Landslide susceptibility assessment using an integrated approach of the analytic network process and fuzzy logic, a case of Urmia Lake Basin

Davoud OMARZADEH, Seyed Ahmad ESLAMINEZHAD, Mobin EFTEKHARI, Mohammad AKBARI

Abstract: *The occurrence of landslides has always been a problem in spatial planning as an environmental threat. The aim of the present study was to zoning landslide sensitive areas in the Urmia Lake Basin and to investigate the correlation between the characteristics of the region and the amount of landslide. To achieve these purposes, the situation of landslide sensitive areas in the Lake Urmia Basin was investigated using a combination of Fuzzy and Analytical Network Process (ANP) methods. The criteria' weight is obtained using the ANP, fuzzy Membership command, linear function, the fuzzy weight of the sub-criteria, and their fuzzy membership degree (between 0 and 1) are calculated. The weighted raster layers were combined using the Gamma overlay function. As a result of this operation, a classified map has been obtained which shows that 16.6% of the area has a very high landslide susceptibility, and the highest area of the study area, i.e., 27.32%, has a relatively high landslide susceptibility. The results of the present study were compared with the data recorded using field observations at landslide sites. The results showed that out of 182 points collected, 148 points (equivalent to 81.31%) correspond to class 6 (very high landslide susceptibility) and class 7 (extremely probable). The results of this research can be used in crisis management, identifying the suitability of the region in terms of geomorphological features, identifying environmental and natural hazards.*

Keywords: *landslide, landslide susceptibility, fuzzy-ANP, Urmia Lake Basin*

Introduction

Landslides are one of the most devastating natural disasters in sloping areas and leave millions homeless worldwide (Oktorie 2017). Landslides and soil mass movements are considered a special type of natural disaster from the perspective of natural hazard management. The occurrence of this type of phenomenon every year in some parts of our country and other parts of the world causes significant human, financial and environmental losses (Zhang et al. 2020). Identifying landslide-prone areas by zoning hazard capability with appropriate statistical models is one of the first steps in reducing potential damage and landslide risk management (Ciurleo, Cascini and Calvello 2017). Natural hazards have permanently destroyed many human-made structures, therefore, identifying high-risk areas should be considered one of the leading programs in land management studies (Jin et al. 2019). Environmental issues and forecasting the Natural hazards using spatial modelling is one of the main branches of *Geographic Information System* (GIS) today, which provides accurate and up-to-date results with very high accuracy compared to reality. In most sources, landslides are considered synonymous with mass movements (Lo, Feng and Chang 2018). Dozens of landslides occur in different parts of the country every year and threaten many residential areas,

DOI: https://doi.org/10.33542/GC2021-1-06

roads, and facilities (Yazdadi and Ghanavati 2016). There are many methods for zoning landslide sensitive areas, but these methods are divided into direct and indirect methods in general. Direct zoning methods are based on judgments based on landslide areas. Still, indirect methods, which are also included in this study, are based on identifying controlling factors and combining these factors as indicators of landslide potential in zoning (Yazdadi and Ghanavati 2016). In the indirect method, the use of real data can help the researcher to achieve accurate results. For example, the exact location of faults in the region or accurate geomorphological information directly impacts the final results. Today, *Spatial Decision Support System* (SDSS) and *multi-criteria decision-making methods* (MCDM) have many applications in modelling environmental issues. Numerous studies have been conducted on landslide zoning maps with approaches based on direct and indirect methods, to name a few:

Neaupane and Piantanakulchai (2006) presented an *Analytical Network Process (ANP)* model for assessing landslide risk in a fragile mountainous terrain in the eastern part of Nepal. The results showed that the ANP model could achieve a complex relationship between landslide control factors and minimise the error caused by subjective judgment.

Xu et al. (2015) conducted a study on landslide sensitivity analysis using a *combination of computer science, GIS and artificial neural network methods* in the Yangtze River Three Gorges Reservoir Area. With the support of remote sensing and GIS, they selected four-factor groups comprising ten separate sub-factors of landslide related data layers to establish a susceptibility evaluation model based on the back-propagation neural network including slope, aspect, plan curvature, strata and lithology, distance to faults, land use/land cover (LULC), Normalized Difference Vegetation Index, Normalized Difference Water Index, distance to roads, and effect of rivers. According to the results, the accuracy of the model is 88%. Comparing the actual recorded data with the product of this research indicates the high accuracy of the model.

Rajabi et al. (2016) investigated the landslide susceptibility in the Azarshahr Chay catchment *using fuzzy logic*. In this research, the criteria of distance to roads, distance to faults, distance to rivers, land use, lithology, elevation classes, slope, and aspect have been used. The results of this study showed that 24.47%, 26.4%, 25.92%, 17.59%, and 5.77% of the area are in very low, low, medium, high, and very high probability occurrence classes, respectively.

Ghorbanzadeh et al. (2019) conducted *a study on the application of MCDM methods and location of potential tourism areas* in East Azerbaijan province. Therefore, the combination of ANP and *Ordered Weighted Averaging* (OWA) was used to achieve potential nature areas.

Baharvand et al. (2020) *used fuzzy logic and GIS methods for landslide susceptibility zoning* in the Sorcha basin as a part of the Zagros. The results showed that a 0.9 fuzzy gamma operator has high accuracy for the landslide susceptibility Zoning (LSZ) map in the study area. Also, the landslide susceptibility zoning map's accuracy showed a strong (R^2) relationship between the sensitivity classes. The importance of investigating and evaluating landslide effects has been clearly stated in recent studies. However, in recent research, spatial analysis and its combination with MCDM methods have received less attention. Besides, Urmia Lake Basin (ULB) is prone to landslides; therefore, according to the importance of the study area, it is vital to assess the landslide susceptibility in this area. The present study seeks to evaluate the landslide susceptibility in ULB, applying a combination of MCDM methods and GIS techniques. The novelty of this study is the use of an appropriate and sufficient combination of criteria for landslide susceptibility assessment. Another important goal of the study is to determine the correlation between landslide-prone areas with different criteria used in the study. To achieve these goals, the ANP method was used to determine the weight and superiority of the criteria, and fuzzy logic was used to standardise and combine the criteria. Besides, in the present study, the remarkable ability of MCDM analysis using ten criteria in a large area of Urmia Lake was utilised. Eventually, the models' accuracy was evaluated using ground control points received from the Department of Soil Science of Tabriz University, enabling us to increase the reliability of results compared to other studies. The results of this research can be used by environmental managers to identify high-risk areas.

Materials and methods

Study Area

The Urmia basin is located between 35°39′ and 38°30′N, and 42°52′ and 44°13′E and area about 51,951 km^2 in the north-western part of Iran (Fig. 1). Its elevation varies between 1,236 m and 3,733 m above mean sea level. According to the National Statistics Center of Iran, the population living in the ULB is equal to 5,518,958 people in 2016, which is about 6.6% of the total population of Iran, while this population in 2000 was approximately 4,322,781 people. Given the population growth, unsustainable agricultural development, and occurrence of frequent droughts in the Lake Urmia Basin in recent decades, this natural habitat has faced a severe ecosystemic and environmental risk (AghaKouchak et al. 2015). People career in rural areas is agriculture and livestock. Urmia Lake is one of the largest and best known permanent hypersaline lakes in the world is the outlet of this basin, which has shrunk by almost 90% in area and 80% in volume during the last four decades (Fazel et al. 2018). The weather in the Urmia basin is pleasant and temperate in summer and cold in winter. The effects of the Mediterranean winds from the Mountain chains located at the North West and west of the study area are quite apparent. The Urmia Lake, naturally, affects the region's humidity. The region's average annual rainfall is about 350 mm, most of which falls in October and November (Mosaffa et al. 2020). The flowchart of this research is also shown in Fig. 2.

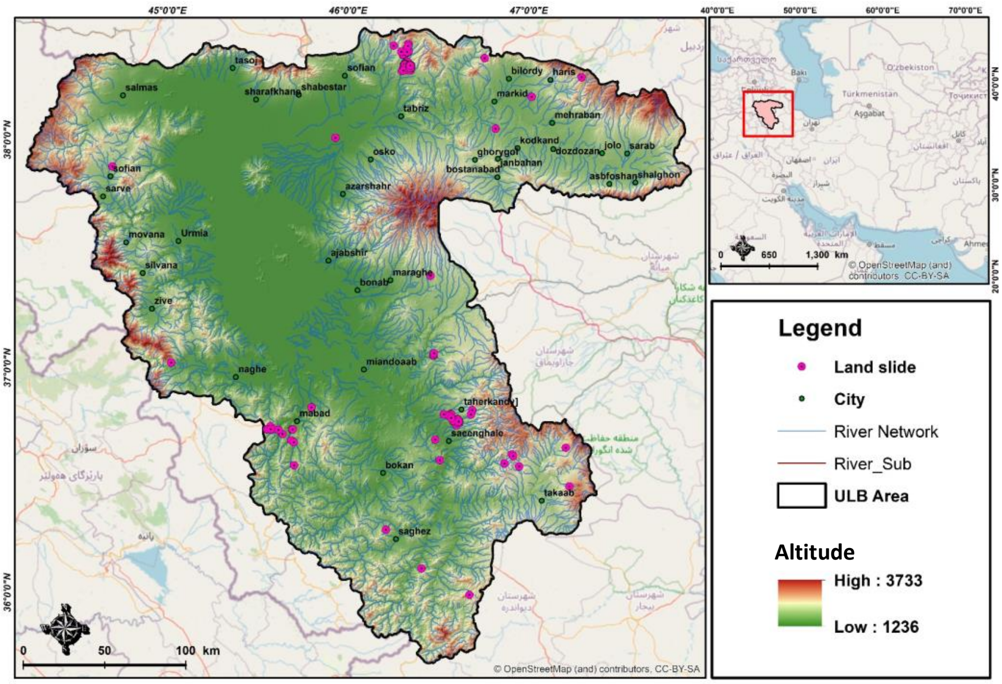

__Fig. 1.__ The geographical location of Lake Urmia catchment in Iran

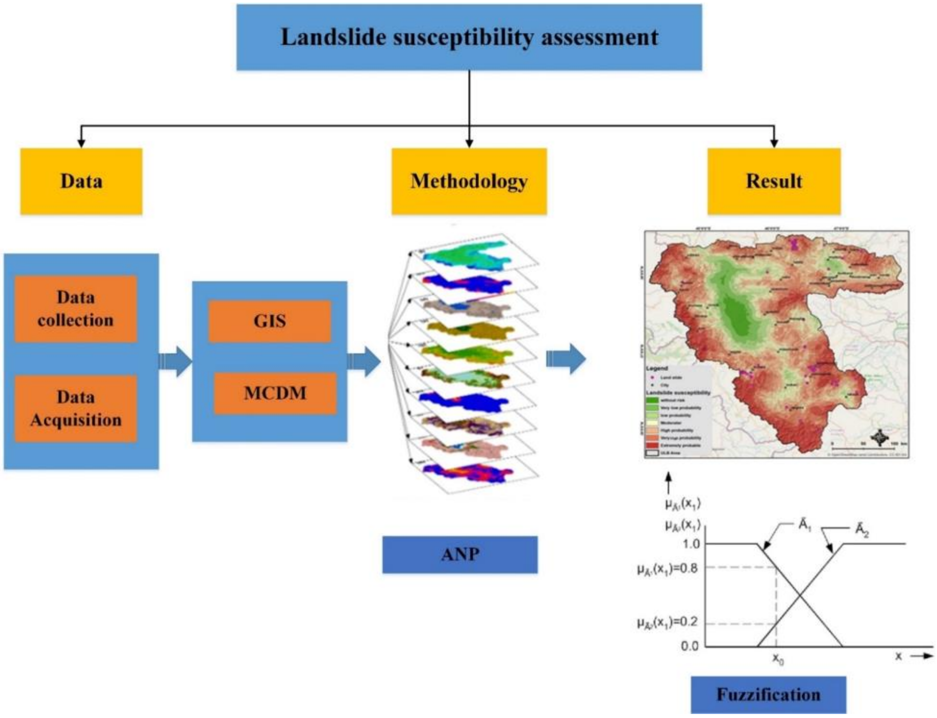

__Fig. 2.__ The flowchart of the research process

Data sets

According to different sources, the most important parameters affecting the landslide susceptibility that have been used in this study include distance to faults, distance to roads, distance to rive network, land use, lithology, soil type, elevation, slope, aspect, and an average rainfall (precipitation) of the study area (Feizizade et al. 2013, Rajabi, Valizadeh and Abedi 2016, Ghorbanzadeh et al. 2019). For this purpose, lithological data and faults of the region from geological maps 1:50,000, map of roads from OSM online layer, precipitation map from the Meteorological Organization of Iran, soil map from the department Natural resources of West and East Azerbaijan provinces were obtained. The network layer of waterways was extracted using *digital terrain model* (DTM) analysis and finally, the layers related to elevation, slope, and aspect were prepared using *digital elevation model* (DEM) related to *Shuttle Radar Topography Mission* (SRTM) satellite with 30 m spatial resolution. It is easier to use matrix calculations to overlap and apply mathematical operations to data. Therefore, surface vector data (polygon) was restored based on the value of each class, which was coded according to expert opinions. Other linear data were transformed into a distance raster layer using the distance analysis. The classifications were based on the importance and impact of each class on landslide susceptibility. The precipitation layer of the region was prepared using the data obtained from the Meteorological Organization, converted to a raster and then reclassified. In the ranking, the higher rank is assigned to the regions that have more precipitation. Data collection and preparation were performed in ArcMap 10.8 software environment. The Euclidean Distance command was used to calculate the distance layers. Moreover, Polygon to Raster command has been used to convert polygon layers to raster. Super Decisions software was used to calculate the weight of the criteria. To evaluate the outcomes' accuracy, ground data received from the Department of Soil Science of Tabriz University were used. These data were collected by geologist and geomorphologist experts using field investigations. An overview of the data used in the study is provided in Tab. 1.

Tab. 1. *Data set used in the present study*

Category	Data	Unit	Spatial resolution	Source	Term of use
Geomorphological	Elevation	Meter above sea level	30 m	SRTM satellite	MCDA
	Slope	Degree	30 m	SRTM satellite	MCDA
	Aspect	Degree	30 m	SRTM satellite	MCDA
Geological	Soil type	---	30 m	Department of Natural resources (West and EAP)	MCDA
	Geology	---	30 m	geological maps 1:50,000	MCDA
	Distance to faults	Meter	30 m	Sentinel-2 imagery	MCDA
Hydrological	Distance to river network	Meter	30 m	SRTM satellite	MCDA
Human-made	Distance to roads	Meter	30 m	OSM online layer	MCDA
	Land use	---	10 m	geological maps 1:50,000	MCDA
Climatic	precipitation	Millimetre per month (average)	30 m	Meteorological Organization of Iran	MCDA
Field data	Ground control points	---	---	Department of Soil Science (University of Tabriz)	Accuracy Evaluation

Analytical Network Process (ANP)

The network analysis process is one of the MCDM methods and developed form of *Analytical Hierarchical Analysis* (AHP) (Nimawat and Gidwani 2020). In some cases, using very simple decision models can achieve the optimal and desired answer. Still, in some cases, the analyses are so sensitive and important that simple models have not been responsive (Assad 2017). Therefore, models that have a relatively strong mathematical basis should be used. In this study, to access landslide sensitive areas in the Urmia Lake Basin and the high number of criteria and their sensitivity to landslides, using the ANP technique and combining it with fuzzy logic has had good results. The ANP method weighs the criteria in a network and considers the internal relationships of the groups and their interactions with other groups, which helps to achieve more accurate results.

To perform this analysis, we first created a hierarchical model and then specified the relationship between criteria and sub-criteria as networks. The most important difference with the AHP method is that the relationships are not only linear from top to bottom, but the interrelationships between the criteria with the sub-criteria and the sub-criteria with each other can also be examined. Then we create pairwise comparison matrices for the desired criteria and calculate the weight vectors.

As a result of pairwise comparisons between the criteria, the weight vector of the criteria is obtained. Saaty (2004) has proposed Eq. 1 for the weight vector:

$$AW = \lambda_{max} W \tag{1}$$

In this relation, λ_{max} is the largest eigenvalue of matrix A. The W vector is normalised using Eq. 2 (Saaty 2004):

$$\alpha = \sum_{i=1}^{n} w_i \tag{2}$$

After obtaining the weight vector, the incompatibility rate for the comparisons should be calculated, which according to the standard, should be less than 0.1. Otherwise, the required corrections should be made in the pairwise comparisons. The incompatibility rate is obtained using the Eq. 3 (Saaty 2004):

$$\alpha = \frac{\lambda - 1}{n - 1} \tag{3}$$

After creating the pairwise comparison matrix of criteria, the normalised weights of the matrices are entered in a primary super matrix through it. The interrelationship between all the parts of the studied system can be observed. Using the initial supermatrix proportional to their relative weight, a factor is taken from its parts to equal the columns' sum, which standardises the matrix. As a result of this operation, a new supermatrix is created, which is called the weighted supermatrix. In this matrix, the sum of each column is equal to 1. In this step, we increase the weighted supermatrix obtained to the extent that the parts of the matrix converge and its linear values are equal (Saaty 2004):

$$\lim_{K \to \infty} (w)^K \tag{4}$$

The criteria used in this research are divided into five general categories, which are human-made (roads and land use), geological (geology, distance to faults, soil classes), climatic (precipitation), geomorphological (slope, aspect, elevation), and hydrological (distance to river network). Unweighted, weighted, and limited matrices have been presented in Tab. 2 and Tab. 3.

Tab. 2. *The unweighted matrix*

Class	Elevation	Precipitation	Aspect	Lithology	Slope	Distance to river network	Distance to road	Distance to fault	Soil type	LULC
Elevation	0.00	0.03320	0.00	0.16	0.00	0.00	0.00	0.00	0.07	0.06982
Precipitation	0.13	0.00000	0.00	0.10	0.00	0.00	0.00	0.21	0.10	0.09028
Aspect	0.13	0.04684	0.00	0.13	0.33	0.00	0.00	0.11	0.12	0.08928
Lithology	0.13	0.08786	0.00	0.00	0.00	0.00	0.00	0.13	0.10	0.15439
Slope	0.13	0.05963	0.00	0.05	0.00	0.00	0.00	0.08	0.09	0.09529
Dist. to river network	0.13	0.19647	0.00	0.06	0.00	0.00	0.33	0.08	0.13	0.11995
Distance to road	0.13	0.02126	0.00	0.08	0.00	0.25	0.00	0.15	0.10	0.07443
Distance to fault	0.13	0.23662	0.00	0.13	0.67	0.25	0.33	0.00	0.08	0.14122
Soil type	0.13	0.01890	0.00	0.10	0.00	0.25	0.33	0.10	0.00	0.06857
LULC	0.00	0.29221	0.00	0.19	0.00	0.25	0.00	0.12	0.09	0.00000

Tab. 3. *The weighted (limited) matrix*

Class	Elevation	Precipitation	Aspect	Lithology	Slope	Distance to river network	Distance to road	Distance to fault	Soil type	LULC
Elevation	0.00	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.09
Precipitation	0.06	0.14	0.05	0.00	0.00	0.00	0.00	0.11	0.05	0.16
Aspect	0.06	0.02	0.04	0.00	0.17	0.00	0.00	0.05	0.06	0.10
Lithology	0.06	0.04	0.08	0.00	0.00	0.00	0.00	0.07	0.05	0.13
Slope	0.06	0.03	0.05	0.00	0.00	0.00	0.00	0.04	0.04	0.09
Dist. to river network	0.06	0.10	0.06	0.00	0.00	0.00	0.33	0.04	0.06	0.05
Distance to road	0.06	0.01	0.04	0.00	0.00	0.25	0.00	0.07	0.05	0.06
Distance to fault	0.06	0.12	0.07	0.00	0.33	0.25	0.33	0.06	0.04	0.08
Soil type	0.06	0.01	0.03	0.50	0.00	0.25	0.33	0.05	0.04	0.13
LULC	0.00	0.01	0.05	0.00	0.00	0.25	0.00	0.00	0.07	0.10

Fuzzy Logic

The fuzzy theory basis can be considered as a set theory in mathematics (Barros, Bassanezi and Lodwick 2017). Membership in a set in classical mathematics is associated with two-value logic such as Boolean logic, binary logic (zeros and ones), but in the fuzzy method, multi-value logic is used and membership in a set is examined using the degree of membership intensity (Yousefi et al. 2018, Baharvand et al. 2020). In Boolean logic, the result is that a region either has landslide susceptibility or does not have a landslide susceptibility. In fuzzy logic, problem-solving is based on the real world and tries to include uncertainties in the model and prevent incorrect results. The purpose of using fuzzy theory is to create a new way of expressing everyday uncertainties and ambiguities (Yousefi et al. 2018). In the fuzzification step, the value of each class is determined by sub-criteria, and based on the functions of fuzzy membership, the rank or fuzzy value of each class in the fuzzy set is determined, which is a value between zero and one. One of the most widely used fuzzy membership degree functions is the linear function that has been used in this research to fuzzy weight the layers of layers (Baharvand et al. 2020). The linear function works in both positive and negative linear forms due to the importance of proximity to the features. Triangular, trapezoidal, and Gaussian linear functions are used to obtain fuzzy membership degrees in a layer. The fuzzy operation is performed in the GIS environment using the Fuzzy membership commend and a linear function. As a result of which this command can be set between 0 and 1 by selecting the desired function for fuzzy. The purpose of this process is to standardise the unit of measurement of the criteria. For example, the precipitation map is in mm per year, the elevation map is in meters, and the slope map is in degrees. Using fuzzy, all layers are placed between zero and one, based on the intrinsic importance of their classes.

Results

All ten effective criteria in the landslide susceptibility including distance to faults, distance to roads, distance to river network, land use, lithology, soil classes, elevation, slope, aspect and precipitation of the study area were prepared in the form of raster maps and normalised values [0, 1] (Fig. 3). The maps of criteria were shown based on equal interval classification (five intervals in stretched type).

As represented in Fig. 3, the criteria used to assess the susceptibility of landslides in the study area are standardised. In these maps, the fuzzy linear function has been applied for standardisation, and based on the effect of each class on the probability of landslides, they are assigned a value between 1 and 0. Technically speaking, applying standardisation, all criteria are prepared for raster calculations and participate in pixel calculations in the same and logical way.

Ranking Layer and ANP weights

Geology layer, soil type, and land use were reclassified using the experts' judgments of GIS. It should be mentioned that this reclassify determines the importance of the inner class of each layer. For example, in the soil type layer, based on the importance of soil type and its effect on landslide probabilities and inspiration from the results of other research, classes from number one (maximum impact) to number 7 (lowest Impact) were coded. Internal classes in the layers of distance to roads, faults, and river network were also reclassified based on proximity or distance to the features (river network, fault, and roads). In this context, inner classes ranked first in the criteria that proximity had a positive effect on the landslide susceptibility.

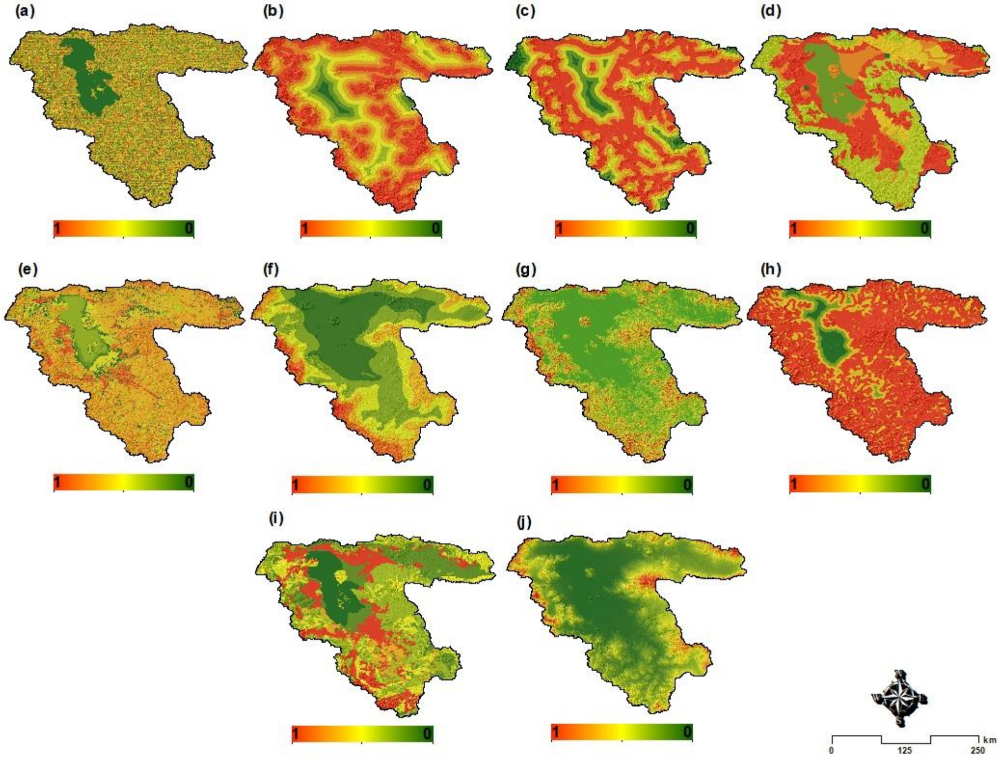

Fig. 3. *Map of criteria used in landslide zoning:*
(a) Aspect, (b) Distance to fault, (c) Distance to road, (d) Soil type, (e) Land use,
(f) Precipitation, (g) Slope, (h) Distance to river network, (i) Lithology (j) Elevation

Fuzzification

In this step, the desired layers were first prepared to enter the weighting stage using the experts' opinion and the results of research conducted in this field. Then, the weighting process was applied to the criteria using ANP multi-criteria spatial decision-making technique. Then, a linear fuzzy function was used to standardise. Using this operation, the internal weight of the layers was set between 0 and 1. Tab. 4 shows the results of fuzzification, ANP weights and also the rank of each inner class for each criterion. In Tab. 4, the fuzzy membership degree column indicates the degree and severity of the impact of each class on the landslide susceptibility. In fact, this membership is based on the numbers observed in the rank column that indicates the importance of each class of layers used to identify the probability of landslides, which has been obtained from the opinions of geology experts. Then, after the calculations, the final weight of each layer was obtained, named ANP weight.

After determining the importance of each of the criteria used in the research, the fuzzy gamma function was used to overlap the layers and create landslide zoning maps. To illustrate the obtained map, verbal variables were used to express the probable severity of the landslide (Fig. 4). The method was as follows: After obtaining the weight of the discussed criteria, first, the weight of each layer was multiplied using ArcGIS 10.8 software and the Raster Calculator command in that layer. Then, using the Fuzzy Overlay command, the weighted layers with a value between zero and one were overlapped, and the final landslide probability map was obtained. The final map was classified based on the Equal interval classification method.

Tab. 4. *Fuzzy membership and ANP weights of criterion*

Criteria	Fuzzy membership degree	Rank	ANP weight	Criteria	Fuzzy membership degree	Rank	ANP weight
	0	1			0	1	
	0.166	2			0.166	2	
	0.333	3			0.333	3	
Elevation	0.499	4	0.093	**Slope**	0.499	4	0.145
	0.666	5			0.666	5	
	0.833	6			0.833	6	
	1	7			1	7	
	0	1			0	1	
	0.166	2			0.166	2	
	0.333	3			0.333	3	
Soil type	0.499	4	0.238	**Lithology**	0.499	4	0.093
	0.666	5			0.666	5	
	0.833	6			0.833	6	
	1	7			1	7	
	0	1			0	1	
	0.166	2			0.166	2	
	0.333	3			0.333	3	
Aspect	0.499	4	0.048	**Distance to fault**	0.499	4	0.040
	0.666	5			0.666	5	
	0.833	6			0.833	6	
	1	7			1	7	
	0	1			0	1	
	0.166	2			0.166	2	
	0.333	3			0.333	3	
Precipitation	0.499	4	0.133	**Distance to river network**	0.499	4	0.016
	0.666	5			0.666	5	
	0.833	6			0.833	6	
	1	7			1	7	
	0	1			0	1	
	0.166	2			0.166	2	
	0.333	3			0.333	3	
Land use	0.499	4	0.135	**Distance to road**	0.499	4	0.054
	0.666	5			0.666	5	
	0.833	6			0.833	6	
	1	7			1	7	

After obtaining the final landslide susceptibility map in the study area, the accuracy of the zoning map was evaluated using the points collected in the real environment. The results showed that out of 182 points collected, 148 points (equivalent to 81.31%) correspond to class 6 (very high landslide susceptibility) and class 7 (extremely probable). Fig. 4 shows the location of the harvested points to evaluate the accuracy of the results. As it can be observed in the obtained map, the areas classified as agricultural lands have a very low landslide susceptibility. This can also highlight the importance of protecting vegetation in preventing natural hazards. In addition, areas with a high landslide susceptibility are in mountainous areas and usually without dense vegetation. Proximity to drainage network and faults also has a high impact on the landslide susceptibility in these areas (Fig 3b, c and j). In order to evaluate the study area in terms of the landslide susceptibility, the area of each potential hazard level was calculated in km^2 and percentage (Tab. 5).

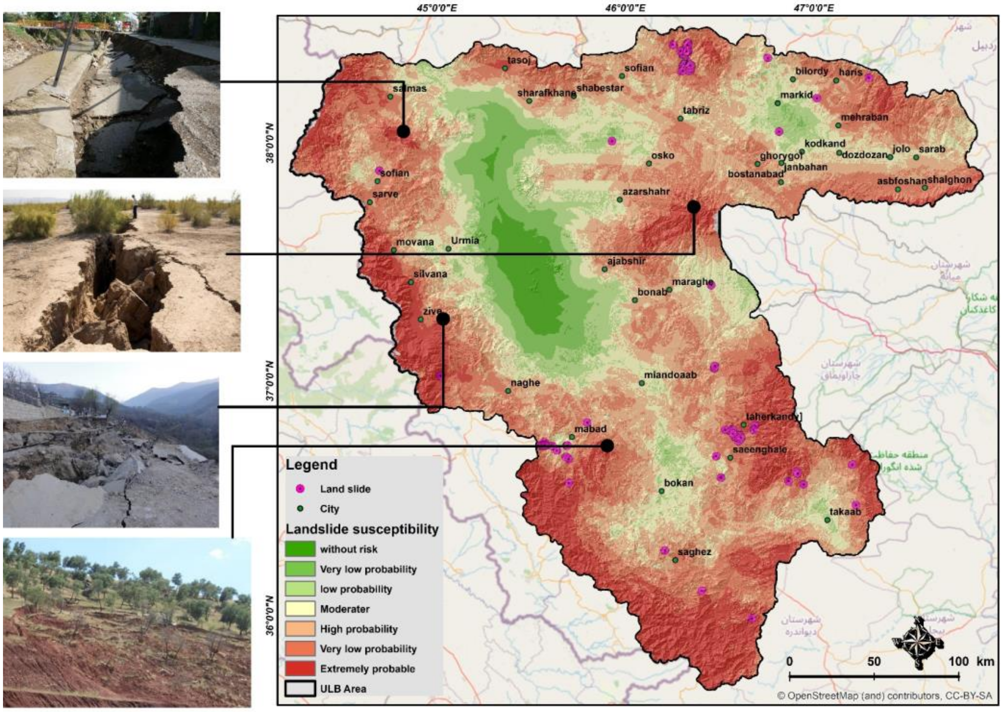

Fig. 4. *Landslide susceptibility areas in Urmia Lake Basin*

Tab. 5. *Percentage of landslide susceptibility*

Fuzzy intervals	Number of pixels	Area (km²)	Percentage of area (%)	Verbal variable
0.0	1,866,011	1,879.410	3.61	Without Risk
0–0.166	3,645,597	3,881.037	7.47	Very low probability
0.167–0.333	8,852,058	10,966.850	21.11	Low probability
0.334–0.499	8,956,115	12,488.500	24.03	Moderate probability
0.50–0.666	7,442,622	10,698.360	20.59	High probability
0.667–0.833	7,168,558	8,451.702	16.27	Very high probability
0.834–1	2,872,366	3,585.129	6.9	Extremely probable

The results of ANP showed that soil type with a weight of 0.23, slope with a weight of 0.14, land use with a weight of 0.135, and rainfall with a weight of 0.133 are the most important criteria in identifying the landslide susceptibility in different areas of ULB. The weight of other criteria was also obtained to determine their relative importance in the landslide susceptibility (Fig. 5).

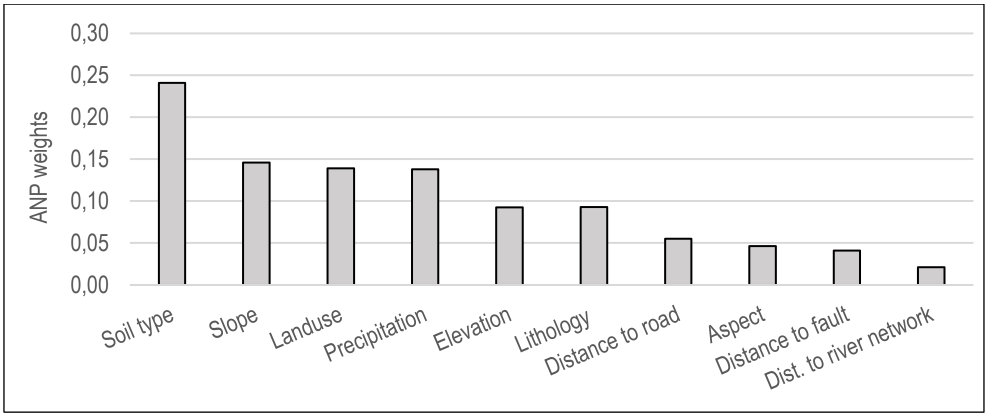

Fig. 5. *The ANP weight of each criterion*

Discussion

Various scientific methods have been proposed for zoning landslide-sensitive areas, some using statistics and some spatial data. Using MCDM methods with emphasis on spatial approach in complex spatial decisions can be a suitable performance method. In this research, spatial analysis and MCDM methods have been used. For instance, the performed studies in this field include the following:

In the study of Feizizadeh and Blaschke (2013), three different GIS-MCDA methods were applied to landslide susceptibility mapping for the Urmia Lake Basin in northwest Iran. To achieve this goal, nine landslide causal factors (lithology, DEM, slope, aspect, land cover, precipitation, distance to streams and the distance to roads and faults) were used. The landslide susceptibility maps were produced based on weighted overly techniques including *analytic hierarchy process* (AHP), *weighted linear combination* (WLC) and *ordered weighted average* (OWA). The research result indicated the AHP performed best in the landslide susceptibility mapping closely followed by the OWA method while the WLC method delivered significantly poorer results.

Furthermore, we can mention the study of Feizizadeh et al. (2014) which aimed to map the landslide susceptibility. They used GIS-based spatial analysis in combination with *multi-criteria evaluation* (MCE) methods. Besides, they applied a combination of AHP and fuzzy to address the landslide susceptibility in the Izeh River Basin, Iran. According to their outcomes, the integration of fuzzy set theory with AHP enables researchers to access reliable accuracies and a high level of reliability in the resulting landslide susceptibility map. Additionally, based on their investigation, approximately 53% of known landslides within our study area fell within zones classified as having very high susceptibility, with the further 31% falling into zones classified as having high susceptibility.

Based on another study, Abedi Gheshlaghi and Feizizadeh (2017) used a combination of two models of the *analytical network process* (ANP) and *fuzzy logic* for 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. 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, Mallick et al. (2018) used an integrated approach of GIS and statistical modelling including *fuzzy analytical hierarchy process* (FAHP), weighted linear combination and MCE models for landslide susceptibility evaluation. In the modelling process, eleven causative factors include slope aspect, slope, rainfall, geology, geomorphology, distance from lineament, distance from drainage networks, distance from the road, land use/land cover, soil erodibility and vegetation proportion were identified for landslide susceptibility mapping. The study results show that the weighted overlay analysis method using the FAHP, and eigenvector method is a reliable technique to map landslide susceptibility areas.

Jana Vojteková and Matej Vojtek (2020) evaluated the landslide susceptibility of Handlová, Slovakia. They applied the AHP technique to heightening the criteria used in their research, which named slope angle, geology, slope aspect, elevation, distance to rivers, distance to faults, and land use. Based on the resulting susceptibility map, 51.98% out of the total study area is characterised by high and very high susceptibility classes. Also, using ground data, the accuracy of their model was equal to 60.8%.

In another study related to landslide susceptibility mapping, Zhou et al. (2020) developed a landslide susceptibility map at the national level in Kenya using the fuzzy analytic hierarchy process method. First, they used a hierarchical evaluation index system containing ten landslide contributing factors to produce a susceptibility map. Then, the weights of these indexes were determined through pairwise comparisons, in which *triangular fuzzy numbers* (TFNs) were employed to scale the relative importance based on the opinions of experts. Ultimately, these weights were merged in a hierarchical order to obtain the final landslide susceptibility map. These factors included mean annual precipitation, altitude, slope, aspect, curvature, topographic wetness index, stream power index, soil texture, land use and landform. The results indicated that the TFN-AHP model showed a significantly improved performance (Area under the curve – AUC = 0.86) compared with the conventional AHP (AUC = 0.72) in LSM for the study area.

Conclusion

In the present study, determining the weight and priority of the criteria over each other, determining the internal weight of the criteria using the fuzzy linear function, and fuzzy overlap using the gamma function were applied. The ANP method was very useful as one of the multi-criteria spatial decision-making techniques in determining the priority of criteria. According to the number of criteria used in the present study, the decision was made in a multidimensional space with ten layers with different values. Fuzzy operations were used to unify the layer units to divide the values of each layer between zero and one. This means that values close to number one have a higher value (greater impact on landslide occurrence), and values that tend to zero have a lower value (lesser impact on landslide occurrence). After weighting and fuzzy operations using the above methods and combining all the criteria with each other, landslide-sensitive zoning maps were obtained in different areas of the Urmia Lake Basin. The result of zoning landslide-sensitive areas in the Lake Urmia Basin shows that only 7.47%, equivalent to 3,881.037 km^2 of the area in question has a very low landslide susceptibility. In contrast, 16.27%, equivalent to 8,451.702 km^2 of the mentioned area has a very high landslide susceptibility, which in general can be said that 67.80% of the area has a moderate to high landslide susceptibility and 56.23% of the area has a moderate to low landslide susceptibility (Tab. 5). Considering the high weight of precipitation in the matrix of pairwise comparisons of criteria and its significant relationship with high areas and areas with high slope, it was concluded that these areas also have a high landslide susceptibility. The best operator for overlapping the effective criteria for landslide susceptibility by trial and error, the Gamma function, was the most suitable. In general, for zoning, the landslide susceptibility, soil type with a weight of 0.23, slope with a weight of 0.14, land use with a weight of 0.135, and rainfall with a weight of 0.133 are among the most important factors that have been used in the present study. The results of this research can be used by managers and planners in resource management and deployment of facilities in different areas to determine the optimal areas. It can also be considered by researchers and geologists for geological studies and similar research.

References

GHESHLAGHI, H. A., FEIZIZADEH, B. 2017: An integrated approach of analytical network process and fuzzy based spatial decision making systems applied to landslide risk mapping. *Journal of African Earth Sciences*, 133, 15-24. DOI: https://doi.org/10.1016/j.jafrearsci.2017.05.007.

AGHAKOUCHAK, A., NOROUZI, H., MADANI, K., MIRCHI, A. et al. 2015: Aral Sea syndrome desiccates Lake Urmia: call for action. *Journal of Great Lakes Research*, 41(1), 307-311. DOI: https://doi.org/10.1016/j.jglr.2014.12.007.

ASSAD, A. 2017: Obituary: Thomas L. Saaty – Creator of AHP/ANP Decision-Making Methodology. *International Journal of the Analytic Hierarchy Process*, 9(2). DOI: https://doi.org/10.13033/ijahp.v9i2.496.

BAHARVAND, S., RAHNAMARAD, J., SOORI, S., SAADATKHAH, N. 2020: Landslide susceptibility zoning in a catchment of Zagros Mountains using fuzzy logic and GIS. *Environmental Earth Sciences,* 79, 204. DOI: https://doi.org/10.1007/s12665-020-08957-w.

BARROS, L., BASSANEZI, R., LODWICK, W. 2017: *A first course in fuzzy logic, fuzzy dynamical systems, and biomathematics: theory and applications (1st edition)*. Berlin (Springer-Verlag Berlin Heidelberg). DOI: https://doi.org/10.1007/978-3-662-53324-6.

CIURLEO, M., CASCINI, L., CALVELLO, M. 2017: A comparison of statistical and deterministic methods for shallow landslide susceptibility zoning in clayey soils. *Engineering Geology*, 223, 71-81. DOI: https://doi.org/10.1016/j.enggeo.2017.04.023.

FAZEL, N., BERNDTSSON, R., UVO, C. B., MADANI, K., KLØVE, B. 2018: Regionalization of precipitation characteristics in Iran's Lake Urmia basin. *Theoretical and Applied Climatology*, 132, 363-373. DOI: https://doi.org/10.1007/s00704-017-2090-0.

FEIZIZADEH, B., BLASCHKE, T., NAZMFAR, H., MOGHADDAM, M. R. 2013: Landslide susceptibility mapping for the Urmia Lake basin, Iran: a multi-criteria evaluation approach using GIS. *International Journal of Environmental Research,* 7(2), 319-336. DOI: https://doi.org/10.22059/IJER.2013.610.

FEIZIZADEH, B., BLASCHKE, T. 2013: GIS-multicriteria decision analysis for landslide susceptibility mapping: comparing three methods for the Urmia lake basin, Iran. Natural hazards, 65(3), 2105-2128. DOI: https://doi.org/10.1007/s11069-012-0463-3.

FEIZIZADEH, B., ROODPOSHTI, M. S., JANKOWSKI, P., BLASCHKE, T. 2014: A GIS-based extended fuzzy multi-criteria evaluation for landslide susceptibility mapping. *Computers & Geosciences*, *73*, 208-221. DOI: https://doi.org/10.1016/j.cageo.2014.08.001.

GHORBANZADEH, O., POURMORADIAN, S., BLASCHKE, T., FEIZIZADEH, B. 2019: Mapping potential nature-based tourism areas by applying GIS-decision making systems in East Azerbaijan Province, Iran. *Journal of Ecotourism*, 18(3), 261-283. DOI: https://doi.org/10.1080/14724049.2019.1597876.

JIN, K. P., YAO, L. K., CHENG, Q. G., XING, A. G. 2019: Seismic landslides hazard zoning based on the modified Newmark model: a case study from the Lushan earthquake, China. *Natural Hazards*, 99, 493-509. DOI: https://doi.org/10.1007/s11069-019-03754-6.

LO, C. M., FENG, Z.-Y., CHANG, K.-T. 2018: Landslide hazard zoning based on numerical simulation and hazard assessment. *Geomatics, Natural Hazards and Risk*, 9(1), 368-388. DOI: https://doi.org/10.1080/19475705.2018.1445662.

RAJABI, M., VALIZADEH, K. K., ABEDI, G. H. 2016: Evaluation and zoning landslide hazard by using the analysis network process and artificial neural network (case study azarshahr chay basin). *Quantitative Geomorphological Research*, 5(1), 60-74.

MALLICK, J., SINGH, R. K., ALAWADH, M. A., ISLAM, S., KHAN, R. A., QURESHI, M. N. 2018: GIS-based landslide susceptibility evaluation using fuzzy-AHP multi-criteria decision-making techniques in the Abha Watershed, Saudi Arabia. *Environmental Earth Sciences*, 77(7), 276. DOI: https://doi.org/10.1007/s12665-018-7451-1.

MOSAFFA, M., NAZIF, S., AMIRHOSSEINI, Y. K., BALDERER, W., MEIMAN, H. M. 2021: An investigation of the source of salinity in groundwater using stable isotope tracers and GIS: A case study of the Urmia Lake basin. Iran. *Groundwater for Sustainable Development*, 12, 100513. DOI: https://doi.org/10.1016/j.gsd.2020.100513.

NEAUPANE, K. M., PIANTANAKULCHAI, M. 2006: Analytic network process model for landslide hazard zonation. *Engineering Geology*, 85(3–4), 281-294. DOI: https://doi.org/10.1016/j.enggeo.2006.02.003.

NIMAWAT, D., GIDWANI, B. D. 2020: Prioritization of important factors towards the status of industry 4.0 implementation utilizing AHP and ANP techniques. *Benchmarking: An International Journal*, 28(2), 695-720. DOI: https://doi.org/10.1108/BIJ-07-2020-0346.

OKTORIE, O. 2017: A Study of Landslide Areas Mitigation and Adaptation in Palupuah Subdistrict, Agam Regency, West Sumatra Province, Indonesia. *Sumatra Journal of Disaster, Geography and Geography Education*, 1(1), 43-49. DOI: https://doi.org/10.24036/sjdgge.v1i1.34.

SAATY, T. L. 2004: Decision making–the analytic hierarchy and network processes (AHP/ANP). *Journal of Systems Science and Systems Engineering*, 13, 1-35. DOI: https://doi.org/10.1007/s11518-006-0151-5.

VOJTEKOVÁ, J., VOJTEK, M. 2020: Assessment of landslide susceptibility at a local spatial scale applying the multi-criteria analysis and GIS: a case study from Slovakia. *Geomatics, Natural Hazards and Risk*, 11(1), 131-148. DOI: https://doi.org/10.1080/19475705.2020.1713233.

XU, K., GUO, Q., LI, Z., XIAO, J., QIN, Y., CHEN, D., KONG, C. 2015: Landslide susceptibility evaluation based on BPNN and GIS: a case of Guojiaba in the Three Gorges Reservoir Area. *International Journal of Geographical Information Science*, 29(7), 1111-1124. DOI: https://doi.org/10.1080/13658816.2014.992436

YAZDADI, E. A., GHANAVATI, E. 2016: Landslide Hazard Zonation by using AHP (Analytical Hierarchy Process) model in GIS (Geographic Information System) Environment (Case study: Kordan Watershed). *International Journal of Progressive Sciences and Technologies (IJPSAT)*, 2(1), 24-39.

YOUSEFI, H., HAFEZNIA, H., YOUSEFI-SAHZABI, A. 2018: Spatial Site Selection for Solar Power Plants Using a GIS-Based Boolean-Fuzzy Logic Model: A Case Study of Markazi Province, Iran. *Energies*, 11(7), 1648. DOI: https://doi.org/10.3390/en11071648.

ZHANG, Y., WU, W., QIN, Y., LIN, Z., ZHANG, G., CHEN, R. et al. 2020: Mapping Landslide Hazard Risk Using Random Forest Algorithm in Guixi, Jiangxi, China. *ISPRS International Journal of Geo-Information*, 9(11), 695. DOI: https://doi.org/10.3390/ijgi9110695.

ZHOU, S., ZHOU, S., TAN, X. 2020: Nationwide Susceptibility Mapping of Landslides in Kenya Using the Fuzzy Analytic Hierarchy Process Model. *Land*, 9(12), 535. DOI: https://doi.org/10.3390/land9120535.

Authors´ affiliations

Davoud Omarzadeh
University of Tabriz
Geography information system and Remote sensing
29 Bahman Blvd.
Tabriz, Iran 5166616471
https://orcid.org/0000-0002-7904-6903
davoud.omarzadeh@stud.sbg.ac.at

Seyed Ahmad Eslaminezhad
University of Tehran
Department of surveying and Geomatics Engineering
16th Azar St., Enghelab Sq.
Tehran, Iran 1417466191
https://orcid.org/0000-0001-7587-3779
Ahmad.eslami73@ut.ac.ir

Mobin Eftekhari
Islamic Azad University
Department of Civil Engineering
Emamieh Blvd.
Mashhad, Razavi Khorasan, Iran 9187147587
https://orcid.org/0000-0002-1031-1270.
mobineftekhari@yahoo.com

Mohammad Akbari
University of Birjand
Department of Civil Engineering
University Blvd.
Birjand, Southern Khorasan, Iran 9717434765
https://orcid.org/0000-0002- 6882-874X
moakbari@birjand.ac.ir