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An integrated approach of analytical network process and fuzzy based spatial decision making systems applied to landslide risk mapping

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ABSTRACT

Landslides in mountainous areas render major damages to residential areas, roads, and farmlands. Hence, one of the basic measures to reduce the possible damage is by identifying landslide-prone areas through landslide mapping by different models and methods. The purpose of conducting this study is to evaluate the efficacy of a combination of two models of the analytical network process (ANP) and fuzzy logic in landslide risk mapping in the Azarshahr Chay basin in northwest Iran. After field investigations and a review of research literature, factors affecting the occurrence of landslides including slope, slope aspect, altitude, lithology, land use, vegetation density, rainfall, distance to fault, distance to roads, distance to rivers, along with a map of the distribution of occurred landslides were prepared in GIS environment. Then, fuzzy logic was used for weighting sub-criteria, and the ANP was applied to weight the criteria. Next, they were integrated based on GIS spatial analysis methods and the landslide risk map was produced. Evaluating the results of this study by using receiver operating characteristic curves shows that the hybrid model designed by areas under the curve 0.815 has good accuracy. Also, according to the prepared map, a total of 23.22% of the area, amounting to 105.38 km^2, is in the high and very high-risk class. Results of this research are great of importance for regional planning tasks and the landslide prediction map can be used for spatial planning tasks and for the mitigation of future hazards in the study area.

1. Introduction

Landslides as a type of mass movements involve slow or fast movement of soil and stone materials, or both on the slopes downwards, under the force of gravity (Crosta and Clague, 2009). Landslides are known as one the most common geological disasters which cause damages and casualties worldwide (Bianchini et al., 2016; Bui et al., 2012; IGOS, 2004; Shahabi et al., 2014; Wang et al., 2016). While landslide occurrences include 9% of all natural disasters in the past decade, it is expected that this trend will increase in the coming years, due to the development of urbanization, deforestation and climate change (Yilmaz, 2009; Zare et al., 2013). The damaging effects of landslides include loss of life, rapid soil loss, and degradation of agricultural lands, gardens, roads, and engineering structures (Hassanzadeh Nafuti et al., 2012). Given the extent of the damages mentioned, it was explicitly stated that the cost of studying this phenomenon is much less than the damage. Therefore, to understand the susceptibility of hill slopes, landslide risk zones in different regions are addressed (Shadfar et al., 2007). Landslide susceptibility has been defined as the probability of a landslide occurring in a region based on local terrain conditions (Brabb, 1984; Ciampalini et al., 2016). Zoning and preparation of a landslide susceptibility map is a complex process (Brabb, 1991; Chen et al., 2016) that shows possible and sensitive areas to landslides through some effective factors by generalizing the occurrence of slope failures (Akgun, 2012; Van Westen, 2000). Landslide susceptibility maps provide important and valuable information for predicting landslides hazards which include an indication of the time scale within which particular landslides are likely to occur in the future (Atkinson and Massari, 2011).

In light of GIS based landslide risk mapping, the multicriteria decision analysis (MCDA) methods provides a rich collection of procedures and techniques for structuring decision problems and designing, evaluating and prioritizing alternative decisions (Feizizadeh and Blaschke, 2014; Feizizadeh and Kienberger, 2017). MCDA has been widely applied to support environmental planning processes, where MCDA can provide a transparent combination of a

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problem from different perspectives and a systematic assessment of the alternatives (Huang et al., 2011; Keisler and Linkov, 2014; Kiker et al., 2005; Mustajoki and Marttunen, 2017; Voinov et al., 2016). There has been a vast body of research around the world on evaluation of landslide mapping based on GIS-MCDA methods (Feizizadeh and Blaschke, 2013; Feizizadeh et al., 2014a, 2014b). The GIS-MCDA methods and models used by researchers to prepare a landslide risk map are the analytical network process (ANP) (Abedi Gheshlaghi et al., 2016; Neaupane et al., 2008; Neaupane and Piantanakulchai, 2006; Roostaei et al., 2015), fuzzy methods (Anbalagan et al., 2015; Bibi et al., 2016; Bui et al., 2015; Pourghasemi et al., 2012; Tangestani, 2009; Vakhshoori and Zare, 2016), neuro-fuzzy hybrid methods (Aghdam et al., 2016; Dehnavi et al., 2015; Pradhan, 2013; Vahidnia et al., 2010), and logistic regression (Ayalew and Yamagishi, 2005; Bui et al., 2016; Demir et al., 2015; Devkota et al., 2013; Sangchini et al., 2016; Umar et al., 2014).

The ANP is one of the GIS-MCDA methods, which has been successfully applied to many decision maker systems. Even though, the ANP is well known approach in GIS-MCDA domain, the method face error for its inability to adequately handle the inherent uncertainties and imprecisions associated with expert based criteria ranking and evaluating the decision-maker's perception to crisp numbers. In order to deal with this issue, the ANP can be integrated with fuzzy logic methods to provide a framework for minimize the inherent uncertainty and making use the advantages of fuzzy membership functions (FMFs) for assessing criteria weights and improving the reliability of the results (Feizizadeh et al., 2014b). Technically speaking, fuzzy set theory employs the membership function which represents the degree of membership value with respect to a particular attribute of interest. Within this process, the attribute of interest is generally measured over discrete intervals and the membership function which respectively inscribed as a table relating map classifications to fuzzy membership values (Pradhan, 2011a, b). It is widely known that fuzzy is straightforward to be understood and implemented. In addition, this method so far has been successfully integrated into a number of GIS-MCDA. The integration of GIS-based MCDA and fuzzy set theory has applied to model imprecise objectives in a variety of research areas (Aydin et al., 2013; Chang et al., 2008; Feizizadeh et al., 2014b). Review of the research background indicated that most published research has used the ANP and fuzzy logic as a single method. Some researchers also compared results of fuzzy based GIS-MCDA with traditional approaches to get better and more accurate in results (Feizizadeh et al., 2014b; Malmir et al., 2016; Razavi Toosi and Samani, 2016; Valmohammadi et al., 2016). By considering the results of early researches, in the reminder of this article, we aim to apply GIS based Fuzzy-ANP for landslide risk mapping and improves the accuracy of the results while measuring and minimizing the uncertainties associated with the traditional ANP methods. Therefore, the purpose of this study is to devolve landslide risk mapping by applying a combination of two models of the ANP and fuzzy logic to identify high-risk areas as well as to take preventive measures to avoid or reduce landslide risks in the Azarshahr Chay basin which is highly susceptible for landslide risk.

2. Material and methods

2.1. Study area

The Azarshahr Chay basin is one of the sub-basins of Sahand that is located in geographic coordinates of 37°37′ to 37°48′ north latitude and 45°49′ to 46°20′ east longitude. The basin with an area of 453.93 km^2 is in east Azerbaijan Province. This basin is surrounded by the Azarshahr, Osku, and Ajab Shir Counties. Its maximum altitude is 3300 m and the minimum altitude is 1239 m above sea level. The Azarshahr River is the main river of this basin (Fig. 1). This area is one of the drainage basins of the Sahand Mountain because of its steep slopes, non-consolidated soil and surface materials, lack of full-scope protection by vegetation, and active different processes over the year. Unprincipled manipulation by humans in recent decades has made it as one of the areas prone to mass movements (Bayati khatibi et al., 2011). Landslides are common in the Azarshahr Chay basin, and the complexity of the geological structure in the associated lithological units, comprised of several formations, causes volcanic hazards, earthquakes, and landslides (Feizizadeh and Blaschke, 2014). A landslide inventory database for the East Azerbaijan Province lists 79 known landslide events (Feizizadeh et al., 2013a; MNR, 2010). The area's geology is very complex and the lithological units comprise several formations causing volcanic hazards, earthquakes and landslides. This geophysical setting makes slopes of this area potentially vulnerable to landslides and mass movements such as rock fall, creeps, flows, topples and landslides (Alayi Taleghani, 2009; Feizizadeh et al., 2013b) According to Feizizadeh and Blaschke (2013) and lithological units and as well as the field observations statements, most of the landslide event can be considered as rotational landslide.

2.2. Dataset

In this research, for landslide risk mapping by literature review, data on field studies and expert opinions in this field relating to factors affecting the landslide including slope, slope aspect, altitude, lithology, land use, vegetation density derived from normalized density of vegetation index (NDVI), rainfall, distance to fault, distance to roads, and distance to rivers determine has been collected (Fig. 2). These data include geological maps of 1:100,000 scale, topography maps of 1:25,000 scale, the map of land capability of East Azerbaijan province, digital elevation model (DEM) obtained from SRTM with a resolution of 30 m, 10-year climatic data (2005–2015) of the Iranian meteorological organization related to the Tabriz, Sahand, Ajabshir, Bonab, and Maragheh stations along with eight Landsat satellite images in 2016.

The above-mentioned dataset was processed by using the software ENVI and ArcGIS to create and convert as criteria for input of GIS based Fuzzy-ANP models. Hence, for layers of slope, slope

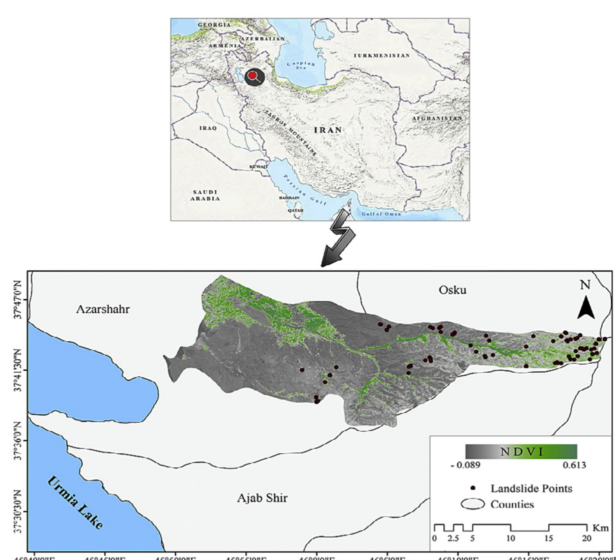

Fig. 1. Location of the study area and distribution of landslide points.

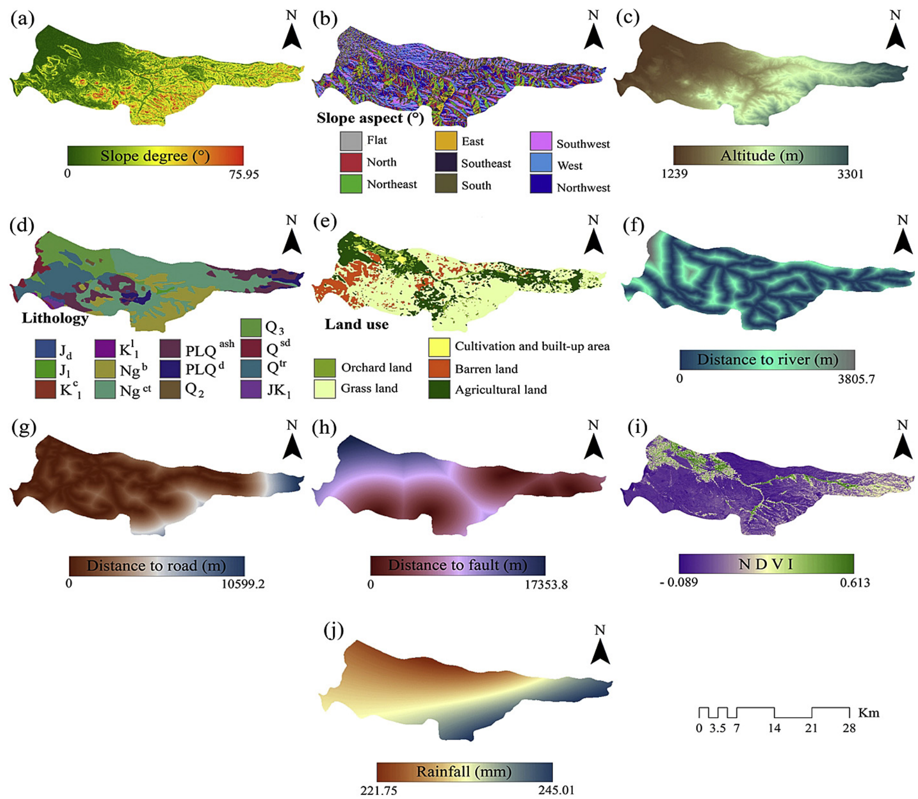

Fig. 2. Landslide conditioning factor maps (a) Slope degree; (b) Slope aspect; (c) Altitude; (d) Lithology; (e) Land use; (f) Distance to river; (g) Distance to road; (h) Distance to fault; (i) NDVI; and (j) Rainfall.

Table 1
Lithology of the Azarshahr chay basin.

Lithological units code	Description
Q^{sd}	Salt-clay deposits
Ng^{ct}	Tuff breccia with intercalations of Conglomerate and sandstone
PLQ^{ash}	Volcanic ashes with block, lahar and welded breccia (Pelean)
PLQ^{d}	Dacitic andesite
Q^{tr}	Travertine
Q_2	Old terraces and alluvial fan deposits
Ng^{b}	Volcanic breccia with pyroxen andesite
Q_3	Young terraces and alluvial fan deposits, locally including cultivated
J_l	Limestone and dolomitic limestone
J_d	Lightgrey to whitish, thin to thick-bedded ammonite and belemnite bearing argillaceous limestone (Dalichai Formation)
K^{l}_{1}	Grey to dark grey. orbitolina bearing, argillaceous-limestone and limestone
JK_{1}	Yellow brecciated limestone and light-grey massive limestone (Lar Formation)
K^{c}_{1}	Red conglomerate, sandstone and siltstone

aspect, and altitude classes images of DEM with a resolution of 30 m have been used; for land use layer mapping, land capability in east Azerbaijan province and topographic maps have been used; for the layer of lithology, geological maps (Table 1) have been used; for the layer distance to fault, distance to roads, and distance to rivers, topographic maps have been used; and for the rainfall layer, climate data of the country's meteorological organization has been used; and to convert point data to surface data and raster mapping, the kriging interpolation method has been applied for more accuracy than other interpolation methods.

To prepare a layer of vegetation, the vegetation index NDVI was applied. This index is one of the simplest and most frequently used indices in the study of vegetation. For this to happen, bands four and five of Landsat 8 satellite images have been used. Values of this index lie between +1 and −1. Negative values indicate water areas; near-zero values usually indicate bare surfaces of stone, sand or snow; while values between +0.2 and +0.4 show shrub and grassland coverage, and values close to +1 of the index NDVI represent dense and congested forests (Schlundt et al., 2011). The NDVI is defined as:

$$NDVI = \frac{IR - R}{IR + R} \tag{1}$$

where IR is near-infrared spectral reflectance, R is red spectral reflectance, and NDVI is the normalized difference vegetation index.

Further, it should be explained that to determine the landslide points in the study area, Landsat 8 satellite images related to OLI sensor, software Google Earth, and extensive field surveys have been used in this study.

2.3. Fuzzing of the layers

Fuzzy logic was proposed as fuzzy in the computing set theory by Lotfi Zadeh in 1965 (Zadeh, 1965). This theory can formulate many concepts and variables that are inaccurate and ambiguous, as in reality, in terms of mathematics and pave the way for reasoning, inference, and decision-making under uncertainty conditions (Taheri, 2006). Fuzzy logic is a method that shows the correctness of anything by a number between 0 and 1. Fuzzy logic provides a grey look into the real world, seeking to draw external truth completely and as it is. For example, if black is 0 and white is 1, then grey will be a number between 0 and 1 (Karam and Yaghoob Nejad Asl, 2013).

One of the ways of doing this is by using the frequency ratio. The frequency ratio is defined as:

$$FR_{ij} = \frac{N_p(SX_i)/\sum_{i=1}^{n} SX_i}{N_p(SX_j)\Big/\sum_{j=1}^{m} SX_j} \tag{2}$$

where $N_p(SX_i)$ is used to represent the total number of landslide occurrence pixels in class i of landslide occurrence factor X; $N_p(SX_j)$ is used to represent the total number of pixels in landslide occurrence factor X_j; n is the number of classes in the landslide occurrence factor X_i; m is the number of landslide occurrence factors.

After the calculation of the frequency ratio, the values obtained by using the following equation are normalized and fuzzy membership values are obtained.

$$\mu_{ij} = FR_{ij}/max_i(FR_{ij}) \tag{3}$$

where μ_{ij} is the fuzzy membership value of class i of parameter j.

In this study, the frequency ratio was used to determine the degree of fuzzy membership. And using these values of fuzzy membership, any criteria fuzzy map was prepared.

2.4. Prioritize and calculate the final weight of criteria in ANP model

The ANP, as one of the multi-criteria decision-making techniques, was proposed to overcome problems of dependence and feedback between criteria and sub-criteria in 1996 by Saaty (Hung, 2011). The ANP considers every topic and problem as a 'network' of criteria, sub-criteria, and options that have gathered together in clusters. All elements in the network can communicate with each other in any way. Using quantitative and qualitative criteria at the same time, flexibility and consistency in judgments are features of the ANP method (Zebardast, 2011).

The final weight calculation process for landslide risk mapping in the ANP model is as follows:

The 1st step: Create the subject model and structure: The subject is clearly expressed and its network structure is formed by decision-makers and through the DEMATEL mathematical method.

The 2nd step: Form binary comparison matrices and extract priority vectors: This step is like the analytical hierarchy process so that by control criterion and by experts, the importance or priority of criteria or sub-criteria is determined within the range of 1–9 (and/or with reverse numerical value) (Table 2).

Then, judgments' inconsistency is measured by the consistency rate. If this ratio is smaller than 0.1, judgments' consistency is acceptable, and, otherwise, the judgments should be revised.

By the following equations, the consistency index and rate can be calculated.

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n} - 1} \tag{4}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{5}$$

where CR is consistency ratio, CI is the compatibility index pair wise comparison matrix, λ_{max} is the maximum eigenvalue of the judgment matrix, RI is the random index and n is the number of compared components in matrix.

After judgments' consistency, it is time to determine the coefficients of the significance of criteria. For that purpose, a common method called special vector method (in accordance with the following Eq.) is used to determine the priority vector of matrices.

$$\mathrm{AW} = \lambda_{\mathrm{MAX}}\mathrm{W} \tag{6}$$

where A is the pair-wise comparison matrix of criteria, W represents eigenvector and λ_{max} is the maximum eigenvalue of the judgment matrix.

The 3rd step: Form Super Matrix: The super matrix is used to show the effect of a cluster with other clusters (representing external communications), and/or the effect of elements within clusters (representing interconnections).

The general form of a 'supermatrix' can be shown as follows (Saaty, 2008; Saaty and Takizawa, 1986):

$$
W = \begin{array}{cc}
 & \begin{array}{cccccccccc} C_1 & & C_2 & & & \cdots & & C_m & & \\ \cdots & e_{1n_1} & e_{21} & \cdots & e_{2n_2} & \cdots & e_{m1} & \cdots & e_{mn_n} \end{array} \\
\begin{array}{cc} & e_{11} \\ e_{11} & e_{12} \\ & \vdots \\ & e_{1n_1} \\ C_1 & e_{21} \\ C_2 & e_{22} \\ & \vdots \\ \vdots & e_{2n_2} \\ & \vdots \\ & e_{m1} \\ C_m & e_{m2} \\ & \vdots \\ & e_{mn_m} \end{array} & \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1N} \\ W_{21} & W_{22} & \cdots & W_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & \cdots & W_{NN} \end{bmatrix}
\end{array} \tag{7}
$$

where C_m denotes the mth cluster, e_{mn} denotes the nth element in mth cluster and W_{ij} is the principle eigenvector of the influence of

Table 2
Scale of relative importance (Neaupane and Piantanakulchai, 2006; Saaty, 1980).

Definition	Numerical rating	Explanation
Equal rating	1	Two activities contribute equally to the objective
Moderate rating	3	Attribute is slightly favored over another
Strong rating	5	Attribute is strongly favored over another
Very strong or demonstrated rating	7	Attribute is very strongly favored over another
Extreme rating	9	The evidence favoring one attribute over another is of the maximum possible order of affirmation
Intermediate ratings between adjoining scale values	2, 4, 6 and 8	When compromise is needed
Opposites	Reciprocals of above	A logical assumption

Table 3
Frequency ratio and fuzzy membership values for causative factors.

Factor	Class	No. of pixels in domain	Percentage of domain	No. of landslide pixels	Percentage of landslide	Frequency ratio	Fuzzy membership values
Slope degree (°)	0–5	17,079	30.48	7	8.86	0.290	0.136
	5–15	22,376	39.93	25	31.65	0.792	0.372
	15–25	12,427	22.18	36	45.57	2.058	0.965
	25–35	3665	6.54	11	13.92	2.132	1.000
	>35	493	0.88	0	0.00	0.000	0.000
Slope aspect (°)	Flat (−1)	1604	2.86	0	0.00	0.000	0.000
	North (0–22.5); (337.5–360)	8893	15.87	25	31.65	1.997	1.000
	Northeast (22.5–67.5)	6231	11.12	8	10.13	0.911	0.456
	East (67.5–112.5)	3142	5.61	2	2.53	0.451	0.226
	Southeast (112.5–157.5)	2686	4.79	1	1.27	0.264	0.132
	South (157.5–202.5)	4995	8.91	1	1.27	0.142	0.071
	Southwest (202.5–247.5)	8215	14.66	11	13.92	0.950	0.476
	West (247.5–292.5)	10,384	18.53	17	21.52	1.162	0.582
	Northwest (292.5–337.5)	9890	17.65	14	17.72	1.004	0.503
Altitude (m)	1239–1500	17,682	31.55	0	0.00	0.000	0.000
	1500–2000	17,391	31.03	10	12.66	0.408	0.024
	2000–2500	15,089	26.93	26	32.91	1.223	0.071
	2500–3000	4819	8.60	18	22.78	2.656	0.155
	>3000	1059	1.89	25	31.65	17.127	1.000
Lithology	Q^{sd}	7639	13.63	0	0.00	0.000	0.000
	Ng^{ct}	234	0.42	0	0.00	0.000	0.000
	PLQ^{ash}	7810	13.94	23	29.11	2.092	0.291
	PLQ^{d}	19,691	35.14	34	43.04	1.225	0.171
	Q^{tr}	84	0.15	0	0.00	0.000	0.000
	Q_2	1352	2.41	0	0.00	0.000	0.000
	Ng^{b}	446	0.80	0	0.00	0.000	0.000
	Q_3	309	0.55	0	0.00	0.000	0.000
	J_l	215	0.38	0	0.00	0.000	0.000
	J_d	125	0.22	0	0.00	0.000	0.000
	K^{l}_{1}	7420	13.24	0	0.00	0.000	0.000
	JK_l	8822	15.74	3	3.80	0.241	0.034
	K^{c}_{1}	1893	3.38	19	24.05	7.182	1.000
Land use	Agricultural land	13,189	23.53	24	30.38	1.291	1.000
	Orchard land	2967	5.29	2	2.53	0.478	0.370
	Grass land	32,805	58.54	45	56.96	0.973	0.753
	Barren land	6463	11.53	8	10.13	0.878	0.680
	Cultivation and built-up area	616	1.10	0	0.00	0.000	0.000
Distance to river (m)	0–200	12,527	22.35	16	20.25	0.906	0.483
	200–400	8788	15.68	11	13.92	0.888	0.473
	400–600	7815	13.95	9	11.39	0.817	0.435
	600–800	7572	13.51	20	25.32	1.876	1.000
	>800	19,338	34.51	23	29.11	0.844	0.450
Distance to road (m)	0–200	10,498	18.73	2	2.53	0.135	0.079
	200–400	6546	11.68	2	2.53	0.216	0.127
	400–600	5399	9.63	3	3.80	0.394	0.231
	600–800	4805	8.57	3	3.80	0.443	0.260
	>800	28,792	51.38	69	87.34	1.702	1.000
Distance to fault (m)	0–1000	2501	4.46	10	12.66	2.844	1.000
	1000–2000	4623	8.25	10	12.66	1.536	0.540
	2000–3000	6190	11.05	24	30.38	2.757	0.970
	3000–4000	6926	12.36	21	26.58	2.154	0.758
	>4000	35,800	63.88	14	17.72	0.277	0.097
NDVI	(-0.09) − 0.2	46,871	83.64	71	89.87	1.075	1.000
	0.2–0.4	7357	13.13	8	10.13	0.771	0.718
	>0.4	1812	3.23	0	0.00	0.000	0.000
Rainfall (mm)	221–227	9919	17.70	5	6.33	0.357	0.095
	227–230	13,308	23.75	9	11.39	0.479	0.128
	230–234	16,431	29.32	12	15.19	0.518	0.138
	234–239	9170	16.36	15	18.99	1.161	0.309
	>239	7212	12.87	38	48.10	3.752	1.000

the elements compared in the ith cluster to the jth cluster (Toosi and Samani, 2014; Yang and Tzeng, 2011).

To form the super matrix and extract components' final priorities, all initial priority vectors obtained from binary comparison matrices are entered into the column matrix (Yüksel and Dagdeviren, 2007). The result of this process is the unweighted super matrix. Then, to calculate the weighted super matrix, cluster super matrix data is multiplied by the unweighted super matrix and normalized.

After calculating the weighted super matrix, the limited super matrix is calculated (Eq. (2)).

$$W_L = \lim_{k \to \infty} W^{2K+1} \tag{8}$$

where W_L is the limit super matrix, W is the weighted super matrix, and k is the exponent determined by iteration.

In fact, similar to the process of Markov chains with the power of the weighted super matrix, the final matrix is convergent. By doing

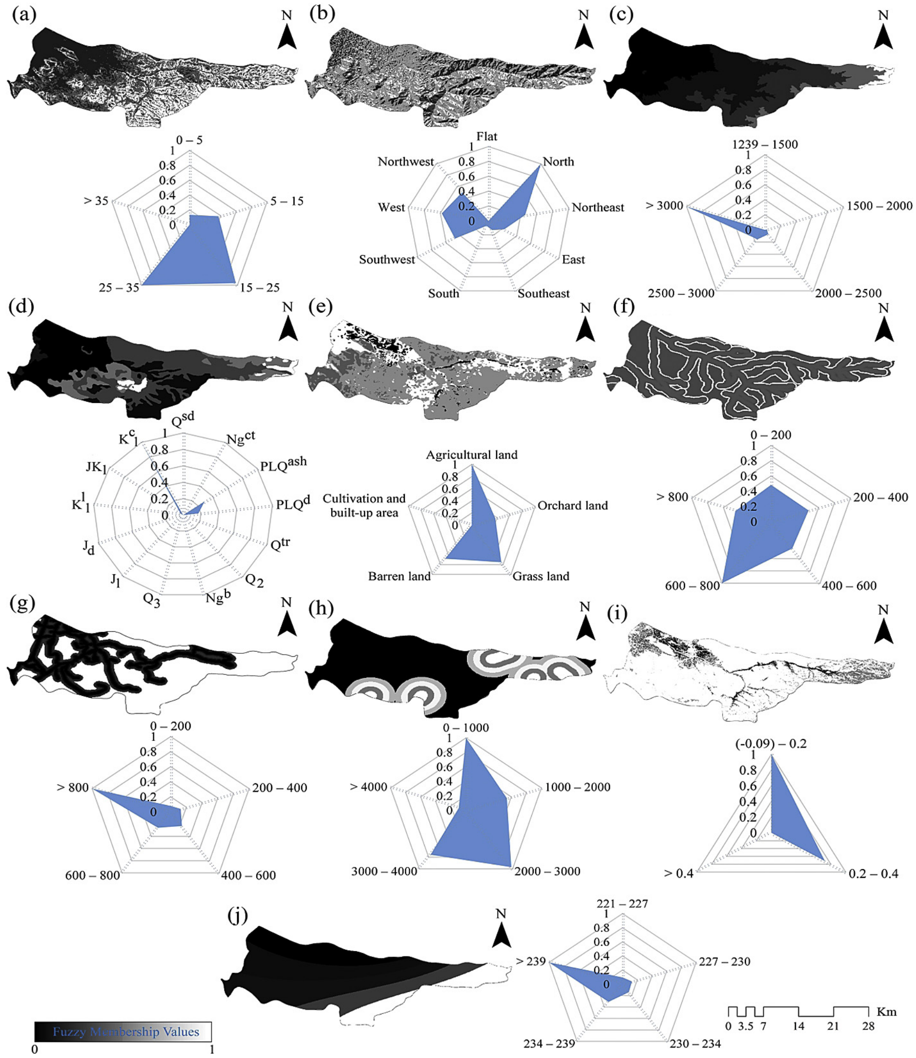

Fig. 3. Membership functions and fazzy maps of the considered factors (a) Slope degree; (b) Slope aspect; (c) Altitude; (d) Lithology; (e) Land use; (f) Distance to river; (g) Distance to road; (h) Distance to fault; (i) NDVI; and (j) Rainfall.

this process, numbers in the rows of the limited super matrix after normalization can be introduced as the final weights of the criteria.

3. Results

In this study, fuzzy logic was applied to derive the sub-criteria weights. For this purpose, by using frequency ratio, fuzzy membership values were calculated for criteria, and the value of each class of criteria was determined within the range of 0 and 1. Hence, levels with the greatest impact on landslides' occurrences have the highest value, which is 1, and levels with the least impact on landslides' occurrences have the lowest value, which is 0 (Table 3). Then, using the calculated fuzzy membership functions, a raster map of each criterion was prepared in a fuzzy form by the ArcGIS software. Fig. 3 shows the radar map and the graph of fuzzy membership functions of each of the criteria effective on landslides' occurrences. In doing so, weighting process was applied based on the ANP method. For this purpose, according to the study subject, a three-layer network model comprising the target layer, clusters, and criteria was designed and organized. In the model, clusters and internal elements of each cluster communication is marked by an arrow (Fig. 4). Then, a pair comparison of clusters and internal

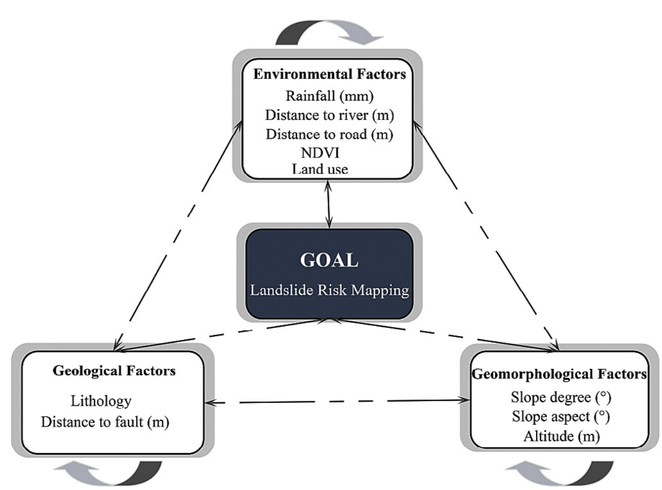

Fig. 4. Network structure for the landslide risk.

elements was done by using from the DEMATEL technique prepared by experts. Following this, three super matrices -

Table 4
Weights of each effective factor of landslide risk.

Clusters	Factors	Weights
Environmental Factors	Rainfall (mm)	0.12,959
	Distance to road(m)	0.05025
	Distance to river(m)	0.05611
	NDVI	0.10,103
	Land use	0.09741
Geomorphological Factors	Slope degree (°)	0.14,567
	Slope aspect (°)	0.07903
	Altitude	0.09701
Geological Factors	Lithology	0.16,635
	Distance to fault(m)	0.07755

unweighted, weighted, and limited - were obtained, along with the coefficients of each element contributing landslide (Table 4). After the completion of pairwise comparisons, the consistency rate was achieved at 0.03419, which is very low and totally acceptable.

With the extraction of coefficients of factors' affecting landslide occurrence, the coefficients are applied by the Raster Calculate function in ArcGIS software on layers, and, finally, the landslide risk map was obtained (Fig. 5). The map was classified in five risk classes of very high, high, medium, low, and very low. How to apply the coefficients to the factors is given in the following:

Landslide Risk Map = (Slope degree * 0.14567) + (Slope aspect * 0.07903) + (Altitude * 0.09701) + (Lithology * 0.16635) + (Land use * 0.09741) + (Distance to river * 0.05611) + (Distance to road * 0.05025) + (Distance to fault * 0.07755) + (NDVI * 0.10103) + (Rainfall * 0.12959).

Examining the zone map of landslide risks shows that 5.18%, 18/04%, 28/05%, 30.46%, and 18.27%, respectively, of the Azarshahr Chay basin is in classes: very high, high, medium, low, and very low (Fig. 6). Also, east and southeast areas of the basin have high potential of landslides; west and northwest areas have the least potential of fire, which is because of high steep, high altitude, and high rainfall in east and southeast area and low slope, low altitude, low rainfall in west and northwest areas.

4. Validation and comparison of the landslide risk mapping

In landslide risk modelling, the most important part is to perform validation of the prediction results (Pourghasemi et al., 2014). The receiver operating characteristic (ROC) curve is a graphical method for evaluating the amount of trade between sensitivity and specificity (Althouse, 2016); it is a graphical chart that is made by using the true positive rate (sensitivity) on the X axis and a false positive rate (1 - specificity) on the Y axis by different thresholds (Altman and Bland, 1994). For this purpose, the landslide points are randomly split into two groups, one for the risk analysis (sensitivity) and one for validation (specificity). Thus, the ROC curve allows us to examine and compare the sensitivity and specificity at any point on the curve. Values of areas under the curve (AUC) vary from 1 to 0.5 and can be categorized as follows: 1–0.9 = excellent, 0.8–0.9 = very good; 0.7–0.8 = good; 0.6–0.7 = average; 0.5–0.6 = poor (Pradhan and Lee, 2010). If the area under the curve is closer to 1, the performance would be better. In this study, AUC and standard error values were obtained as 0.815 and 0.033, respectively, which represent a very good performance of the method used in landslide risk mapping (Fig. 7).

The predictive value of a landslide risk map depends not only on scale but also on the accuracy and completeness of the landslide inventory map and the different factor maps from which it is derived (Choi et al., 2012). The hybrid method used in compared to other methods such as: analytical hierarchy process (Intarawichian and Dasananda, 2010; Kayastha et al., 2013) and logistic regression (Lee, 2004, 2005), the shows that have accuracy relatively high for landslide mapping.

5. Discussion

Landslide mapping is an important step in the management and prevention of landslides in landslide-prone areas. The landslide susceptibility maps provide fundamental knowledge of the effective and causes factors on landslide occurrence. Obviously, such information can be helpful, in risk management and its mitigation measures (Pourghasemi et al., 2013). Based on this assumption, the main objective of this study was to develop a landslide risk map by applying an integrated approach of fuzzy logic and the ANP technique. For this purpose, the frequency ratio was used and fuzzy membership values for each of the criteria used in landslide risk mapping were calculated, while the fuzzy map of each of them was prepared. Based on the results, we can conclude that the parameterization of fuzzy-ANP approach requires a full understanding of how the factors' tradeoffs against each other determine the resulting uncertainty. Within this approach, a Fuzzy-ANP was employed to determine the criteria weightings from subjective judgments of decision-making domain experts. This Fuzzy-ANP approach includes careful selection and standardization of

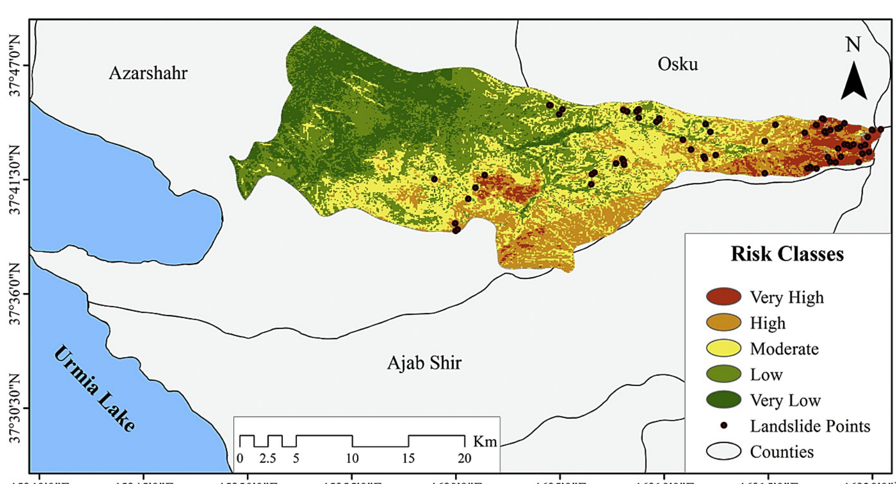

Fig. 5. Landslide risk zonation map.

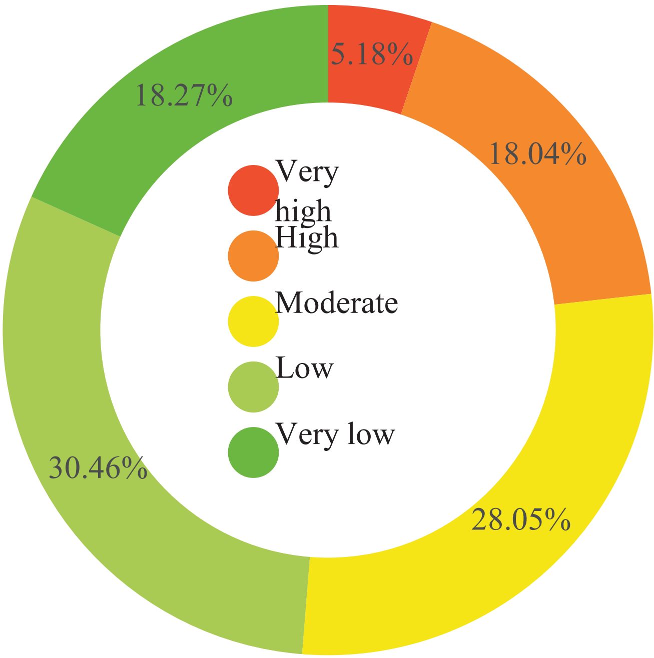

Fig. 6. The distribution of area in different landslide risk classes.

landslide-related criteria and weighting procedures using objective methods, which determine the criteria weights by solving mathematical models without any consideration of the decision maker's preferences (as is conventional in subjective methods). The results confirm that the integration of fuzzy set theory with ANP can result in high-reliability landslide susceptibility maps. Comparing results of this research to similar research indicated the integration approach of Fuzzy-MCDA could minimize the chance of error and optimize the accuracy of research (Feizi et al., 2017; Feizizadeh et al., 2013a, 2014b; Pandey and Kumar, 2017; Roodposhti et al., 2014; Sarkar et al., 2017).

In terms of the considered criteria, examining final weights extracted from the ANP showed that for the risk lithology of landslide occurrence by a factor of 0.17 and slope by a factor of 0.15, which have the highest significance and effect. In contrast, the distance to roads by a factor of 0.05 and the distance to rivers by a factor of 0.06 are less important than other factors. According to the zoning map of landslide risks, zones with a very high and high-risk of landslides in east and southeast area have been studied. Evaluating the results achieved in this research by using the ROC curve indicate that the combined method used with the area under the curve 0.815 had very good accuracy in landslide risk mapping. Owing to the high percentage of sliding zones in the Azarshahr Chay basin, which, in two classes of very high and high forms, 23.22% of the basin area that is necessary to minimize the risk of landslide occurrence by taking action such as reducing the slope in different parts of the basin, stabilization by using the embankment method and increase vegetation.

6. Conclusion and future work

Our research aimed to integrate fuzzy set theory with ANP-MCDA for landslide mapping. We introduced an approach that integrates fuzzy set theory and information theory algorithms which could be a useful geospatial tool for integrating multiple features/attributes that affect the landslide mapping process. In conclusion, the work has explored an integrated approach for combining spatial data in a fuzzy-ANP based multi-criteria evaluation of landslide mapping. The approach described could significantly improve the results of GIS-MCDA based modelling. Based on the results achieved from this research, future research is foreseen, which will include the application of the ANP and spatially explicit reliability models for spatial sensitivity and uncertainty analyses of GIS-MCDA. Our future work will include applying the neural networks and comparing with frequency ratio and bivariate logistic regression modelling for landslide risk mapping. We also aim to study the functionality of these approaches by assessing their

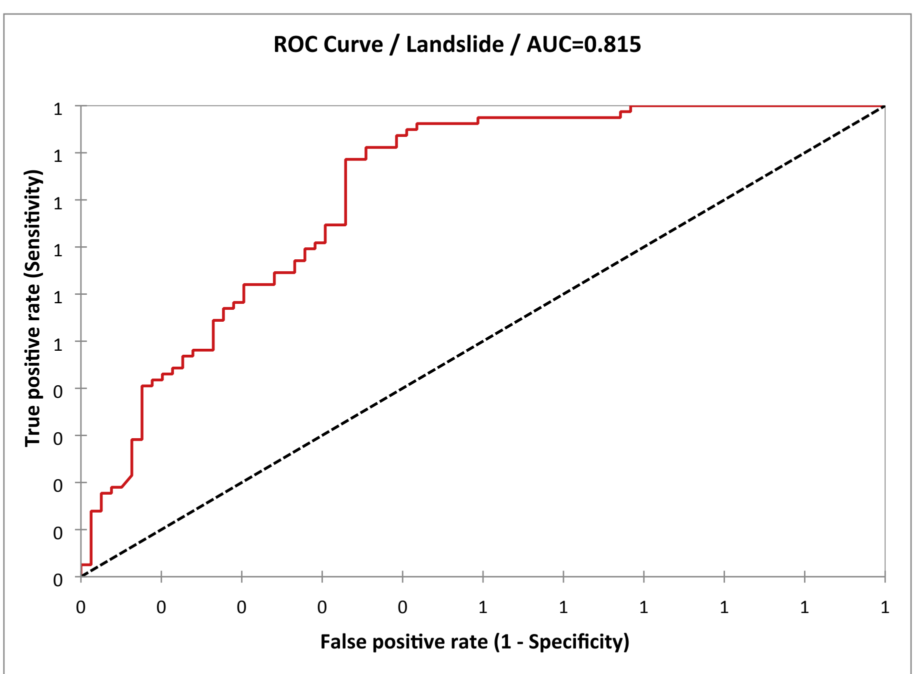

Fig. 7. ROC curve of the landslide risk map.

results through certainty analyses methods. Finally, we conclude the importance of accuracy in landslide susceptibility maps, for variety of applications especially when they are used as a basis for decision-making plans in light of reducing and mitigating the further hazards. The information provided by these maps shall help citizens, planners, and engineers to reduce losses caused by existing and future landslides by means of prevention, mitigation, and avoidance.

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