:~~

~~Please insert Figure 6 here:~~

$$\cancel{sum_k = \sum_{i=1}^{n} \mathrm{w_{ki}}\ \mathrm{x_i}} \qquad \cancel{(6)}$$

$$\cancel{\mathrm{out}_k = \mathrm{f}\,(sum_k)} \qquad \cancel{(7)}$$

~~n: the hidden layer occurs at the output of two outputs:~~

~~1- Synaptic Weight Summing, which represents system memory.~~

~~2- Activation function that calculates the amount of activation of neurons. k output neurons, $\mathrm{w_{ki}}$ synaptic weight in terms of input i.~~

Finally, it can be noted that ANN converts input information into output (Nedic, 2014). Many researchers applied the ANN as a powerful tool for analysis in varied contexts, such as for example traffic noise pollution (e.g., Bravo-Moncayo et al., 2016; Mansourkhaki et al., 2018), landslide susceptibility (Benchelha et al., 2019; Arabameri et al., 2019), flood forecasting (Kim and Newman, 2019; Goodarzi et al., 2019), and seismic hazard (Sharma and Arora, 2005; Gul and Guneri, 2016; Plaza et al., 2019; Huang et al., 2019).

Multilayer perceptron (MLP) is flexible, popular, and simple and versatile form of ANN (Ahmed et al., 2015). MLP can model highly non-linear functions, and when trained, accurately predicts even using new data. It consists of an input and output layer, and one or more hidden layers (Fig. 7) (Roy et al., 1993). The hidden layers enhance the network's ability to model complex functions (Paola and Schowengerdt, 1995). Each layer consists of neurons that process information independently, and that are linked to neurons in other layers through the weight. Input (factors) and output (responses) vectors are influenced by assigning the weight and biased values (Alkhasawneh et al. 2013).

Adjusting the weights between the neurons without a learning algorithm is difficult. The back-propagation learning algorithm with momentum used in this study reduces the error rate between the actual output and the neural network output. A feed-forward back-propagating (BP) MLP was used with a feed-forward phase in which the external input information is propagated forward to calculate the output information signal, and a backward stage in which modifications to the connection strengths are accomplished based depending on the observed and computed information signals at the output units (He et al., 2011).

Caption 8:

Please insert Figure 7 here:

In MLP models, all the input nodes are in one layer and the hidden layer is distributed as one or more hidden layers. Fig. 7 shows the general structure of a simple feed-forward network. In order to reduce the error, the back propagation algorithm will be used in the present study (Salarian et al., 2014). The output signal is obtained from the following relations:

$$0= \mathrm{f}\ (\mathrm{net}) = \mathrm{f}\ (\textstyle\sum_{j=1}^{n} w_i \ \ x_i\ ) \tag{8}$$

When $\mathrm{w_i}$ is a weight vector, the function f (net) is an active transfer function

$$\mathrm{net} = w^{\mathrm{T}}\,\mathrm{x} = \ \mathrm{w_1\, x_1} + \ \ldots . \mathrm{w_n\, x_n} \tag{9}$$

As such, Where T is a transfer matrix; the output value zero is given by Abraham (2005):

$$0 = f\,(\text{net}) = \begin{cases} 1 \;\text{ if }\; w^T X \;\geq \theta \\ 0 \;\;\text{other wise} \end{cases} \tag{10}$$

Where, θ is called the threshold level; and this type of node is called a linear threshold unit.

The weights of criteria derived from the AHP are presented in Table 2.

Caption 9:

Please insert Table 2 here:

The MLP in this study was trained with a back-propagation algorithm; the most frequently used neural network method (Fig. 8). The MLP with the back-propagation algorithm was trained using exemplary sets of input and output values (Pradhan and Lee 2010b).

Caption 10:

Please insert Figure 8 here:

3.7.1 Neural network training and testing

A "training set" and a "test set" are required to establish the ANN architecture. To develop possible network weights, the former is applied so the performance of the trained network can be properly ascertained. Data need to be prepared to create an accurate probability map. The selection of acceptable criteria is critical for this (Nedic et al., 2014; Alizadeh et al., 2018a). We used complete earthquake data from the USGS site across various magnitudes for this purpose. However, even a great amount of data may be insufficient for modelling and circumvent this issue the model needed to be trained. The 13 spatial layers from the identified earthquake indicators were then used in the earthquake probability mapping adopting a trial and-error approach (Nedic et al., 2014). Judging by their importance the initial 13 layers were reduced by those that were deemed unnecessary for the analysis. The ranking of layers and weights was analyzed by using the ANN.

3.7.2 Applying FAHP for the Training Site

In order to implement the MLP model, we need two training datasets and a test to analyze the model and select a precise training network (Aghazadeh et al., 2017). Since data lacked we trained the ANN. For this purpose the FAHP model was created to generate a suitable training database. The combination of these two methods solved the complex problem of selecting suitable training sets for the ERA, and adequately considered all the relationships among the earthquake indicators. Seventy percent of those indicators with the highest weight resulting from the AHP model (Table 2) were transferred to ArcGIS to create the base map (Figure 10) while 500 points were selected randomly from the base map to produce a final training site map. These were input in the feed-forward Multilayer Perceptron (MLP) model, and also to measure the accuracy of the trained network.
~~we have proposed a new method to select training points by combining the F-AHP model and ANN.~~
Finally the FAHP output was classified into five categories of very high, high, medium, low and very low earthquake vulnerability. This map was then converted into a network of 500 randomly selected point sites.

3.7.3 Transferring Layers to IDRISI Software

After being standardized, the obtained training map along with the 13-layer map were transferred to the IDRISI software as the input and of neural network after converting the format as explained in the next section.
After standardizing the 13 vulnerability criteria layers in the study and generating one layer of training points, a total of 13 raster layers with a cell size of 30 m (pixel size 30*30) were output in ENVI format using ArcGIS 10.4. The IDRISI software environment was prepared for use in the ANN MLP model. All the GIS operations were performed using Idrisi Kilimanjaro software (Eastman, 2006). The neural network was trained in IDRISI Kilimanjaro (Clark Labs), using a highly popular supervised method known as multi-layer perceptron (MLP), run in hard classification mode. The MLP classifier is based on the back-propagation algorithm (Haykin, 1999). Furthermore, in order to classify earthquake zones on the map, we applied the ANNs classifier of the IDRISI Kilimanjaro software

(Eastman, 2006). Since the IDRISI software works with raster layers all polygon-based vector format layers had to be converted to create the final map.

In the next phase, all raster layers were exported into the IDRISI software, and we performed the analysis steps needed for the AHP model using the weight tool. At this stage, the relative importance of criteria in relation to their importance in the process of modernization priorities will be performed based on expert opinions and their relative importance of criteria in the weighting matrix.

3.7.4 Implementing the MLP Neural Network Model

The aim of the ANN computing is to build a new model of the data generating process so that it can generalize and predict outputs from inputs (Atkinson and Tatnall, 1997). If the model result is larger than the threshold, the Percepron output is 1 otherwise the output is -1. Our model had 13 input variables in the input layer, 1 hidden layer including 8 neurons, and 5 output layers. This model outcompeted other models based on the highest R^2 and lowest RMSE, indicating that predicted and actual indices are closely aligned.

The numbers of nodes of the hidden layers were calculated by the following equation (Eastman, 2009):

$$N_h = \text{INT} (\sqrt{N_i \times} \; N_0 \qquad (11)$$

In Equ.11, N_h is the hidden layer, N_i the input layer and N_0 the output layer. Table 3 illustrates the amount and manner of entry of effective parameters in the model implementation process.

The raster map that resulted from the FAHP-ANN method was converted to a vector format in the GIS environment, and finally the dissolve function was administered to calculate earthquake vulnerability of Sanandaj City (Table 4). Sanandaj was broadly classified into five zones, namely, very high, high, moderate, low, and very low classes describing the likelihood of future earthquakes.

Caption 11:

Please insert Table 3 here:

4. Results

In Fig. 9 we present the earthquake vulnerability maps based on the 13 earthquake vulnerability criteria using different modelling techniques for the map production. We present three different maps here as they were needed to validate the results, as described in the next section. Sanandaj City has been broadly classified into the five vulnerability zones. All maps show that the zones of increased vulnerability are mainly situated in the urban areas of Sanandaj City which is in accordance with historical earthquake observations (Karimi, Boussauw, 2018).

Caption 12:

Please insert Figs. 9 here:

Zones 1 and 2 are the high-risk zones for future earthquakes in Sanandaj. The earthquake prone zones are located in the vicinity of the active faults of Morvarid, Nahavand and Sanandaj-Sirjan, the latest being the closest fault at a 3 km distance from the city.

Most parts of the city are located in low and medium vulnerability classes. Highly vulnerable areas are distributed among Zone 1 and 2 of the city. The highest seismic vulnerability occurring in Zone 1 is due to the higher number of buildings in this district as this is the oldest part of Sanandaj. Also, in Zone 1, population numbers are the greatest, which increases the chance for human casualties in case of an earthquake. The most prevalent type of housing structure in the city of Sanandaj is masonry brick, decreasing in building height from Zone 1, 3, to 2. Over 60% of the buildings in Zone 1 and 2 are made of masonry bricks, mostly constructed without considering seismic regulations. Reconstructing buildings in these areas based on careful planning is necessary in the future, especially as there are few high-quality steel and concrete buildings; and where they exist they are of a low-quality construction, not adhering to building codes which needs to be addressed in the future. The validity of the results is supported by previous studies by Alizadeh et al. (2018a), Umar et al. (2014) and finally Jena et al. (in press) who also presented earthquake vulnerability maps. Our hybrid framework delivered useful results to evaluate a city's vulnerability dimensions, and to inform preparedness strategies in the future.

4.1 Validation

The overall aim of the FAHP-ANN model was to make sure that a trained ANN model works without known flaws and can be confidently used. Validation of the results was examined by converting the vulnerability map to a probability map (refer to Mohammady et al., 2012; Pradhan et al., 2014; Tehrany et al., 2014; Aghdam et al., 2016; Tien Bui et al., 2016b; Fanos and Pradhan, 2019). ~~The trained earthquake probability map was presented with five different classes to recognize various zones of probability, as shown in Fig. 10.~~

In this section, two validations were used that are effective in assessing the sensitivity of models to earthquake vulnerability. First, by analyzing the degree of consistency between the maps obtained from the FAHP, AHP and FMLP hybrid models. These were evaluated according to the validation points selected from the five F-AHP map classes (see Fig. 10). Subsequently, we randomly compared a number of points in the high-vulnerability spectrum on the FAHP hybrid model and the FMLP hybrid model where the points on both maps are in common spectra. In the next phase of validation, the receiver operating characteristic (ROC) curve was used to evaluate the sensitivity of the models to seismic vulnerability (Yariyan et al., 2019). Fig. 11 depicts that the curve can show a comprehensive relationship between the true positive value (TPR) and the false positive value (FPR) for seismic vulnerability. In this curve, the AUC is a measure of the accuracy of the susceptibility to seismic vulnerability. The area under the curve (AUCs) shows that more accurate pixels represent the scene than inaccurate pixels. According to the results, the FMLP hybrid model has good accuracy amounting to a value of 0.930. If the AUC is equal to 1, it indicates perfect prediction accuracy (Pradhan and Lee 2010c).

The MLP model results in a hard and soft classification. In the classification the resulting map, each pixel belongs to a specific class. The value of the sigmoid function was introduced in Eq. 8, 9, and 10. Also, an ideal accuracy of 95% was introduced to stop the operation if 90% accuracy was observed in the output.

An AUC value of >0.8 indicates that the performance of the model is good (Chen et al., 2017, Tien Bui et al., 2016b; Tien Bui et al., 2016c). The result of the combined F-AHP model and the FMLP combination model in the study area is presented in Fig. 10.

Caption 13:

Please insert Figure 10 here:

Averaging all ROC curves and comparing TPR with FPR generates an optimum threshold which at its best will produce a saliency map with maximum sensitivity and minimum fall out rate. Calculated AUC values from the ROC curves are presented among the results in Fig. 11.

Caption 14:

Please insert Figure 11 here:

According to Fig. 11, the receiver operating characteristic (ROC) curve was used to evaluate and compare the classification models (Bradley 1997). As a graphical plot ROC shows the performance of a binary classifier system while the discrimination threshold is varied (Bradley 1997). The sensitivity or true positive rate (TPR) is defined as the percentage of seismic records which are correctly identified in terms of seismicity. As plotted in Fig. 11, sensitivity, which is also called the true positive rate (TPR), and the false positive rate (FPR), that was obtained for Sanandaj City were on average 0.93 and 0.07, respectively. Thus each time we call it a positive; there is a 7% probability that we obtain this specific probability of being wrong. The graphical representation of accuracy is presented in Fig. 11.

4.2 The amount of vulnerability based on population and area

~~In order to more accurately understand what is affected by an earthquake in terms of area and population, it is necessary to calculate the percentage of that.~~

Sanandaj City population data per municipality zone was used for assessing the impact of the population vulnerability (PV) in various zones of Sanandaj City, as illustrated in Fig 12.

This information is highly relevant for informing crisis management. Fig. 12 shows the steps for calculating the 'amount' of vulnerability by applying the population and area software functions of ArcGIS 10.4.

Caption 15:

Please insert Figure 12 here:

The details of population in risk, vulnerability classes, area, and corresponding percentages are presented in Table 4.

Caption 16:

Please insert Table 4 here:

As can be seen in Table 4, the greatest percentage of land was classed as high risk covering 28.28% of the city. In addition, as can be seen in Table 4, 25.39% of the city was under very high risk. High, moderate, low, and very low-risk zones represent 28.28%, 22%, 12.88%, and 11.45% of the total area, respectively.

5. Discussion and conclusions

In this research, a novel hybrid model of FAHP-ANN was developed for earthquake risk assessments (ERA), in the context of a case study of Sanandaj City, Iran. The modelling was coupled with a GIS-based spatial analysis useful for the regional scale. A literature review helped in identifying earthquake vulnerability criteria incorporating knowledge about demographic, environmental and physical criteria. These in conjunction with historical earthquake data enabled us to produce an earthquake risk map for the city. The ANN method helped determine earthquake probability measurements, while the AHP method helped with the weight calculation of the parameters for the earthquake vulnerability assessment. The ranks and weights were assigned by experts in the field. Given that the root mean square error (RMSE) was very low, the ANN model has a high chance for correct interpretation.

The geological earthquake vulnerability criteria, forming part of the environmental criteria, had the highest impact on the earthquake probability assessment in Sanandaj. ~~whereas demographic factors contributed the most for the vulnerability assessment of Sanandaj.~~ However, the importance of different criteria varied in different zones of Sanandaj. The highest risk zones were clustered in the northern part (Zone 1) of the city. The other parts were exposed to low-to-moderate earthquake risk. Developmental infrastructure plans show that the city is expanding towards the South with various schools, universities, and informal settlements located in the vicinity of the fault. Growing towards the fault may cause serious problems for the city in the future. If the same planning and building mistakes made in Zone 1 are repeated here where the natural risk is increased due to the proximity to the fault, many people and structures will be at great danger. The highest population density coincides with building density in zones 1, 2 in very highly vulnerable zones for earthquakes. Government offices and the main transportation junctions here are under great threat and earthquakes here could quickly impact on all areas of the city as they depend on the critical services provided in these zones. This demonstrates that local earthquake effect have wide-spread repercussions for the city as a whole.

It is obvious from these results that Sanandaj City urgently requires a reassessment of the strategies for managing natural disasters, not the least because the 2017-2018 earthquakes showcased serious consequences. Appropriate policies are needed to manage the city and inform decision-makers on vulnerability factors and the unique deficiencies of each zone and the locations where to prioritise. Zone 3 for instance is not yet as vulnerable and priorities may need to be given to Zone 1 to reassess existing structures and relief plans addressing the high population density. However with planned expansions to Zone 3, forward planning is needed to avoid issues prevalent in Zone 1. The critical condition of buildings and high population density in high risk zones should be closely monitored by the government, and programs of risk reduction be improved. Lack of managing more even population distributions across the city and poor city development planning are the main issues to address to proactively manage risk in the future.

This study aimed at developing a user-friendly geographic information system (GIS) tool coupled with a novel FAHP-ANN model that provides an effective and practical estimation of ERA. This technique can become an important tool for city planning, thereby confronting crises resulting from future earthquake incidences. This is supported by related works of Nazmfar (2019), Ningthoujam and Nanda (2018), Moradi et al. (2015), Zamani et al. (2013) and Sarris et al. (2010). The hybrid FAHP-ANN model filled spatial gaps in a map that are now fully covered because of using a combination of three main earthquake vulnerability criteria groups including demographic, environmental and physical criteria (Cardona et al., 2012; Pelling and Wisner, 2012). By comparing the F-AHP and F-MLP maps, the final map of the F-AHP is derived from the AHP weight. Interestingly, The F-AHP map pinpoints precisely the same areas as highly vulnerable. This is reflected in the FMLP model, which indicates a high accuracy in weighting, and in the selection of training points, and in the implementation of the ANN.

The major drawback of the FAHP-ANN technique is the time-consuming model development and implementation because the ANN training requires a large amount of training data (Dahmani et al., 2014). The key limitations specific to our study situation included a lack of high-quality infrastructure data and long processing times.

The developed hybrid framework of the FAHP-ANN model is easily replicable elsewhere for urban management. Hence, future scenarios may include the application of artificial intelligence technique or a 3D city model. Future research also should concentrate on the use of more intelligent analysis such as back-propagation neural networks, probabilistic neural networks, supervised associating networks, multi-layer perceptron neural network architectures, genetic algorithms, support vector machine and multi-layer neural networks. Neural networks will provide a better performance in tackling diverse and complex challenges of life. In the future, more attention should be afforded to conducting research for ERA and multi-criteria analysis using the predication and accuracy algorithms for incremental updates. Accordingly, in our future work we will focus on evaluating our technique for ERA on large multi-criteria datasets to show how it can overcome the scalability drawback of traditional and multi-criteria analysis.

Finally, the integration of the FAHP-ANN and GIS applications for earthquakes serves as a framework that has potential application in other disaster contexts such as extreme geological, hydrological and meteorological events with devastating effects for landscapes, humans and infrastructures.

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Statistical Center of Iran (2017). National Census, 2017. Tehran.

Caption 1:

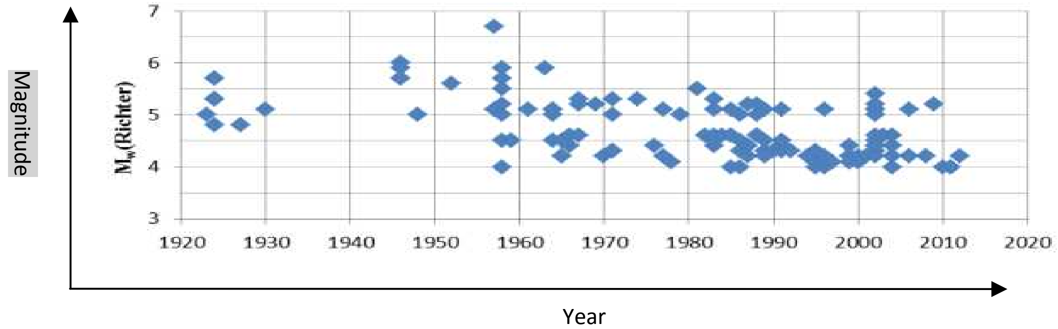


Fig. 1. Earthquakes in a 150 km radius around Sanandaj City between 1920 and 2014 (Institute of Geophysics University of Tehran, IGUT. http://irsc.ut.ac.ir).

Caption 2:

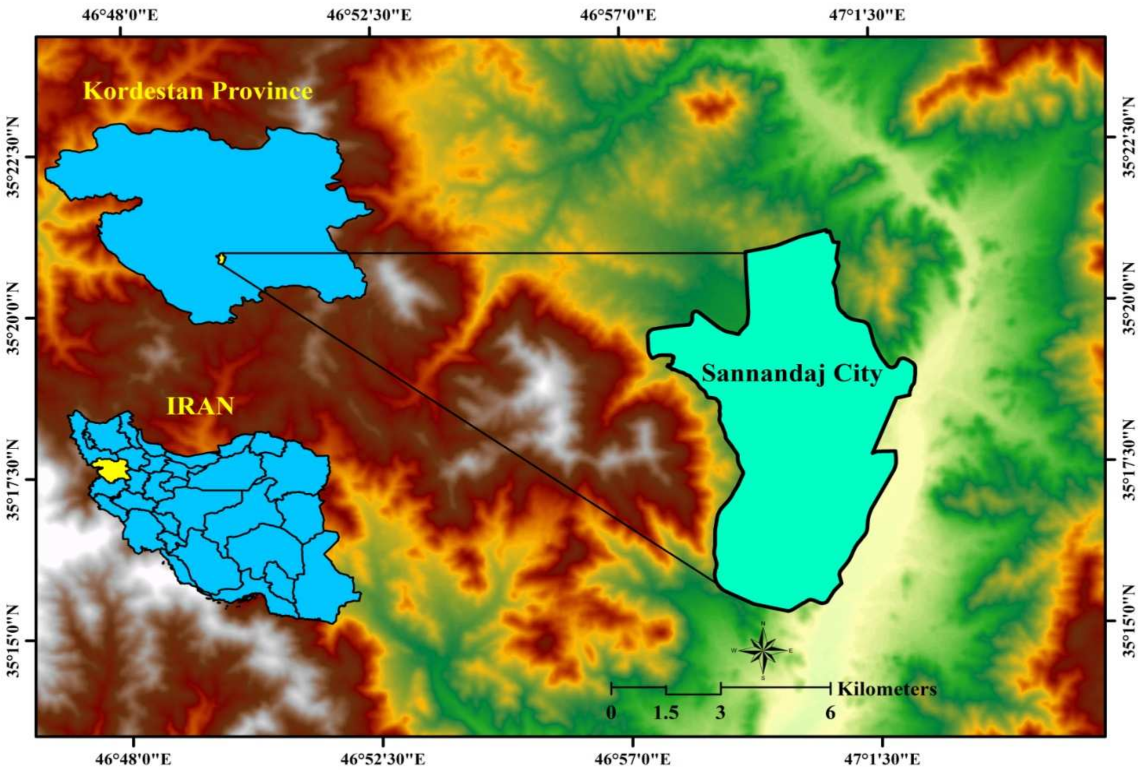


Fig. 2. The case study area's geographical location (Sanandaj City, Iran).

Caption 3:

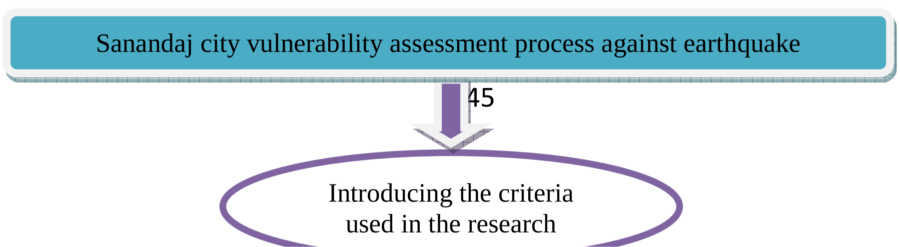


Fig. 3. Conceptual framework of the ERA based on a hybrid FAHP-ANN model.

Caption 4:

Table 1. Criteria selected for an earthquake vulnerability assessment of Sanandaj City.

Criterion	Layer	Up/ Down	AHP first weight	Source	Scholars
Environmental	Distance from the runway	0 – 3930 m	4	1	(Alizadeh, 2018 a,b; Raj Meena, 2019)
	Distance from fault	0 – 6030 m	9	1	
	Slope	0 – 50 %	6	2	
	Elevation	1370 – 1720 m	5	2	
	Geology		7	3	
Physical	Building with quality materials	0 - 152930	6	4	(Babayev et al., 2010; Ahadnezhad Reveshty, 2014; Meslem and Lang, 2017)
	Building with no quality materials	0 - 16977	6	4	
	Distance from the road network	0 – 1390 m	7	1	
	Building area	4 – 29950277 m	7	4	
	Number of floors	0 – 5	7	4	
	Land use	-	8	4	
Demography	Population density	0 – 444 per hectare	9	5	(Beck et al., 2012; Dou et al., 2015)
	Family density	0 – 114 per hectare	6	5	

Data sources: Department of road and Urbanity (Kurdistan Province). http://www.std2800.ir/, 2. DEM 30 m Landsat. https://www.usgs.gov/, 3. Iranian Geological organization. https://gsi.ir/, 4. The municipality of Sanandaj City. http://www.Sanandaj.ir, 5. Census Center of Iran. http://www.amar.org.ir/.

Caption 5:

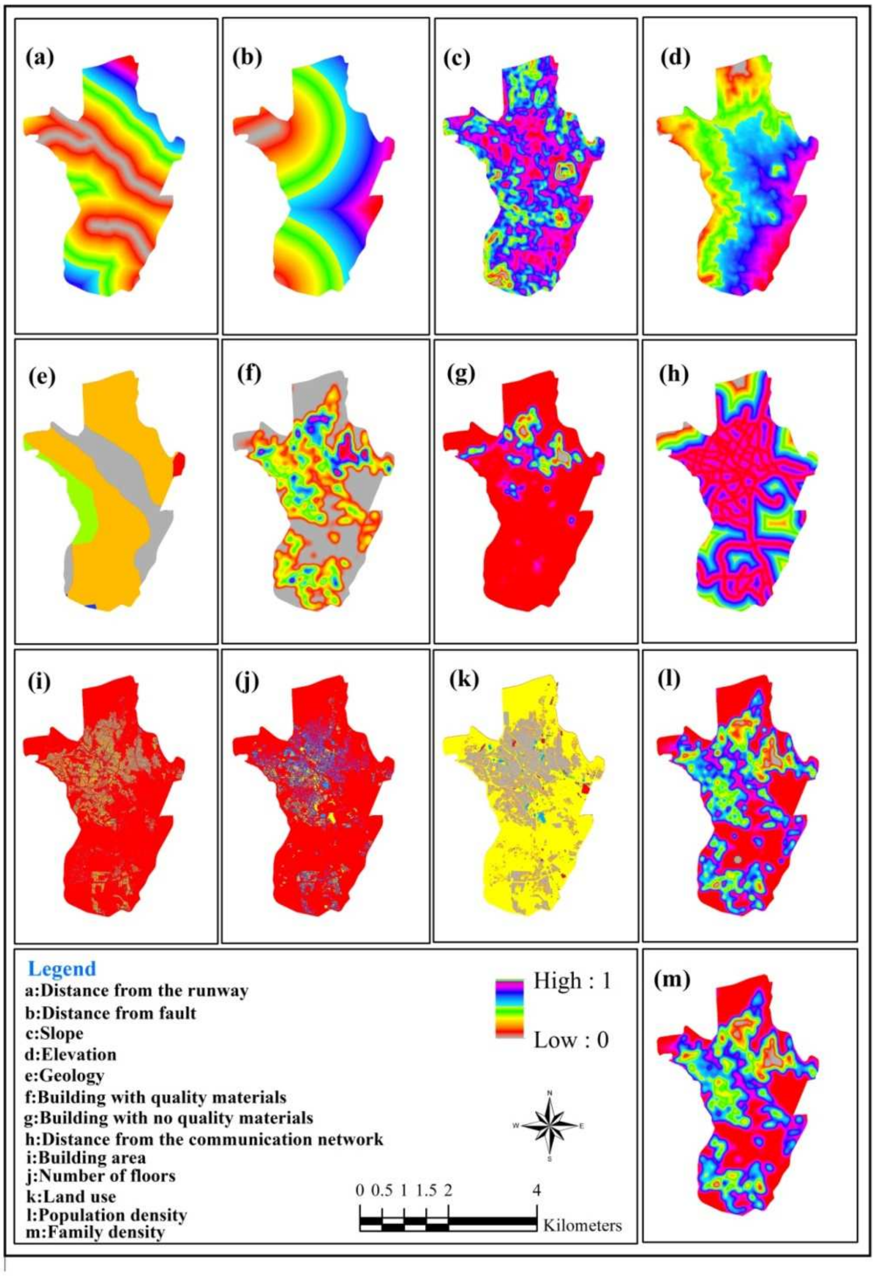


Fig. 4. Standardized vulnerability criteria layers used for building the FAHP-ANN as part of an earthquake risk assessment for Sanandaj City, Iran.

Caption 6:

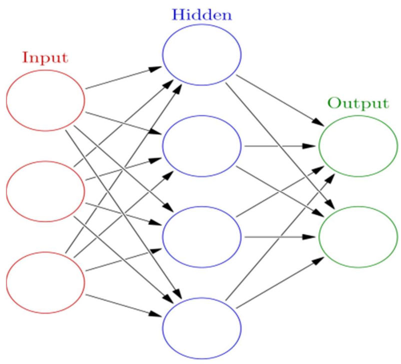
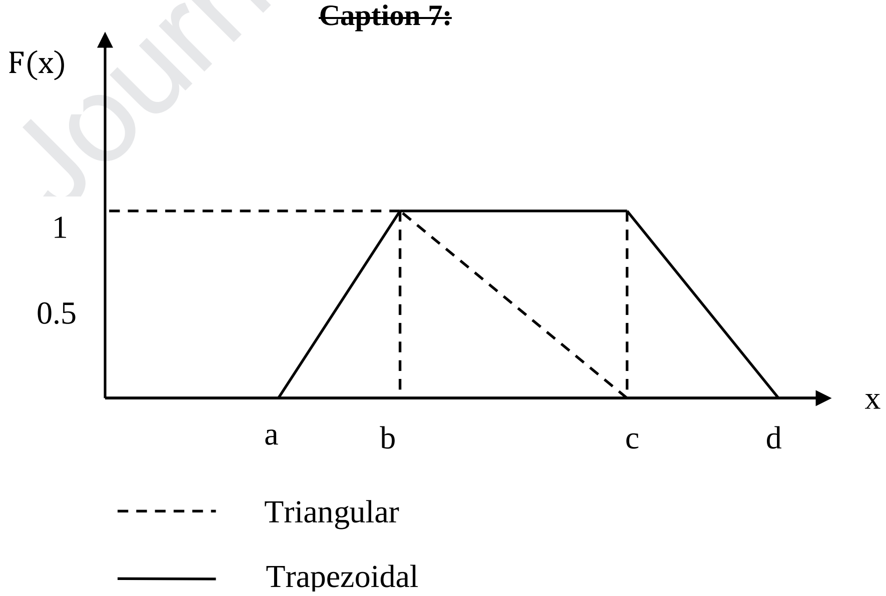


Fig. 5. Fuzzy triangle representation graph.

~~**Caption 7:**~~



~~**Fig. 6.** Neural network structure.~~

Caption 8:

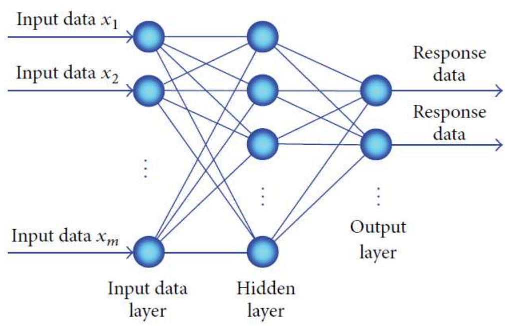


Fig. 7. ANN Multilayer perceptron (MLP) (Sušanj et al., 2016).

Caption 9:

Table 2. The importance of the criteria used in the MLP neural network.

Criterion	Layer	AHP Final weight
Environmental	a. Distance from the runway b. Distance from the fault c. Slope d. Elevation e. Geology	0.36
Physical	F. Building with quality materials g. Building with no quality materials h. Distance from the communication network i. Building area j. Number of floors k. Land use	0.47
Social	l. Population density m. Family density	0.17

Caption 10:

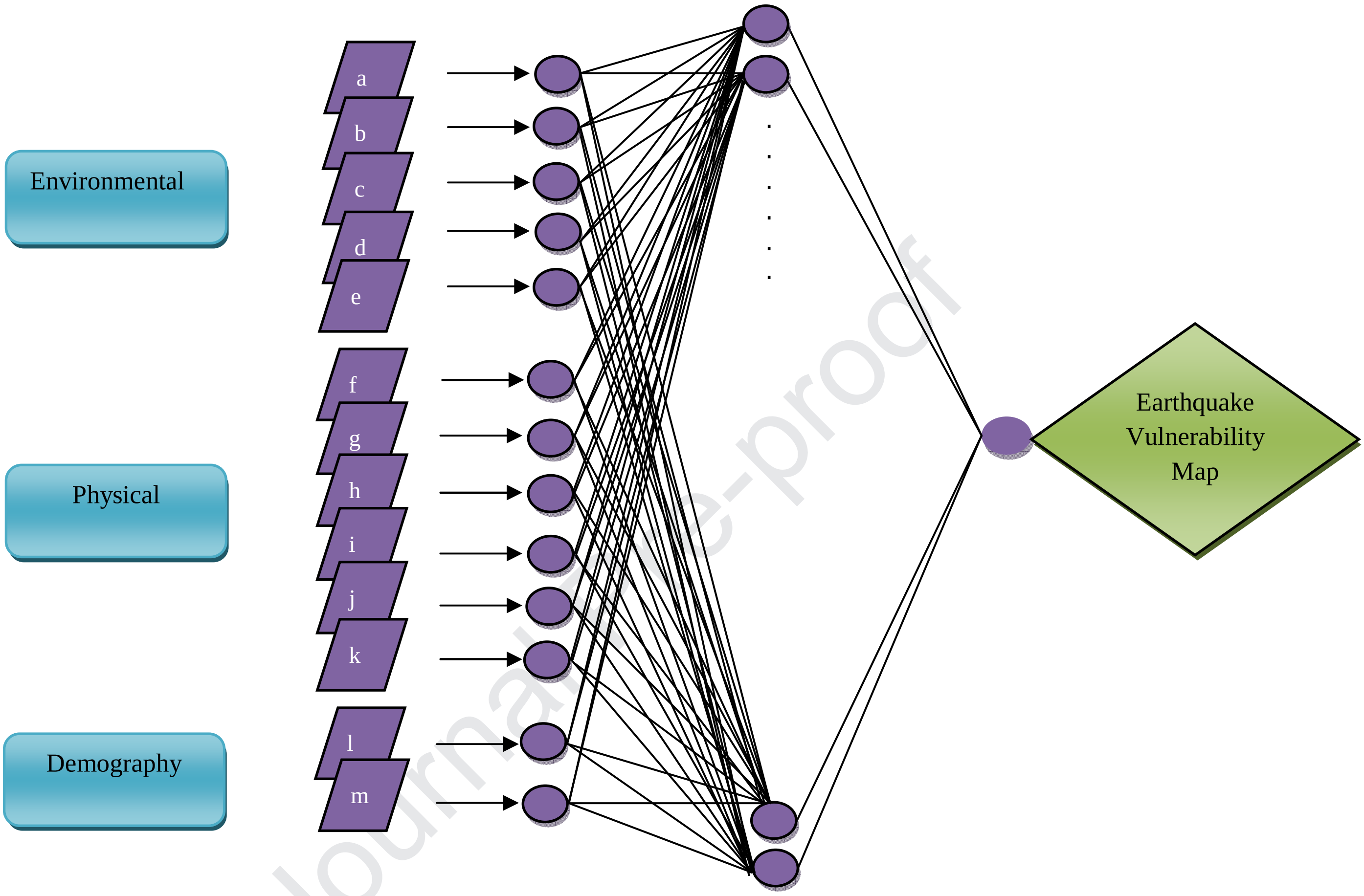


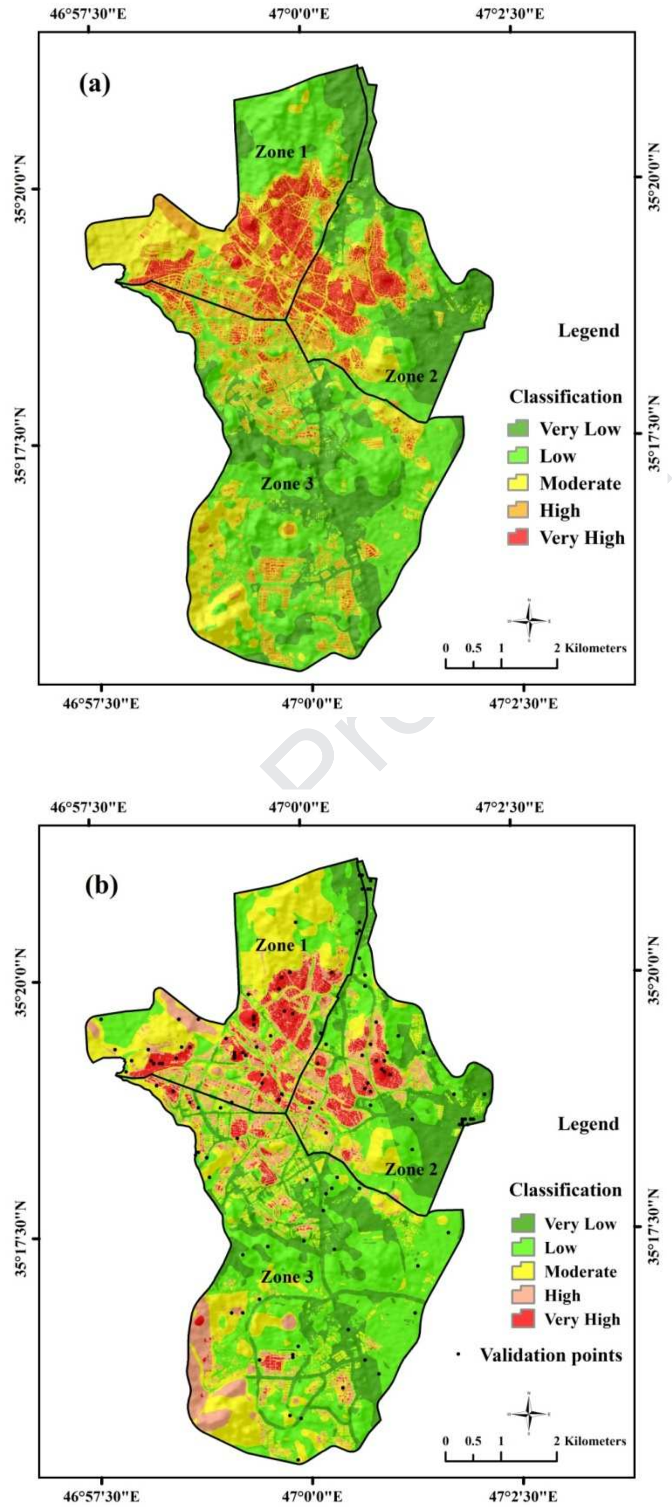
Fig. 8. Artificial Neural Network MLP architecture used in this study.

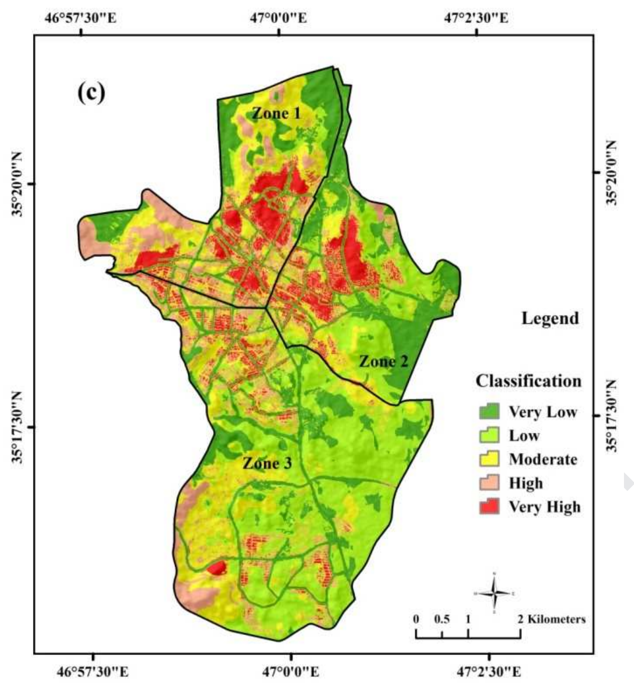
Caption 11:

Table 3. Input parameters for implementing the MLP model.

Parameters	**Application type**	**Classification**
Input specifications	Avg. training pixels per class	500
	Avg. training pixels per class	500
Network topology	Hidden layers	1
	Nodes	8
	Input Layers Node	13
	Output Layer	5
Training parameters	Automatic training dynamic	Yes
	Dynamic learning rate	Yes
	Start learning rate	0.001
	End learning rate	0.0056
	Momentum factor	0.5
Stopping criteria	RMSE	0.1455
	Iterations	10000
	Accuracy rate	95

Caption 12:


46°57'30"E
47°0'0"E
47°2'30"E
35°20'0"N
35°17'30"N
(a)
Zone 1
Zone 2
Zone 3
Legend
Classification
Very Low
Low
Moderate
High
Very High
0 0.5 1 2 Kilometers
(b)
Zone 1
Zone 2
Zone 3
Legend
Classification
Very Low
Low
Moderate
High
Very High
Validation points
0 0.5 1 2 Kilometers



Figs. 9. Earthquake vulnerability of Sanandaj City, Iran, according to three different models: (a) analytical hierarchy process (AHP), (b) fuzzy-AHP (F-AHP), and (c) Hybrid Model F- Multilayer Perceptron (F-MLP).

Caption 13:

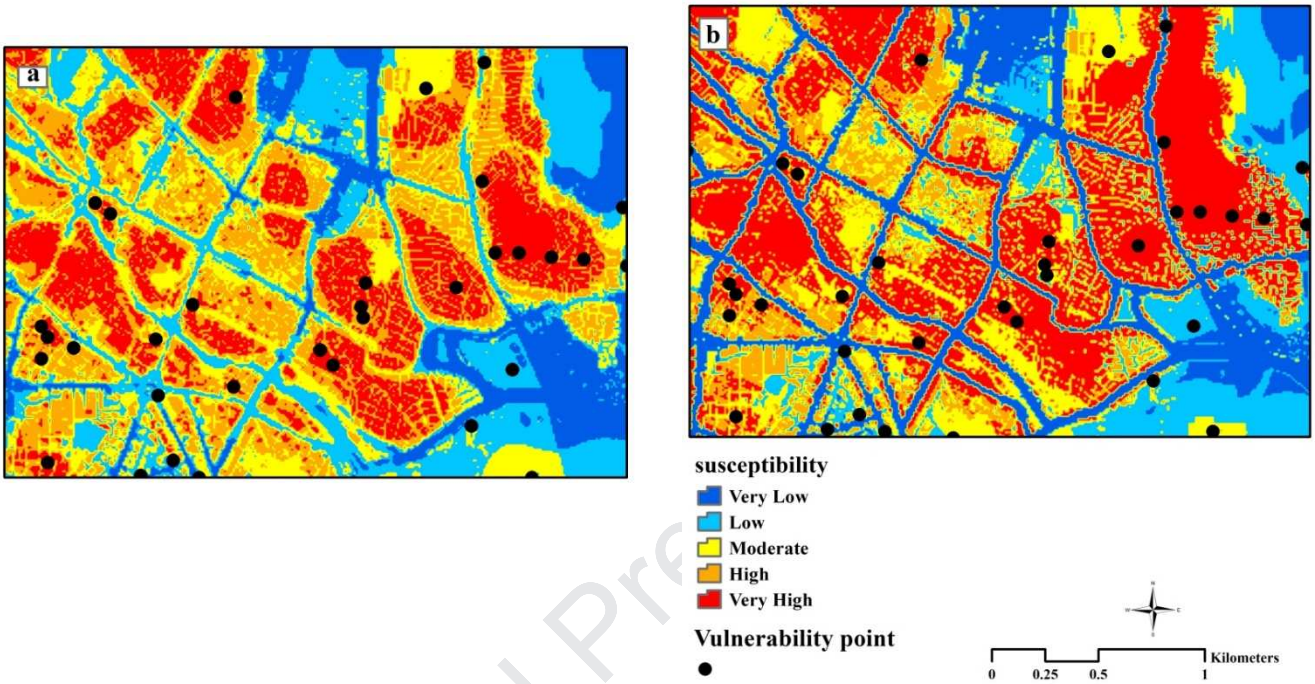


Fig. 10. Comparison of the performance of two susceptible seismic vulnerability points (training site) in Sanandaj City in Iran. (a) the combined F-AHP model; (b) the F-MLP combination model.

Caption 14:

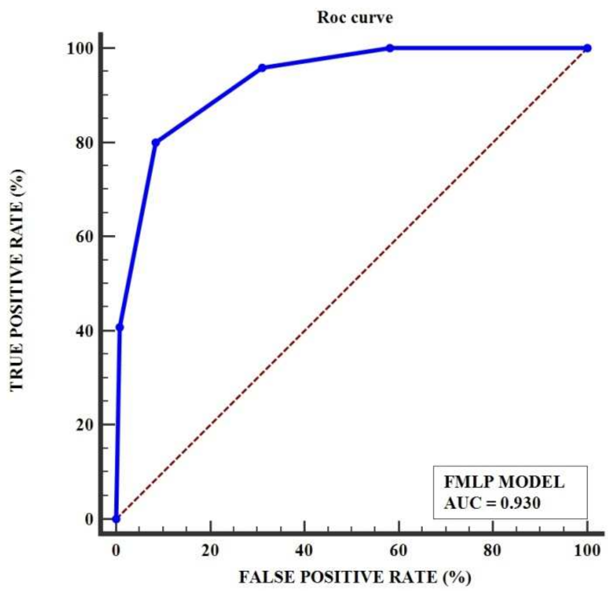


Fig. 11. Curve specifications (ROC) to demonstrate the success of the analytical model.

Caption 15:

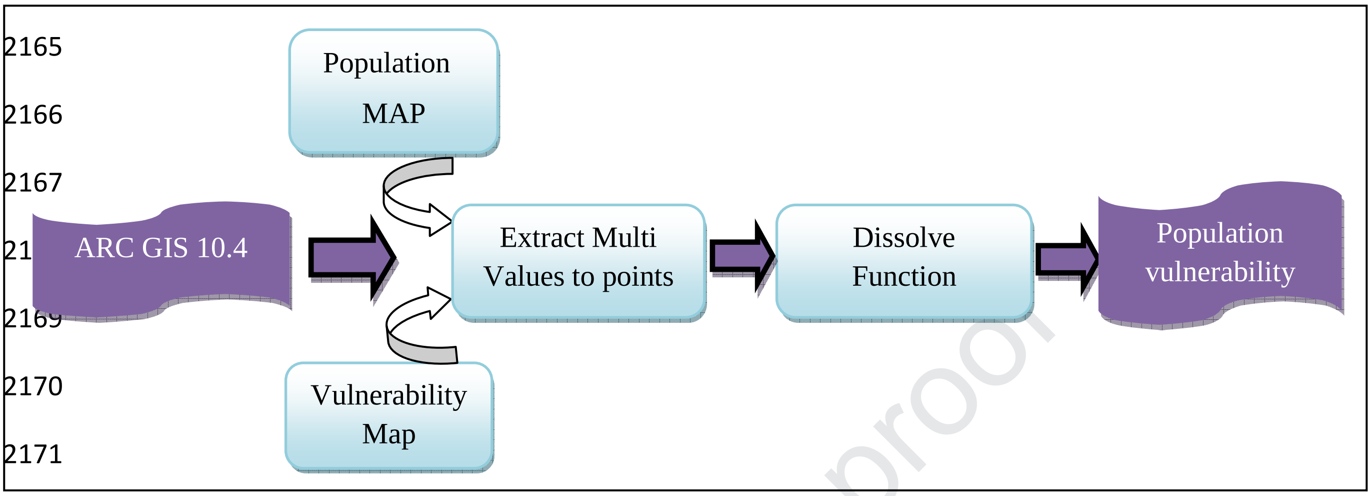


Fig. 12. The process of calculating population vulnerability.

Caption 16:

Table 4. Sanandaj City's vulnerability to earthquake based on population at risk, and affected number of families and area

Vulnerability class	Percentage	Population at risk	Number of Families	Area (m^2)
Very High	25.39	15415	4596	10728300
High	28.28	45162	13772	11949800
Moderate	22	75592	22513	9297200
Low	12.88	67818	21322	5445600
Very Low	11.45	130846	41564	4837900

- An integrated model by combining FAHP-ANN to produce an earthquake risk map is proposed.
- The model is applied to the city of Sanandaj in Iran, a seismically active Sanandaj-Sirjan zone (SSZ).
- The developed model can be considered as a significant tool through multiple parameters.
- The proposed model can produce the earthquake probability map with an accuracy of 95%.
- The FAHP-ANN hybrid model is effective for earthquake vulnerability map.