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Identifying Landslides Prone-Areas Using GIS-based Fuzzy Analytical Hierarchy Process Model in Ziz Upper Watershed (Morocco)

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ABSTRACT

Landslides cause massive damage to human lives, infrastructure, and property in many regions of the world. These disasters arise on unstable slopes in mountainous regions. The recent increase in these incidents in many regions, including Morocco, has attracted more attention to their study. In this paper, a combination of GIS techniques, fuzzy analytical hierarchy process (FAHP) were integrated to model landslide susceptibility in the upper Ziz catchment, south-eastern Morocco. The data used for this purpose included several geo-environmental and climatic factors affecting susceptibility to landslides. The results of this modeling showed that 16.7% of the studied area has a high susceptibility to landslides, and that the upstream western part is considered the most susceptible. Evaluation of the resulting map's accuracy using the inventory of 148 landslide events showed that the FAHP model has an important performance, as the value of the area under the curve was about 0.885.

Keywords: landslides susceptibility, GIS, fuzzy analytical hierarchy process, Ziz, Morocco.

INTRODUCTION

In mountainous areas, landslides occur on slopes under the influence of either direct gravity or external factors such as earthquakes and rain (Manaouch et al., 2021). They manifest as mass movements of rocks, soil and debris. Because of its wide spread as one of the most dangerous natural disasters, it has been studied by many researchers in different places: recently in Iran (Bahrami et al., 2020), in Kenya (Tan et al., 2020), in Serbia (Dokanovic, 2019), in India (Saha and Roy, 2019), in Malaysia (Lee and Pradham, 2007), in Turkey (Akgun and Bulut, 2007), in Italy (Pellicani et al., 2014), in Austria (Zieher et al., 2016) and in many other areas. These disasters have resulted in a large number of casualties across the world (Flentje and Chowdhury, 2016) and the loss of many properties, facilities, roads, forests and agricultural fields. Recently, an increase in the frequency of landslides has been observed and all the damage caused by them is often counted. Hence, the importance of studying landslides has increased, as it has become very important to know the areas prone to that in the future to reduce their damage as much as possible.

Similar to other landslide-threatened regions of the world, the Ziz upper catchment in SE Morocco suffers from landslides, but no attempt has been made to predict their locations or prevent their damage. During each rainy period, landslides can cause a large number of the traffic accidents along the only national road N°13 between the cities of Midelt and Errachidia in south-eastern Morocco. As a result, traffic has been stopped on several occasions due to landslides and rocks along the road section between Errich and Errachidia. Therefore, several efforts are needed to reduce the risk of landslides in this area. In this context, identifying the landslides prone-areas using landslide susceptibility mapping (LSM) is proving to be a good tool to mitigate their risk of landslides. Despite the enormous damage caused by landslides in Morocco, literature reviews indicate that only a few limited investigations have been conducted in the Rif, northern Morocco (El Kharim et al., 2021; Es-Smairi et al., 2021; Benzougagh et al., 2020) and no previous studies on LSM in SE Morocco have been published yet. Filling this research gap is the reason why this work was performed.

Over the past three decades, many LSM methods have been proposed due to the availability and cost of geospatial data and the enormous development of computer science. Most of these methods have been built on geographic information systems (GIS). Generally, the LSM is done according to two approaches: the first is based on subjective judgments of experts (Qualitative) while the second is based on mathematically rigorous objective methodologies (Quantitative) (Zare et al., 2012).

In qualitative approaches, each factor influencing the landslide is weighted based on expert judgments. Then, the derived weights are used to calculate the sensitivity to the landslide. Heuristic analysis, Inventory analysis and Analytical Hierarchy Processing (AHP) are the most important qualitative LSM models. The quantitatively developed methods showed that the most widely used are frequency ratios (FR), logistic regressions (LR), weights of evidence (Wof E), artificial neural networks (ANN) and support vector machines (SVM).Whereas, SHALSTAB, SINMAP and TRIGRS are the most important physically based LSM models, developed based on the integration of slope stability models and groundwater flow models to calculate the safety factor per each slope unit (Zhou et al., 2020).Looking at all these models, it was found through comparative studies that the optimal choice of one of the LSM methods depends largely on nature and availability of data in the study area.

Over the two past decades, a number of researchers led by Pradhan, Lee and Pham and others have increasingly improved machine learning (ML) algorithms for landslides susceptibility assessment. Examples are: Logistic regression (LR) (Lee and Pradhan, 2007), Frequency Ratio (FR) (Arabameri et al., 2019), Bayesian network (BN), Naïve Bayes (NB) (Lee et al., 2020, Pham et al. 2021), Weight of Evidence (WOE) (Pradhan et al., 2010), Artificial neural networks (ANN) (Zare et al., 2013), SIGMA model (Abraham et al., 2021), ANFIS model (Moayedi et al., 2019; Zhou et al., 2018; Saha et al., 2020; Arabameri et al., 2020), Support Vector Regression (SVR) (Panahi et al., 2020; Balugon et al., 2021), Support Vector Machines (SVM) (Zhang et al., 2019; Saha et al., 2020), Decision Tree (DT) (Pham et al., 2020), Logistic Regression (LR), Random Forest (RF) (Saha et al., 2020; Nhu et al., 2020; Saha et al., 2021), Teaching-learning based optimization and Satin Bowerbird optimizer (TLBO-SBO) (Chen et al., 2021), Statistical Index and linear discriminant analysis (SI-LDA) (Arabameri et al., 2020), radial basic function (RBF) (Zare et al., 2013; Pham et al., 2020), Artificial Intelligence (AI) (Dikshit et al., 2020), Conditional probability and the boost regression tree (CP-BRT) (Saha et al., 2021), RSS (Pham et al., 2021), SVM-ANN (Saha et al., 2020), SVM-LR (Saha et al., 2020), Convolutional neural network (CNN)-SVM, CNN-RF and CNN-LR (Saha et al., 2020), Convolutional neural network (CNN) (Ngo et al., 2020). All these methods and models were used to assess susceptibility to landslides in different regions of the world and were also used in the same areas to compare the results and determine the most appropriate ones. These studies are very important for evaluating landslides and predicting future landslides.

In conjunction with these researches, many comparisons have been made between landslide susceptibility assessment models using different ML methods. For example, Saha et al. (Saha et al., 2020) stated a comparison research of individual and ensemble of machine learning and probabilistic approaches like an artificial neural network (ANN), support vector machine (SVM), random forest (RF), logistic regression (LR), and their ensembles such as ANN-RF, ANN-SVM, SVM-RF, SVM-LR, LR-RF, LR-ANN, ANN-LR-RF, ANN-RF-SVM, ANN-SVM-LR, RF-SVM-LR, and ANN-RF-SVM-LR for mapping landslide susceptibility in Garhwal Himalaya, India and found that the ANN-RF-LR ensemble has the best performances. In other studies, comparing the results of landslide assessment models and methods, it has been shown that one model can be successful in one area and vice versa in another.

Although there are several methods and models to assess the landslides susceptibility, some researchers suggest taking into account the scale of the study area. Thus, they concluded that qualitative methods, such as spatial multicriteria evaluation (SMCE) and heuristic weighting, are the most popular existing LSM on a large-scales study (Waithaka et al., 2015).

Hence, the purpose of this study was to accomplish a susceptibility map to landslides for the large Ziz upper catchment (4435 km^2). To do this, the fuzzy analytical hierarchy process (FAHP) method was adopted. The landslide inventory and landslide responsible factors used in this work were collected from various sources. Highly landslide-prone areas in the Ziz upper watershed have been identified as a basis for further landslide hazards studies. In addition, the provided map can be used as a valuable tool for those interested in land planning and risk management.

MATERIALS AND METHODS

Study area

The mountainous area of southeastern Morocco represents a suitable area to study the risk of landslides, and the upper Ziz basin is one of the areas where they occur most. The basin covers an area of about 4,435 km^2, and extends between longitudes 32° 05' 48" and 32°64'19" North and latitudes 04° 11' 72" and 05° 46' 20" West (Figure 1). Altitude values are between 1023 and 3687 m above sea level. The Ziz upper basin has a semi-arid climate, with harsh winters and mild summers, with a large temperature difference according to altitude. Recorded annual rainfall rates fluctuate between 119 to 377 mm. yr^{-1} (Fenjiro et al., 2020). Average annual temperature values are between 19.2 °C and 10.2 °C. The basin soil patterns are poorly developed mostly: eroded soils, alluvial soils or even raw minerals not yet developed. The Jurassic marl limestone layers are more prevalent in the basin (Hinaje, 1995; Sadki et al., 1999; Charire, 1990) and the Plio-quaternaries continental fill formations (Figure 4e) (PNABV, 2014). LULC in the basin are distributed as follows: rangelands, which are the most common; degraded forests limited to the Phoenician Juniperus, Thurifera juniper, Atlas cedar, Aleppo pine, Holm oak and thorny xerophytes; agricultural fields scattered on the banks of the waterways and finally the water bodies represented exclusively by the dam reservoir (Mohamed et al., 2020).These geo-environmental conditions have greatly contributed to making the region highly vulnerable to landslide.

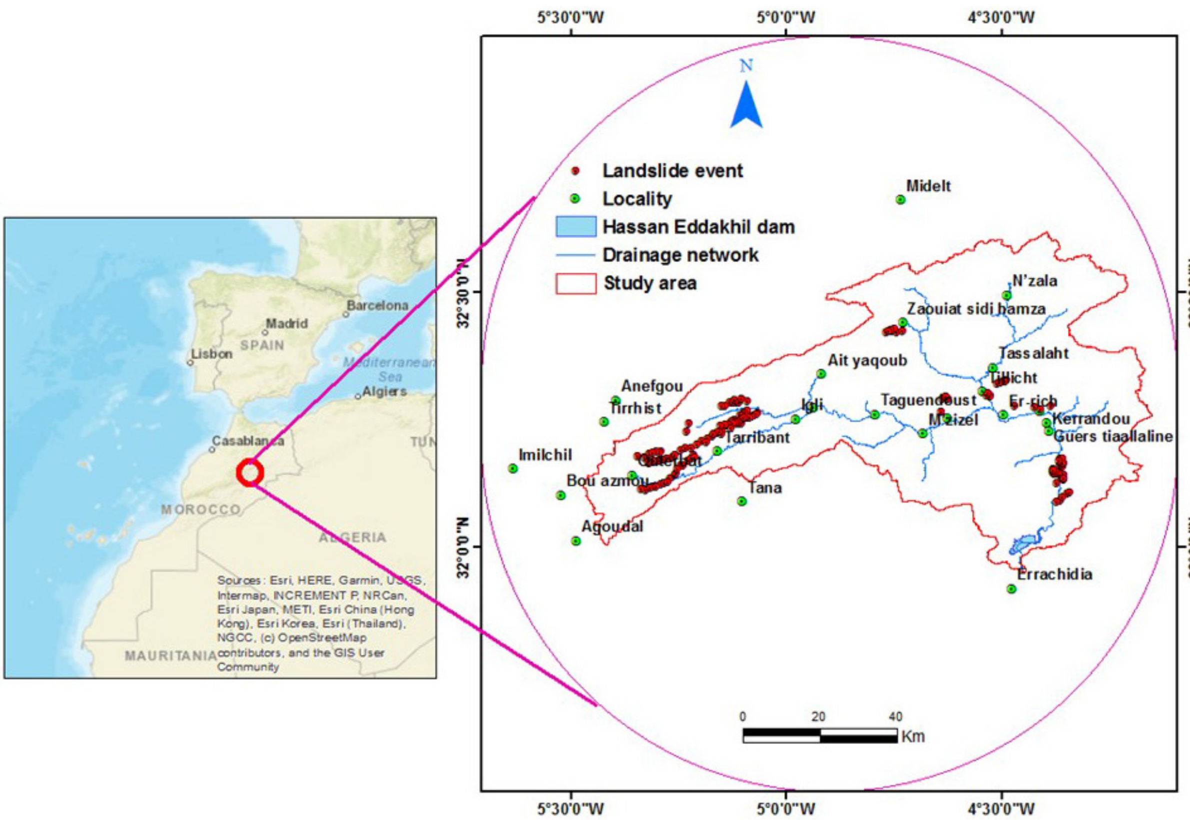

Figure 1. Location of the study area and landslide inventory map (red circle)

Data sources

In this paper, the DEM-SRTM with 30 m resolution (Digital Elevation Model of the Shuttle Radar Topographic Mission) was used for extracting topographic data for aspect, slope and drainage network by ArcGIS 10.5. While the geological maps of the studied area were used to prepare the faults and lithological maps. As for the rainfall data, its averages were calculated from the data of four meteorological stations within the studied area. The LULC map was extracted after processing the Landsat 8 Operational Land Imager (OLI) satellite data uploaded in March 2017 (Mohamed et al., 2020). Finally, the base maps of ArcGIS 10.5 were used as a source for roadmap. Table 1 provides more details on the data sources used in this research.

Landslide inventory map

The landslide inventory map is a critical element in identifying areas of landslide occurrence (Pourghasimi et al., 2012). It is prepared based on different information and data such as old landslides, satellite images and then field survey (Figure 1). In this study, several field visits and Google Earth images enabled the identification of a total of 148 landslides. Then, the process of determining the relationship between the factors controlling the occurrence of a landslide and the weight of each factor is carried out based on the information provided by the inventory in the GIS environment (Yalcin et al., 2011). Furthermore, landslide inventory data are used to validate the LSM map resulting from FAHP modeling.

The fuzzy logic method

The values 0 and 1 were used in classical set theories, where 0 means that the element is not a member or does not belong to the set. Whereas a value of 1 means that an element is a member of the set or belongs to it, and on this basis, there are two consequences: belonging or not to the set (Hines, 1997). But starting in 1965, Zadeh's 'fuzzy set' theory came with a new content that the element can belong relatively to the set, meaning the value of belonging can be other than 0 and 1 as in the traditional theories. Then Zadeh's theory became one of the widely adopted methods in various disciplines and many researches. In geographical sciences, for example, fuzzy logic deals with spatial objects on the map as objects in a set. In the study of susceptibility to landslides for example, a fuzzy logical approach is used taking into account the pixel values of any influencing factor layer as a susceptibility object to landslides. In factor maps, pixels have values between 0 and 1. A value of 0 means that the location is "unsusceptible" or has no effect on susceptibility to landslide, while a value of 1 means that it is "very susceptible" or has a significant effect on susceptibility. According to fuzzy logic, input raster maps are converted into maps with a scale of values between 0 and 1, each value has a certain membership in the set of susceptibility to landslides, based on several algorithms.

In this paper, to prepare the fuzzy map for each factor, the linear membership function (LMF) was used. Each parameter, according to its membership, is given a value between 0 and 1 (Zadeh, 1965). If the value of "a parameter" x equals 0, it means that it is not an influential member of susceptibility to landslide and if the value of x equals 1, it means that it is a member with a full influence in that. The following equations provide more detail about the fuzzy logic set (McBratney and Odeh, 1997).

For each element x belonging to X:

Table 1. Data used and their sources

Used data	Data format	Period
Rainfall[a]	Digital excel	1976 to 2019
Geological maps[b]	Digital vector	1939 & 1956
Landsat 8 OLI[c]	Digital raster	2017
DEM – SRTM[c]	Digital raster	2017
Base map[d]	Digital vector	2020
Google earth image[e]	Digital raster	2018

Note: [a]Guir-Ziz-Rhris hydrologic agency (ABH-GZR, 2019), [b]Geological map of Midelt high Atlas geological map (Gonzague et al., 1939) and high Atlas north Ksar essouk and Boudenib geological maps (Lyazidi et al., 1956), [c]Website:www.earthexplorer.usgs.gov, [d]BBase maps online in ArcGIS 10.5, [e]website and Google earth.

$$A = \{x, \mu_A(x)\} \tag{1}$$

where: $f(A)$ – the MF of x in the fuzzy logic set A then:

Display quotations of over 40 words, or as needed.
- If element x does not belong to A, then A = 0;
- If element x belongs entirely to A, then A = 1;
- If element x belongs in a certain proportion to A, then:

For numbered lists:

$$0 < A(x) < 1 \tag{2}$$

From the above equations, LMF was used for the following factors: elevation, slope, lithology, LULC, and precipitation (Feizizadeh and Blaschke, 2013).

$$\mu_A(x) = f(x) = \begin{Bmatrix} 0 & x \le a \\ \dfrac{x-a}{b-a} & a < x < b \\ 1 & x \ge b \end{Bmatrix} \tag{3}$$

where: x – one of the factors and a, b is the minimum and maximum values.

While the effect of stream distance, fault distance, and road distance on landslide susceptibility was evaluated using the following LMF (Feizizadeh and Blaschke, 2013)

$$\mu_A(x) = f(x) = \begin{Bmatrix} 0 & x \le a \\ \dfrac{b-x}{b-a} & a < x < b \\ 1 & x \ge b \end{Bmatrix} \tag{4}$$

where: x – representing the value of the distance from the river, the distance from the fault and the distance from the road; a, b – the cut-off values.

In this study, fuzzy raster map was prepared for each of the following LSM factors: fault distance, road distance, river distance, DEM, aspect, slope, lithology, precipitation and LULC.

Analytical hierarchy process

Analytical hierarchy process (AHP) is a method for Multi-Criteria Decision Making (MCDM), first introduced by Saaty in the 1980s. It is based on assigning weights to criteria using the pairwise comparison method for a factor or combination of factors. Each factor is weighted between 1 and 9 according to its importance in influencing susceptibility to landslides. Table 2 provides a description of the factor comparison method.

Pairwise comparisons of both qualitative and quantitative data were applied to produce a matrix (A):

$$A = \{a_{ij}\}_{n\times n} =$$

$$= \begin{bmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \cdots & \dfrac{w_1}{w_n} \\ \vdots & \ddots & \vdots \\ \dfrac{w_n}{w_1} & \cdots & 1 \end{bmatrix} \tag{5}$$

$$a_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad i,j=1,2\ 3,..n \tag{6}$$

$$w_i = \left(\frac{1}{n}\right)\sum_{j=n}^{n} a_{ij} \quad i=1,2,....n \tag{7}$$

Nine geo-environmental factors were considered as affecting susceptibility to landslides:

DEM, rainfall, slope, lithology, aspect, proximity to streams, proximity to roads and proximity to faults. According to Saaty's scale and expert judgment, factor weights were evaluated with a number between 1 and 9 for each factor. These weights represent the relative importance of factors in their influence on susceptibility to landslides according to expert opinion.

RESULTS

Raster maps

The DEM-SRTM resolution of 30 m was adopted for all other factor maps involved in the LSM determination of the Ziz upper watershed as they included aspect, lithology (erodibility), fault, slope, LULC, rivers, roads and precipitation maps shown in Figures 2a-i.

The Ziz basin's average elevation is 1812 m (above sea level), and the values range between 1023 m at the catchment outlet and 3687 m in the northwestern parts (Manaouch et al., 2021)

Table 2. Scales for pairwise comparisons (Saaty, 1980)

Signifiance	Definition
1	Equal importance
3	Moderate importance of one over another
5	Essential importance
7	Demonstrated importance
9	Absolute importance
2, 4, 6, 8	Intermediate values between the two adjacent judgments

(Figure 2a). For slope, its values are between 0.004 and 66.08 degrees and values from 0 to 15 degrees represent 82%. As for aspect, the values range from -1 (flat) to 360 (N) with the northern and western sides being the rainiest and most sensitive to landslides. As for the precipitation map, it was developed based on datasets of four meteorological stations, most of which are located in the watersheds, and the IDW interpolation method (Inverse Distance Weighted) was

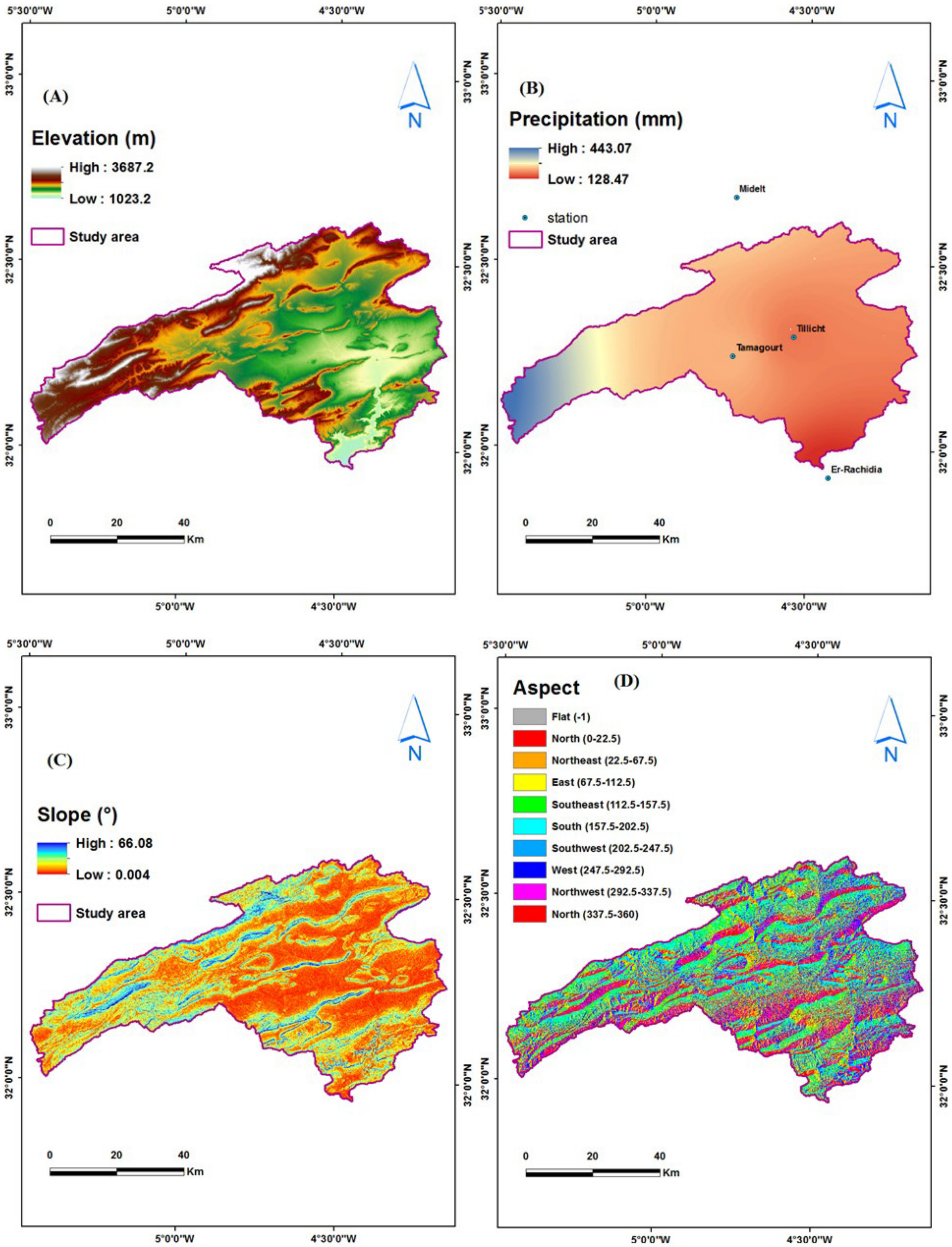

Figure 2. Raster maps used for LSM in this study: (a) DEM, (b) rainfall, (c) slope, (d) aspect

adopted to estimate the spatial distribution of precipitation, so the values were obtained for all points in the studied area. Average precipitation values fluctuate between 120 and 470 mm. -1 year. The southern and eastern parts receive lower amounts compared to the rest of the parts. Whereas, the western and northwestern parts of the border receive significant amounts of rain (Figure 2b).The mountainous regions of the western and northwestern parts receive the

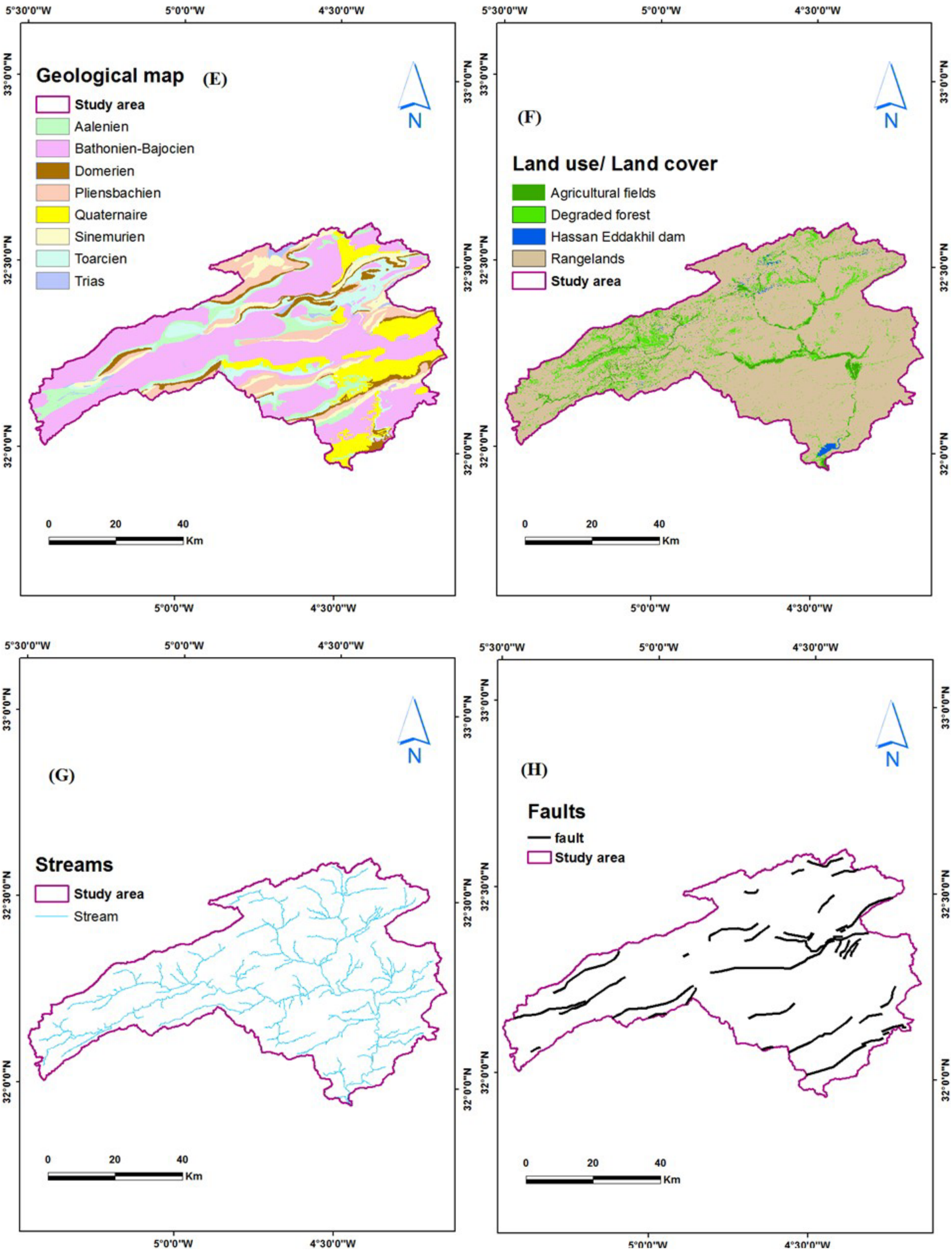

Figure 2. Raster maps used for LSM in this study: (e) lithology (sensitivity), (f) LULC, (g) streams, (h) fault

highest values (Figure 2a). Generally, five types of LULC predominate in the study area (Figure 2f), the most important of which are rangeland or poorly vegetated areas, degraded forests, agricultural fields, water bodies and built-up areas. Regarding the influence of the lithological factor on the susceptibility of landslides, the soil erosion factor was used instead (Fenjiro et al., 2020). The lower the value of the soil erosion factor, the higher the susceptibility to landslides. Then, raster maps of road distance, fault distance, and stream distance (Figures 2g, 2h, 2i) were prepared using the values shown in Table 3 by the Euclidean distance tool in the ArcGIS 10.5 spatial analysis toolbox. Finally, all these maps were combined and overlaid in ArcGIS 10.5 and a landslide susceptibility map was obtained.

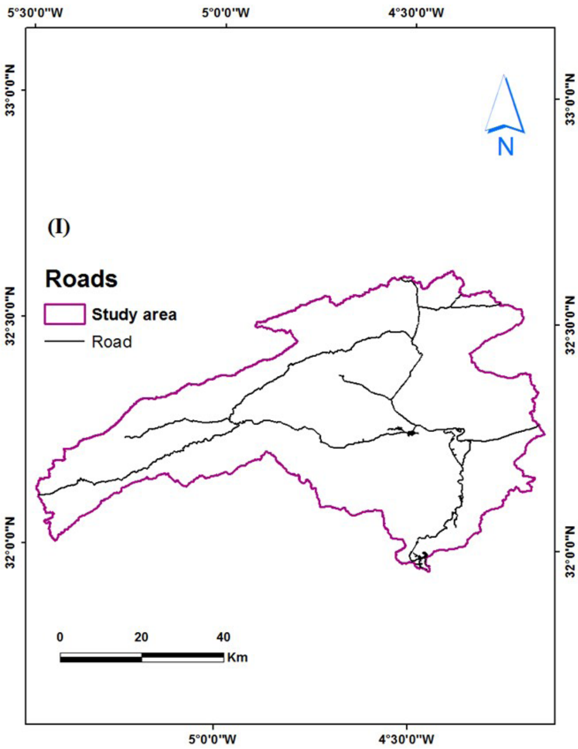

Figure 2. Raster maps used for LSM in this study: (i) road raster map

Table 3. Values of distance to fault, distance to stream and distance to road approved for landslide susceptibility

Feature				
Proximity to roads (m)				
0–25	25–50	50–75	75–100	>100
Proximity to streams (m)				
0–50	50–100	100–150	150–200	>200
Proximity to faults (m)				
0–1000	1000–2000	2000–3000	3000–4000	>4000

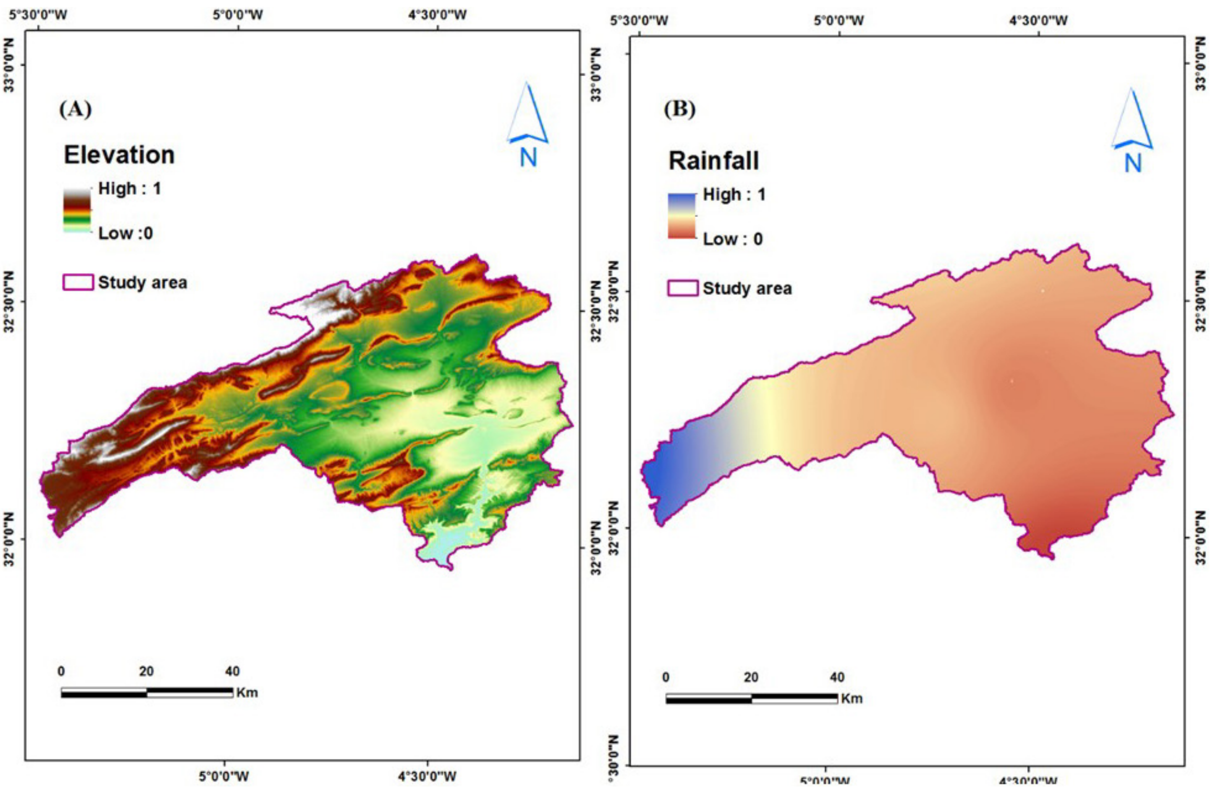

Figure 3. Fuzzy map of studied area for each landslide susceptibility parameter: (a) DEM, (b) rainfall

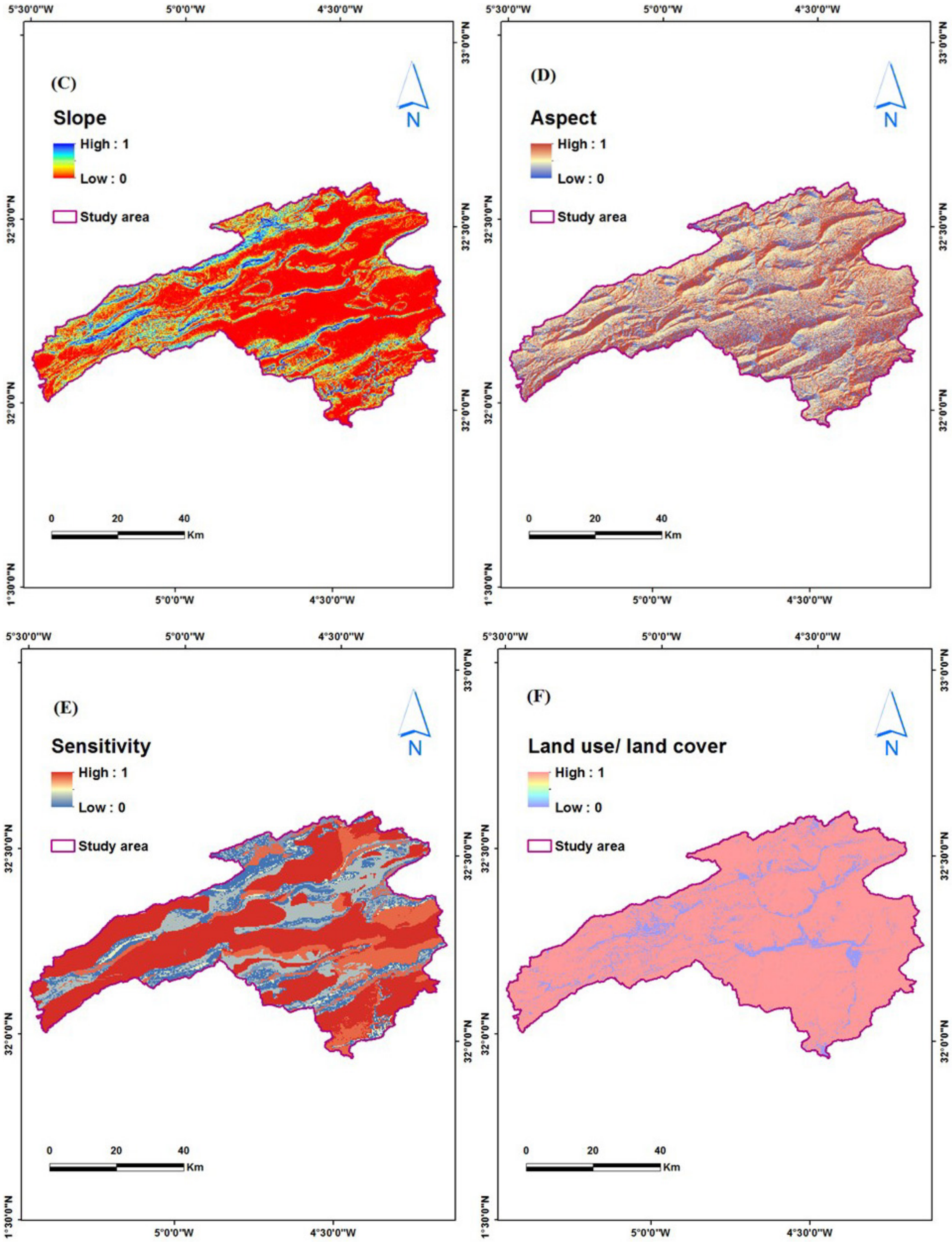

Figure 3. Fuzzy map of studied area for each landslide susceptibility parameter: (c) slope, (d) aspect, (e) lithology (sensitivity), (f) LULC

Fuzzy method

In ArcGIS 10.5, there are several ways to define fuzzy mapping of parameters. The linear method is the most widely used. According to Tables 3 and 4, a minimum and an upper bound for each parameter is adopted in order to implement the LMF to convert parameter maps into maps with parameter values all between 0 and 1. For DEMs, values above

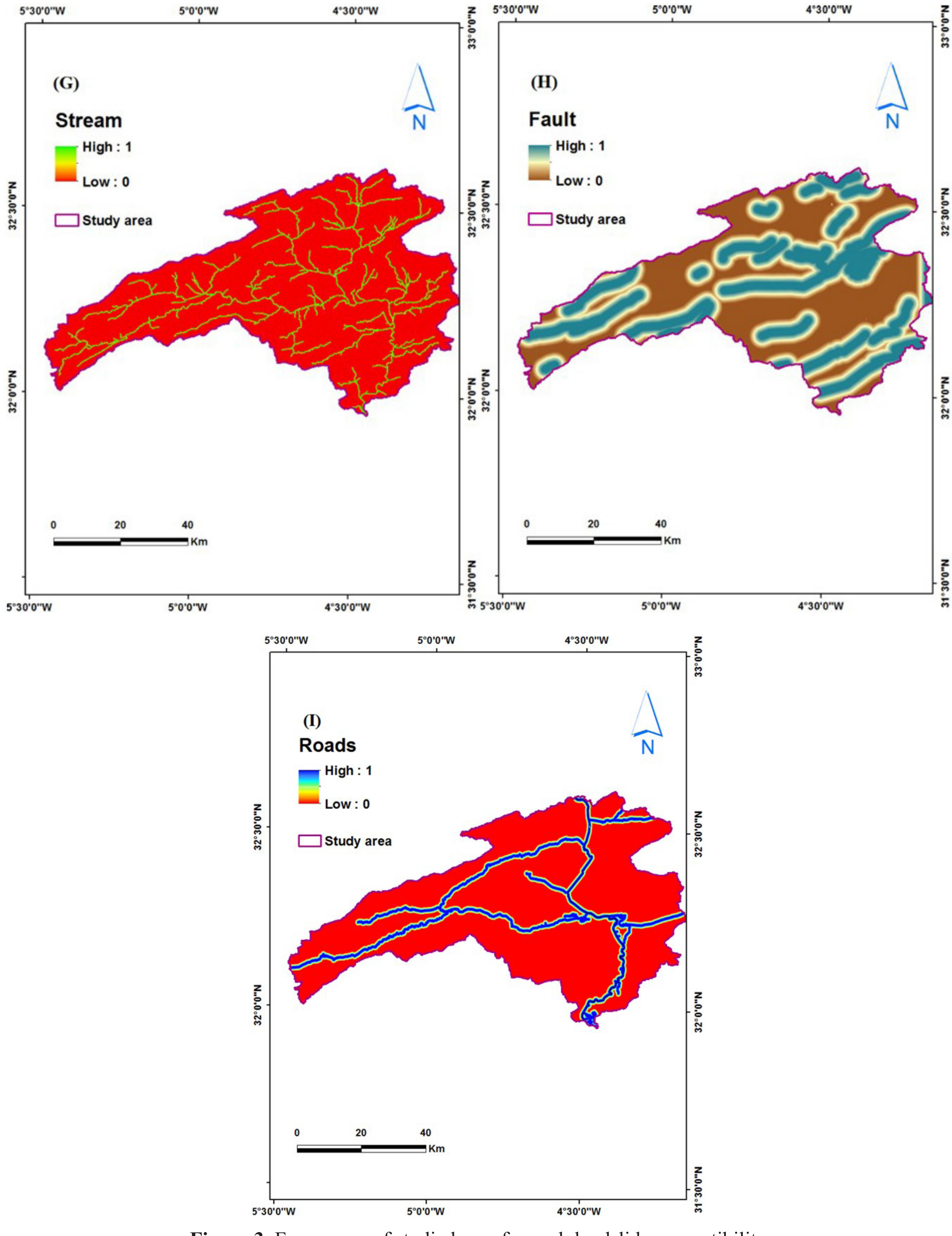

Figure 3. Fuzzy map of studied area for each landslide susceptibility parameter: (g) streams, (h), fault, (i) road fuzzy map

3000 m take the value 1 and smaller than 1000 m take the value 0. Thus, the elevation map has values ranging between 0 and 1 instead of between 1000 and 3000 m. In the same way the values of all other parameters were converted to raster maps with values between 0 and 1. According to Figure 3, regions with a value of 1 in fuzzy maps prepared for parameters are considered to be more prone to landslides. Whereas, the regions with values closer to 0 are considered less susceptible.

Table 4. Criteria values: maximum and minimum (Feizizadeh and Blaschke 2013)

Parameters	Maximum	Minimum
Rainfall (mm)	>400	<100
LULC	Degraded forest, rangeland	Water bodies, agricultural fields
Distance to streams (m)	<50	>200
Distance to faults (m)	<1000	>4000
Distance to roads (m)	<25	>100
DEM (m)	>3000	<1200
Slope (°)	>40	<10
Aspect	South	Flat
Lithology (Soil Erodibility factor)	0.05	0.16

Table 5. Pairwise comparison matrix, factor weights and consistency ratio

Parameter	Lith	Ra	LULC	Sl	d to F	d to S	d to R	Asp	DEM	Weight
Lith	1	2	3	4	5	6	7	8	9	0.31
Ra	0.5	1	2	3	4	5	6	7	8	0.22
LULC	0.33	0.5	1	2	3	4	5	6	7	0.15
Sl	0.25	0.33	0.5	1	2	3	4	5	6	0.11
d to F	0.2	0.25	0.33	0.5	1	2	3	4	5	0.08
d to S	0.16	0.2	0.25	0.33	0.5	1	2	3	4	0.05
d to R	0.14	0.16	0.2	0.25	0.33	0.5	1	2	3	0.04
Asp	0.12	0.14	0.16	0.2	0.25	0.33	0.5	1	2	0.03
DEM	0.11	0.12	0.14	0.16	0.2	0.25	0.33	0.5	1	0.02
Consistency Ratio (CR) = 0.02										

Note: Lith – Lithology; Ra – rainfall; LULC – land use / land cover; Sl – slope; d to F – distance to faults; d to S – distance to streams; d to R – distance to roads; Asp – aspect; DEM – digital elevation model.

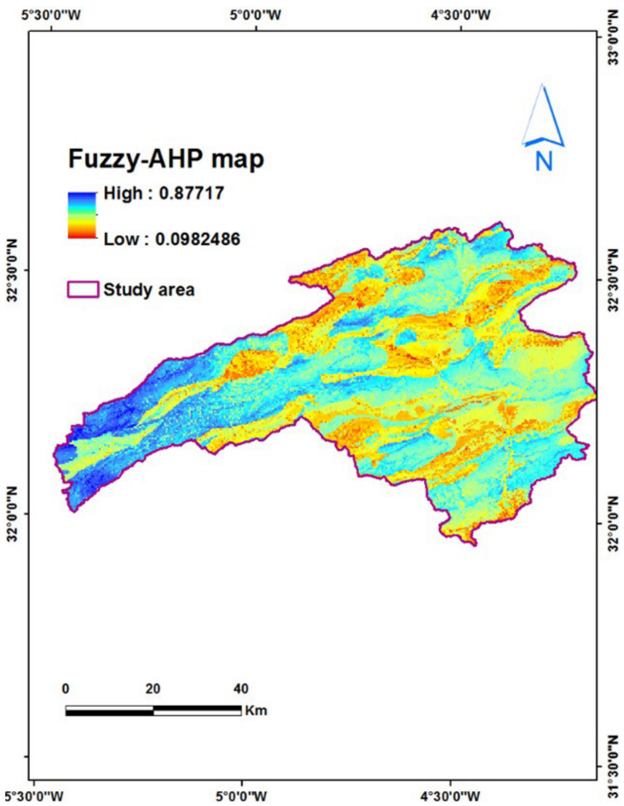

Figure 4. LSM based on the FAHP model

According to Figures 2a-i, it is shown that all parameters are closer to the value 1 in the upstream western parts of the study area (Manaouch et al., 2021).

AHP results

By pairwise comparison of Feizizadeh and Blaschke (2013) shown in Table 5, it turns out that lithology and DEM have the most important and least weight, respectively. Where the lithology got the highest weight 0.31 followed by the precipitation 0.22. The aspect weight was 0.03 followed by the elevation 0.02.

FAHP results

Integrating FAHP with GIS is a good tool for susceptibility mapping to landslides. After assigning weights to the parameters according to the AHP method, the parameter maps are converted to fuzzy maps and using the Raster spatial analysis tool in ArcGIS 10.5 a landslide susceptibility map is produced. According to the resulting map (Figure 4), it is found that the vulnerability is very high in the upper western and northern parts of the study area (Manaouch et al., 2021). These areas are dominated by mountain pastures. For the areas of medium susceptibility, they are found

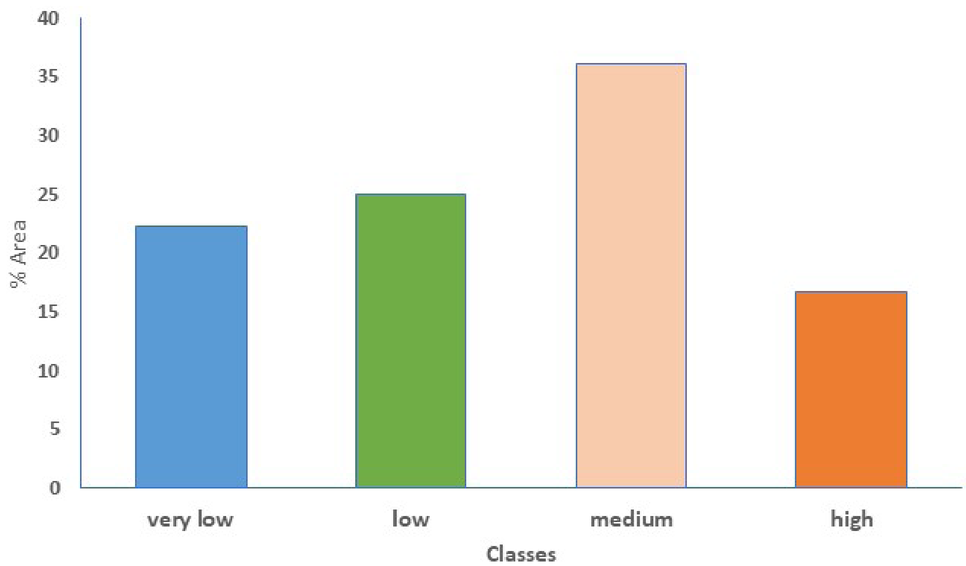

Figure 5. The area (%) for each class of the landslide susceptibility

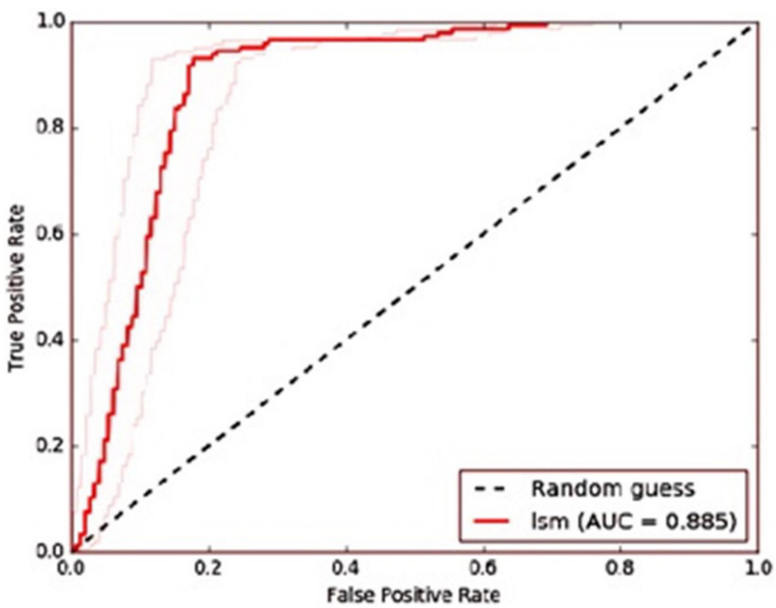

Figure 6. Prediction rate curve for the LSM produced by FAHP model

in abundance in the eastern, southern and central parts. While it is mainly spread in the northwest and some central areas, areas with weak or no susceptibility.

The natural break method is often used to divide and classify the susceptibility map for landslides (Figure 4) (Pourghasemi et al., 2012). Figure 7 represents the results of dividing the resulting map into four domain regions which are very low, low, medium and high.

The categories of susceptibility to landslides are distributed according to Figure 7 and the graph of Figure 5, as follows: areas with high susceptibility account for about 16.7%, areas with medium susceptibility accounting for about 36.1%, with low susceptibility representing about 25% and very weak susceptibility covering about 22.2%.

LSM's accuracy

Several methods are used to calculate the accuracy of the modeling results, but the method of calculating the area under the curve remains the most common. In this work, this method was used as well, where the classified map of the model was compared with the landslide inventory of the study area. In a classified FAHP model map, each pixel has a value that belongs to one of the landslide susceptibility classes and is either very low, low, medium, or high. By overlapping the classified map with the inventory, the modeling success rate is determined. In other words, if the inventory of 148 landslides occurred in the area of high potential, this indicates that the prediction rate is very good. The ArcSDM software package is used for this purpose where the area under the curve (AUC) of the ROC curve is calculated and the AUC represents the accuracy of the model in predicting the occurrence of landslides (Chen et al., 2016). AUC values are usually between 0.5 and 1. The closer the values are to 1, the better the accuracy of the model. Whereas, values less than 0.5 represent poor accuracy or random predictions.

After calculating the AUC, the prediction accuracy was about 0.885 in this study, which indicates that the model succeeded in predicting the locations of landslides by 88.5%. These results, show that the FAHP model is a valuable tool for predicting landslide-prone areas in the case of Ziz upper watershed (Manaouch et al., 2021).

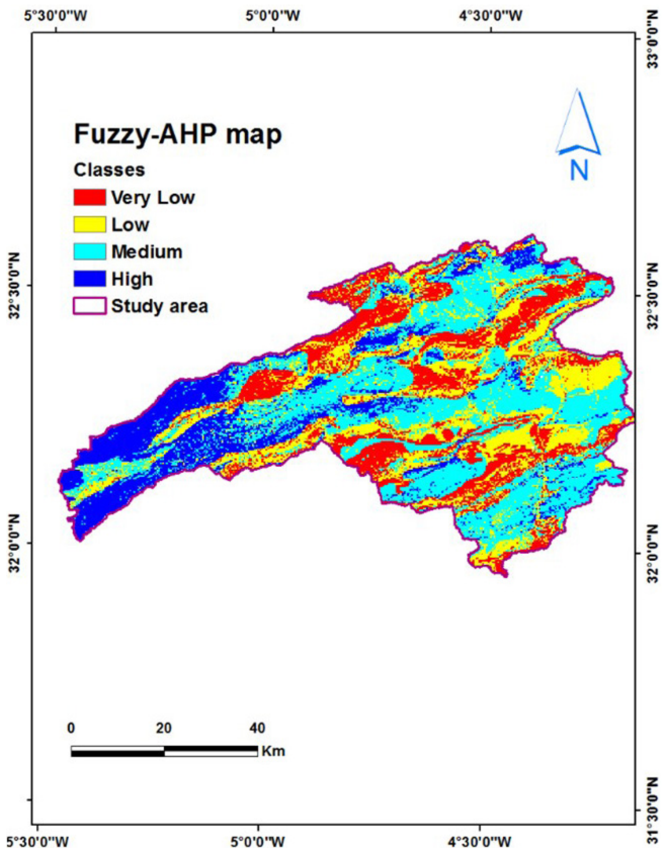

Figure 7. Classified landslide susceptibility map based on FAHP model

DISCUSSION

From Figure 7, it was observed that 16.7% of the study area is classified as places with high sensitivity, while 47.2% have low and very low susceptibility. High and extremely high landslide susceptibility zones predominantly cover the extreme western regions and some northern areas.

These results can be attributed to several reasons: altitude often exceeding 2000 m, large amounts of rain, steep slopes and faulted geological formations. Low and very low landslide-prone areas are common in the south, southeast and central regions except for the roadsides linking Errich and Errachidia near the Ziz valley known for frequent landslides. The western parts upstream of Oued Ziz have experienced the majority of historical landslides (Figure 1). This region is mountainous and receives significant amount of precipitation each year. Therefore, it has the greatest coverage of very high and high susceptibility to landslide areas.

Recently several methods have been developed in LSM at different scales. Some research has shown that for large areas with low availability of historical landslide inventories, the MCDA methods are suitable due to their significant advantages over statistical and physical methods (Glade et al., 2012 ; Barella et al., 2018; Zhou et al., 2020). For large areas, a review of previous studies has shown that AHP and Fuzzy-AHP are one of the best approaches for landslide susceptibility mapping (Zhou et al., 2020).

In this study, the new methods for assessing landslide susceptibility that we mentioned earlier were not applied due to the limited number of historical landslides in the inventory (148) and this may affect the validity of the results. Nevertheless, this number of historical landslide inventories has been used to validate the FAHP results. To apply modern methods to compare their results with traditional methods, we are now in the stage of collecting a larger number of historical landslides in this large study area.

The validation results show that the used FAHP gave a promising accuracy with an AUC of 0.88 (Figure 6) and the resulting accuracy appears to be good compared to similar studies in different regions (Poughasemi et al., 2012 ; Shahri et al., 2019; Zhou et al., 2020). For this type of LSM accuracy control, the greater the number of historical landslides included in the "high" susceptibility areas of the resulting map, the higher the precision. In other words, the fewer historical landslides there are in "extremely low" areas, the better the accuracy of the results. It should also be noted that the number of landslides conditioning factors used in this study is 9, and in other studies we found that it ranges between 3 and 25. So, this may constitute another source of subjectivity involved in comparing the results of this study and other similar studies using MCDA methods. After reviewing several recent publications, it was found that the availability of data, the size and nature of the study area are responsible for the number selection of LCFs (Reichenbach et al., 2018; Zhou et al., 2020). Even elsewhere, no specific universal rules have yet been proposed in the methods of landslide susceptibility studies. Hence, the solution adopted is to conduct several studies using different models and methods to select the best LSM maps for a particular study area.

CONCLUSIONS

Landslides in mountainous areas are considered the most important geo-environmental hazards. Predicting where they will occur is critical to preventing larger losses. With ease of access to remote sensing data and the geographic information system revolution, landslide susceptibility studies have become much easier.

In this work, GIS techniques with the FAHP method were used to assess LSM in the large upper watershed of Ziz, south-eastern Morocco. To this end, a landslide inventory was prepared using 148 landslide events. By analyzing the inventory data, it was found that lithology and precipitation are the two most influential factors in landslides susceptibility. While DEM and Aspect have less effect. After identifying the nine factors affecting susceptibility to landslides, they were evaluated and then weighted for use in modeling by combining fuzzy logic and AHP method. Based on the susceptibility map to landslides of the FAHP model, it appears that 16.7% in the studied area has high susceptibility, 36.1% has medium susceptibility, 25% has low susceptibility, and finally 22.2% has very low susceptibility.

Looking at the results of the validation of LSM using ROC/AUC curves, it was found that the FAHP model applied in the upper Ziz watershed has a success rate of 88.5%. This means that this model can be used to predict where landslides will occur because the accuracy of its predictions is really consistent with the inventory. Based on the FAHP modelling results, it appears that it represents a good tool for the decision maker to avoid the area's most prone to landslides through appropriate preventative measurements.

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