Geotech Geol Eng (2021) 39:5675–5691
https://doi.org/10.1007/s10706-021-01855-3

ORIGINAL PAPER

Landslide Susceptibility Mapping Using GIS-based Fuzzy Logic and the Analytical Hierarchical Processes Approach: A Case Study in Constantine (North-East Algeria)

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Received: 20 February 2020 / Accepted: 15 May 2021 / Published online: 28 July 2021

Abstract The main purpose of this study was to compare and evaluate the performance of two multi-criteria models for landslide susceptibility assessment in Constantine, north-east of Algeria. The landslide susceptibility maps were produced using the analytic hierarchy process (AHP) and Fuzzy AHP (FAHP) via twelve landslides conditioning factors, including the slope gradient, lithology, land cover, distance from drainage network, distance from the roads, distance from faults, topographic wetness index, stream power index, slope curvature, Normalized Difference Vegetation Index, slope aspect and elevation. In this study, the mentioned models were used to derive the weighting value of the conditioning factors. For the validation process of these models, the receiver operating characteristic analysis, and the area under the curve (AUC) were applied by comparing the obtained results to The landslide inventory map which prepared using the archives of scientific publications, reports of local authorities, and field survey as well as analyzing satellite imagery. According to the AUC values, the FAHP model had the highest value (0.908) followed by the AHP model (0.777). As a result, the FAHP model is more consistent and accurate than the AHP in this case study. The outcome of this paper may be useful for landslide susceptibility assessment and land use management.

Keywords Susceptibility mapping · AHP · Fuzzy AHP · Landslide · Conditioning factors · Land use management

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1 Introduction

Landslides are the most common and prejudicial geohazards in many parts of the world (Anis et al. 2019). This phenomenon has several direct and indirect effects on the natural and urbanized environment. Landslides have recently become a major preoccupation for geoscientists, engineers and civil authorities around the world. The growing international interest in landslides is due to the growing awareness of the socio-economic severity of these phenomena and the increasing pressure of development and urbanization on the environment (Aleotti and Chowdhury 1999). In order to mitigate the damage associated with landslide hazards, it is important to develop tools or techniques that help decision-makers make the right town planning and development decisions. For this reason, the development of a Landslide susceptibility Map (LSM) is used to assess and indicate the degree of vulnerability of the area to landslide occurrences, taking into account the effect of causative factors. To achieve the mentioned. To achieve the mentioned objectives, three main approaches are generally discussed in the literature, quantitative, semi-quantitative, and qualitative approaches.

The quantitative approach is based on probabilistic and statistical calculation rules and the concept of homogeneous units. According to Thiery et al. (2014), this method has some limitations due to the tendency to simplify environmental factors and assumptions that landslides occur under the same combination of variables. While the qualitative approach is based on expert knowledge of the phenomena, this type of analysis can give very different results depending on the experts (Van Westen 2000). The semi-quantitative approach makes it possible to formalize the rules defined by the experts. It retains the flexibility of the expert approach but is considered more objective by the formal framework it imposes on its application (Poiraud 2012). Over the past decade, several studies have been conducted to assess the landslide susceptibility in different regions using different methods. Sema et al. (2017) used the Fuzzy gamma operator model. Sahana and Sajjad (2017) evaluated the effectiveness of the frequency ratio, fuzzy logic and logistic regression models for the landslide susceptibility assessment. Moradi et al. (2012) proposed the Analytic Hierarchy Process (AHP) method to produce the LSM. Demir et al. (2013) employed likelihood-frequency ratio model and analytical hierarchy process. Bourenane et al. (2015) carried out a landslide susceptibility zonation (LSZ) by using bivariate statistical and expert approaches. Stanley and Kirschbaum (2017) used heuristic fuzzy approach to create a global landslide susceptibility map.

With geological and geomorphological specificity, Algeria is classified among one of the countries most affected by landslides (Hadji et al. 2013). For this reason, numerous studies were conducted to assess the landslide susceptibility in this country such as Merghadi et al. (2018), Achour et al. (2017), Karim et al. (2019), Dahoua et al. (2017a, b), El Mekki et al. (2017), Manchar et al. (2018), Mahdadi et al. (2018), Hadji et al. (2013), Hadji et al. (2014) and Dahoua et al. (2017a, b). The city of Constantine in north-eastern Algeria, has a long history of destructive landslides in various important districts such as Belouizded, Kaidi Abdellah, Belle vue, Ciloc, Boudraa Salah, Boussouf, Benchergui et Bardo (Fig. 1) (e.g., Machane et al. 2008). Few studies were carried out to assess the landslide susceptibility in Constantine. As example Bourenane et al. (2016) used FR, WoE, LR and weighting factors (WF) [frequency ratio (FR), weighting factors (Wf), logistic regression (LR), weights of evidence (WOE), and analytical hierarchy process (AHP)] methods to evaluate landslide susceptibility in Constantine city. Achour et al. (2017) used analytic hierarchy process and IV methods to assess landslide susceptibility along A-1 highway. Manchar et al. (2018) assessed the landslide susceptibility for the east of Constantine Province, using the WoE, IV and FR models. This paper aims to assess and map landslide susceptibility in the city of Constantine using Geo informatics technology and the AHP and FAHP model which limit vagueness of semi qualitative models. Twelve landslides conditioning factors are considered for this study, such as lithology, slope gradient and aspect, distance from the road, drainage distance and stream power index. The database was compiled from satellite images and existing thematic information.

2 Study Area

The city of Constantine is one of the most important cities in north-eastern Algeria (Fig. 1), home to

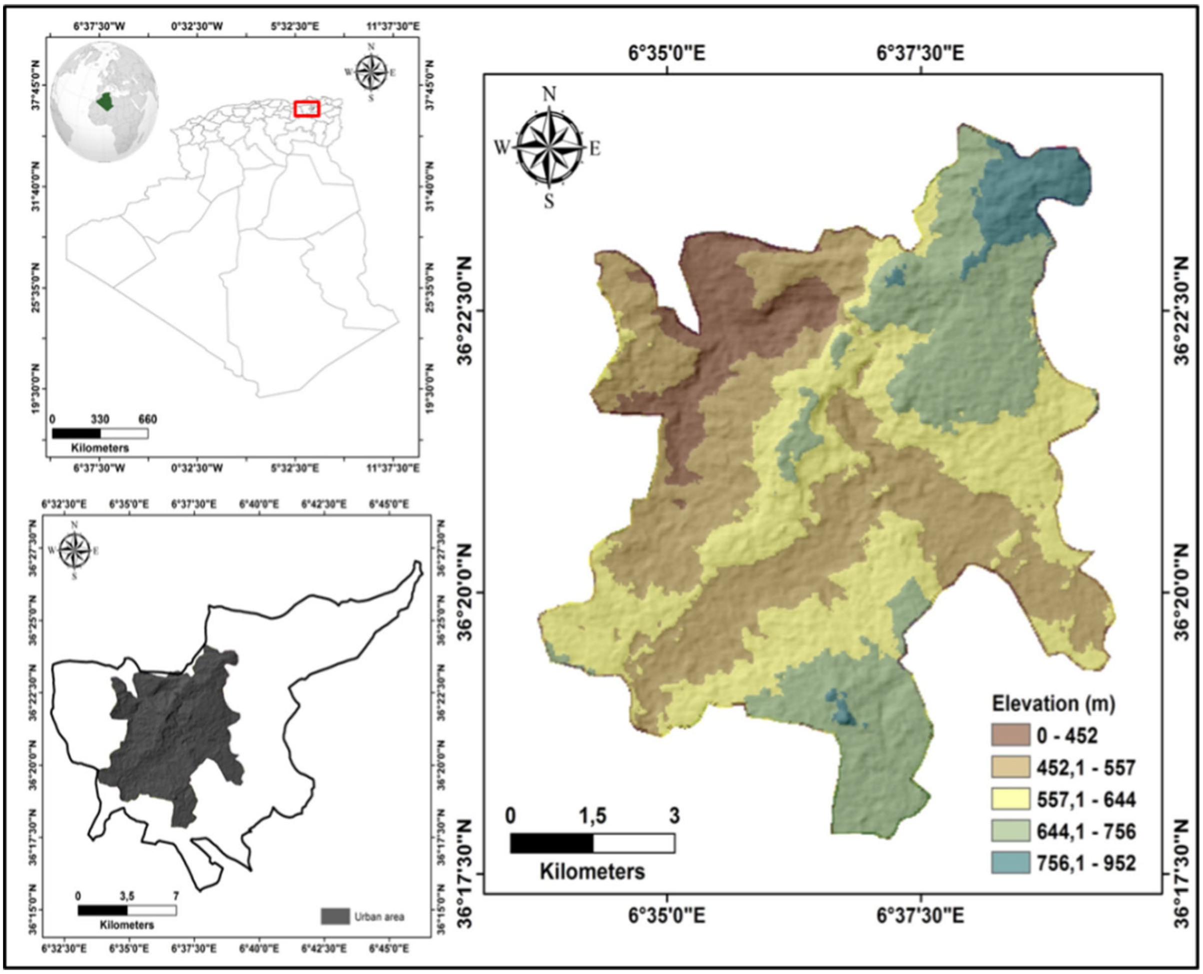

Fig. 1 Geographical setting of the study area

important economic, cultural and scientific aspects of Algerian activities. This city covers an area of about 183.063 km^2 extends between longitudes of 6°32′ to 6°45′, and latitudes of 36°27′ to 36°16′. The area concerned in this study is the perimeter of the master city's plan, which represents 60.14 km^2. The study area is situated between 6°33′ and 6°39′ longitudes, and 36°17′ to 36° latitudes, with an elevation ranging from 328 to 952 m, and slope varied between 7.08 and 59.88. This region is characterized by complex morphology combining mountains, deep gorges, hills, plains and plateaus. In the study area the climate is semi-arid, with mainly two seasons rainy and dry, characterized by high temperatures and humidity (Bourenene et al. 2015). The dry season is long, lasts from March to September with annual mean temperature around 16 °C. The short rainy season was usually between October and February, in which the average annual precipitation was about 600 mm/year (Mezhoud 2006).

The study region fits in the external domain of the Tellean Atlas chain belongs to the North African Alps, formed during the main paroxysmal compressional phases of Eocene, Miocene, and Quaternary periods (Bourenene et al. 2016). The lithology of this study area presents four main lithostratigraphic units: The Cretaceous-Eocene marls and calcareous marls of the Tellian thrust sheet unit; the Mio-Pliocene sandy clays, marls and conglomerates; and the Quaternary alluvial terraces and lacustrine calcareous formations (Bourenene et al. 2015; Bougdal et al. 2006). Due to the particular natural conditions and human activities, the city of Constantine has a long history of landslides. Like the Bardo landslide, the landslide from the Sidi

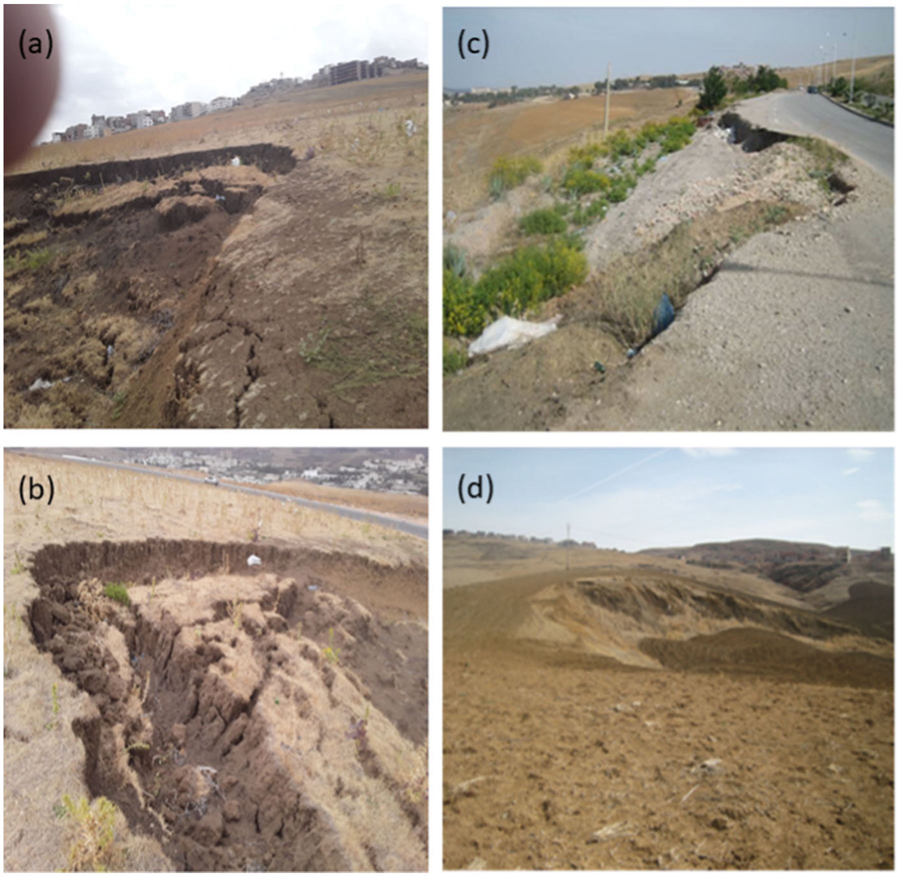

Fig. 2 Photographs of inventoried landslides in Constantine city **a** and **b** landslide in Boussouf; **c** and **d** landslide in Massinissa

Table 1 details of the data used for the susceptibility analysis

Sources	Data	Causative factors
https://earthexplorer.usgs.gov/	Digital Elevation Model (DEM)	Slope gradient
		Elevation
		Topographic wetness index
		Distance from rivers
		Stream power index
		Slope curvature
		Slope aspect
		Distance from road
		Distance from fault
	Satellite images	Normalized vegetation index
		Land use and land cover
Geotechnical studies (DUC 2004)	Lithological formation map	Lithology

Table 2 Fundamental scale for pair-wise comparisons (following Saaty and Vargas 1991)

Scale	Degree of preference	Explanation
1	Equally	Two activities contribute equally to the objective
3	Moderately	Experience and judgement slightly to moderately favour one activity over another
5	Strongly	Experience and judgement strongly or essentially favour one activity over another
7	Very strongly	An activity is strongly favoured over another and its dominance is showed in practice
9	Extremely	The evidence of favouring one activity over another is of the highest degree possible of an affirmation
2, 4, 6 and 8	Intermediate values	Used to represent compromises between the references in weight 1, 3, 5, 7 and 9
Reciprocals	Opposites	Used for inverse comparison

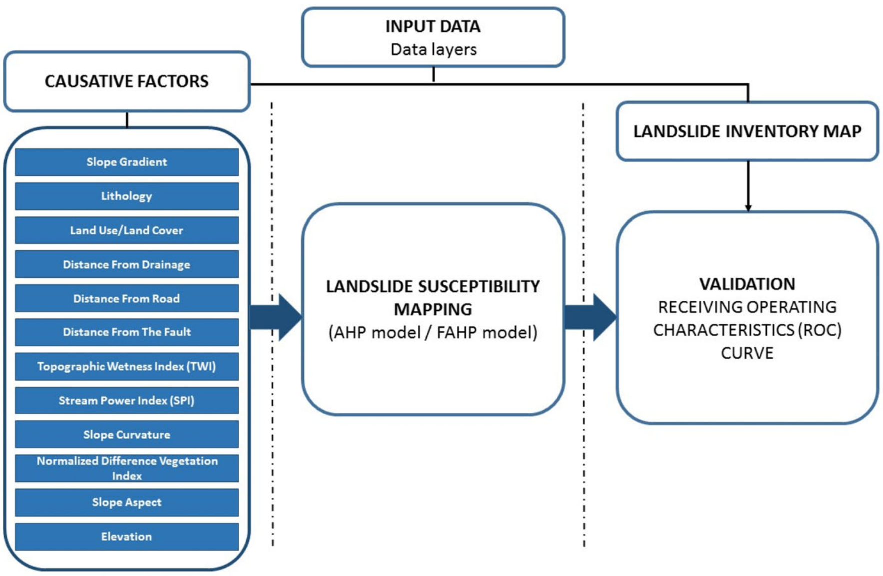

Fig. 3 Flowchart of the proposed Methodology

Rached bridge to Constantine railway station are examples of landslides in the region (Fig. 2).

3 Methodology

The objective of this study was to create a susceptibility map for the perimeter of the master city's plan. Firstly, a landslide inventory was prepared based on the combination of the field survey, satellite images analysis and an analysis of available data: scientific publications, archives from the direction of town planning of Constantine city. Then the variability maps of twelve conditioning factors were created after the data collection in from source the form of satellite images and/or spatial data (Table 1). Then, two landslide susceptibility maps were modelled by applying the AHP and fuzzy AHP models under the influence of the conditioning factors. The final step was to verify and compare the results of the susceptibility analysis by applying the receiving operating characteristics (ROC) curve analysis using a landslide inventory. The Fig. 3 presents the methodology flowchart.

Table 3 Pair-wise comparison matrix and factor weights of the data layers for the AHP

	A	B	C	D	E	F	G	H	I	J	K	L	Criteria weight
A	1.00	2.00	3.00	4.00	5.00	5.00	6.00	6.00	6.00	7.00	7.00	8.00	0.2784
B	0.50	1.00	1.00	2.00	3.00	3.00	4.00	4.00	4.00	5.00	5.00	6.00	0.1633
C	0.33	1.00	1.00	1.00	2.00	2.00	3.00	3.00	3.00	4.00	4.00	5.00	0.1238
D	0.25	0.50	1.00	1.00	1.00	1.00	2.00	2.00	2.00	3.00	3.00	4.00	0.0867
E	0.20	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	3.00	0.05950
F	0.20	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	3.00	0.05950
G	0.17	0.25	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	0.04472
H	0.17	0.25	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	0.04472
I	0.17	0.25	0.33	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	0.04472
J	0.14	0.20	0.25	0.33	0.50	0.50	1.00	1.00	1.00	1.00	1.00	1.00	0.03457
K	0.14	0.20	0.25	0.33	0.50	0.50	1.00	1.00	1.00	1.00	1.00	1.00	0.03457
L	0.13	0.17	0.20	0.25	0.33	0.33	0.50	0.50	0.50	1.00	1.00	1.00	0.025510

A: slope gradient; B: lithology; C: land cover; D: distance from drainage; E: distance from road; F: distance from faults; G: topographic wetness index; H: stream power index; I: slope curvature; J: NDVI; K: slope aspect; L: elevation

3.1 Data Layers

3.1.1 Landslide Inventory

The landslide inventory map (Fig. 4) is an important level to assess the mutual relationship between landslide occurrence and its conditioning factors. In this task the landslides inventory map has been produced based on the combination of a field survey using GPS, analyzing satellite imagery derived from Google Earth and analysis of available data such as archives of scientific publications, and local authorities: Town planning Direction of the Wilaya of Constantine.

3.1.2 Slope Gradient

The slope is presented by the angle between the earth's surface and a horizontal data, there is a limit slope beyond which there is an optimum favorable for landslides (Chen et al. 2019). The value of the slope cannot be used as a determining factor, it is associated with other factors such as the lithological nature and the presence or absence of water. The slope map layer (Fig. 5a) shows the slope values, presented in degrees of inclination with the horizontal. In this study area, there are five (5) classes according to the slope.

3.1.3 Lithology

Lithology is one of the most important factors influencing landslides. Each lithological formation is different from the others in its properties and structure, so that there are different degrees of susceptibility to landslides depending on the lithology. The lithological map (Fig. 5b) defined ten (10) formations (reference). An analysis of the percentage density of landslides shows that it is mainly observed in the Miocene clay marl formation (61.22%), the calcareous marls of the Tellian thrust sheet Cretaceous-Eocene formation (17.30%), Miocene conglomerates (9.04%), recent alluvial terraces of the Quaternary (4.64%) and lacustrine calcareous formations of the Quaternary (4.53%). The most prevalent lithology is the Miocene marly clay and conglomerates (Bourenane et al. 2016) (DUC 2004), which makes this region vulnerable to landslides.

3.1.4 Land Use/Land Cover

Different land use has a different impact on landslides, and is therefore a key factor in assessing landslide susceptibility in many studies (Pawluszek and Borkowski 2017). Forested land is less sensitive to landslides, because plant roots are considered to be soil protection, they reduce the presence of water in the soil, and also evapotranspiration controls slope

Table 4 the values of the ratio index according to number of factors

N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.59

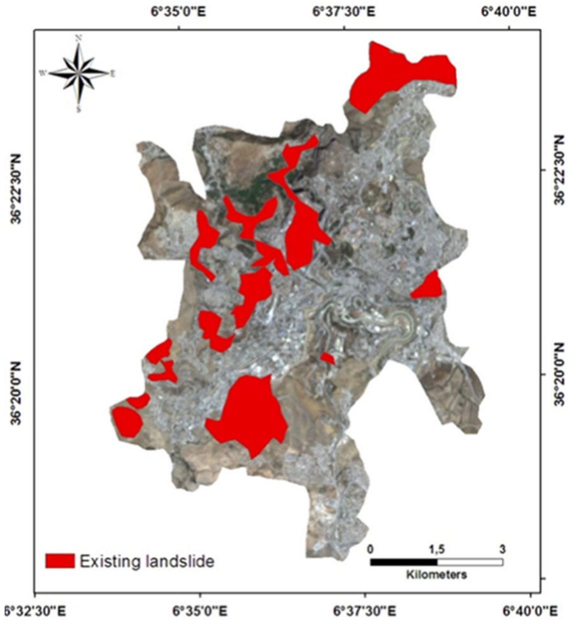

Fig. 4 Landslide inventory map of the study area

moisture (Moradi et al. 2012), and it is an important issue for marly and clay soils, the dominant lithologic formations in the south of Constantine city. Land use transformation, due to human activities, has an influential relationship with landslide occurrences. In this city, there are five land use classes: dense forest, urban area, discontinuous urban individual, vegetation cover and agricultural land (Fig. 6a).

3.1.5 Distance from Drainage

Potential slope failure areas extend along drainage lines. High pore pressure in water leads to a degradation of the shear strength of the soil, which causes a landslide (Bourenane et al. 2015). The city of Constantine has an intensive drainage network, where the distance from rivers varies from 0 to 1644.55 (Fig. 6b), which is an important indicator of the high risk of slope failure in this region.

3.1.6 Distance from Road

Road construction in hilly terrain severely affects the stability of slopes as anthropogenic factors; during their construction, there are some common actions that occur along the road network, such as major excavations, vegetation removal and the application of external loads (Bourenane et al. 2015). They have a significant impact on reducing the resistance of the slope (Pawluszek and Borkowski 2017); the further away from the road the slope is, the more stable it is. Therefore, a road map was prepared for the covered distance (Fig. 7a). the distance from roads varies from 0 to 128.72.

3.1.7 Distance from the Fault

Geological structures include faults, fractures, shear zones, etc., is considered to be a factor triggering landslides. In the vicinity of these structures, the landslide phenomenon increases due to weakness and soil degradation due to erosion and water movement in these structures (Chawla et al. 2017). The closer the slope is to defects, the more likely it will fail. For this reason, the distance from the fault map was generated (Fig. 7b), it varies from 0 to 3217.806.

3.1.8 Topographic Wetness Index (TWI)

The topographic moisture index (Fig. 8a) is a hydrological factor, which is mainly used in landslide studies, it presents the saturated source zone due to surface runoff under the influence of topographical conditions. The presence of water in the soil causes soil to release and mechanically degrade, so the TWI map was created to identify potentially wet areas and define those with high sensitivity to landslides, using the Eq. 1 (Pawluszek and Borkowski 2017):

$$\mathrm{TWI} = \ln(\mathrm{As}/\tan\beta) \tag{1}$$

where As is the specific catchment's area (m^2/m), and β is the slope gradient (in degrees).

Table 5 The factor weights of the data layers for the FAHP

	A	B	C	D	E	F	G	H	I	J	K	L
Weights	0.225370514	0.184850325	0.108724826	0.065336174	0.065336174	0.058855251	0.046672901	0.046672901	0.039158029	0.061666255	0.048678325	0.048678325

A: slope gradient; B: lithology; C: land cover; D: distance from drainage; E: distance from road; F: distance from faults; G: topographic wetness index; H: stream power index; I: slope curvature; J: NDVI; K: slope aspect; L: elevation

3.1.9 Stream Power Index (SPI)

One of the most important hydraulic parameters in assessing landslide susceptibility is the stream power index (Mohammady et al. 2012) (Fig. 8b), which indicates the erosive power (tearing off particles) of surface water flows and expresses the susceptibility of a terrain to erosion by runoff. The erosion effect on slope stability is by reducing the stabilizing forces at the toe of the slope.

3.1.10 Slope Curvature

The curvature of the line formed by the intersection of the surface with a random plane sets out the slope curvature. In general, the curvature map is divided into three classes where negative values were classified as concave, positive values as convex and zero values as flat as shown in (Fig. 9a). Positive and negative curvature values indicate that the surface is more sensitive to landslides. After heavy rainfall, a concave slope maintains the water for a long time, leading to soil saturation and decreasing the mechanical properties of the soil. On the other hand, the mechanism that triggers landslides for a convex slope is explained by the disintegration and decomposition of rocks, due to frequent expansion and contraction processes (Lee et al. 2004).

3.1.11 Normalized Difference Vegetation Index

Vegetation cover (Fig. 9b) is of considerable importance to stabilize slopes, as roots strengthen and fix soil layers. The denser the vegetation, the more stable the banks are with respect to landslides. The normalized difference vegetation index is a well-adapted tool to differentiate and classify the density of vegetation cover in a region. The values of the NDVI are between -1 and 1, the negative values corresponding to non-plant surfaces, such as snow, water, for bare soils, the NDVI presents values close to 0. Plant formations have positive NDVI values, generally between 0.1 and 0.7. The highest values correspond to the densest cutlery (Hu et al. 2019).

3.1.12 Slope Aspect

The sloping terrain direction is described by the slope aspect map (Fig. 10a) and has an indirect effect on the

Table 6 The percentage of the study area for each degree

The susceptibility degree	AHP model	FAHP model
Very low susceptibility	12.53	9.84
low susceptibility	23.41	19.93
Moderate susceptibility	28.36	25.74
High susceptibility	26.27	29.21
Very high susceptibility	9.43	15.28

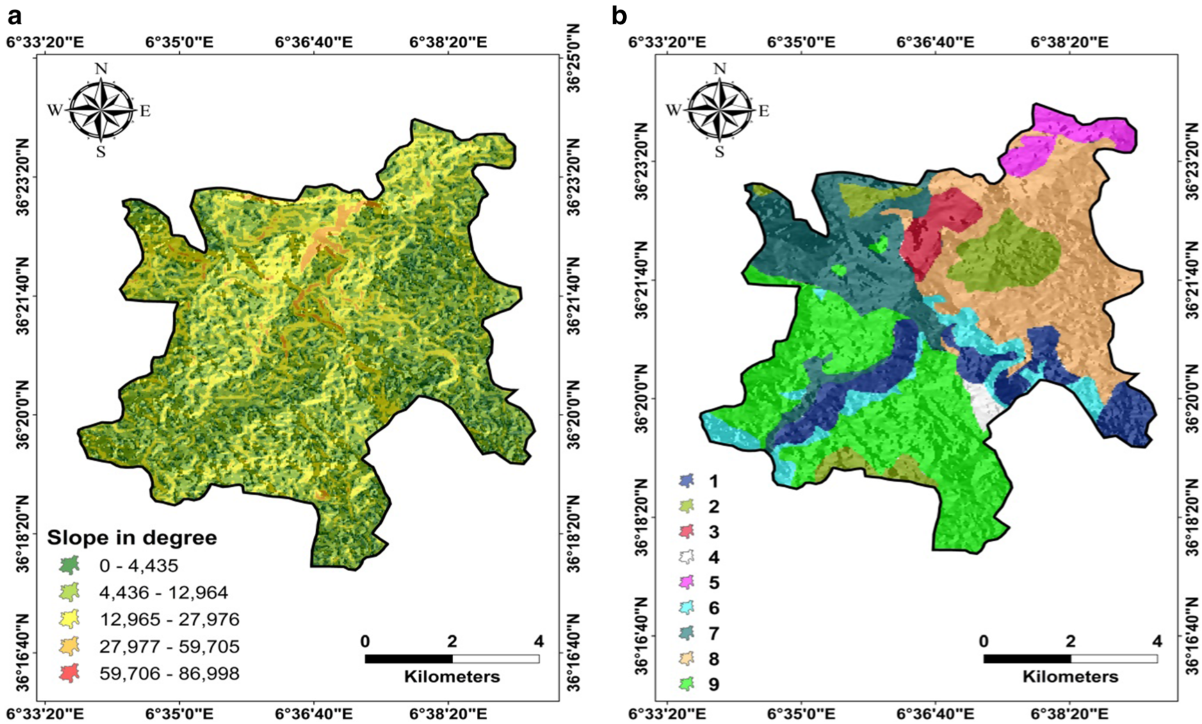

Fig. 5 Causative factor maps of the study area: **a** slope gradient, **b** lithology: (1) Quaternary colluviums, conglomerate and thick fill. (2) Quaternary recent alluvial terraces. (3) Quaternary ancient alluvial terraces. (4) Quaternary lacustrine calcareous formations. (5) Pliocene lacustrine calcareous formations. (6) Miocene marly clay. (7) Miocene conglomerates, (8) Flysh Massylian formations (Upper cretaceous). (9) Tellian Calcareous marls (Cretaceous Eocene). (10) Neritic limestone (Cenomanian–Turonian)

slope instability with respect to other parameters such as sun exposure, rainfall and dry winds (Sema et al. 2017). The slope aspect is divided into eight directional classes: flat, north, northeast, east, south, southeast, southwest, southwest, west and northwest.

3.1.13 Elevation

Elevation is identified by the spatial variation of altitude (Fig. 10b); it is the most inherent factor causing a landslide. Elevation influences on landslides are often presented as indirect relationships or by other factors such as slope gradient and aspect (Pawluszek and Borkowski 2017). In this study area the elevation varies from 328 to 952 m.

3.2 The Analytic Hierarchy Process (AHP)

The analytic hierarchy process invented by the mathematician Thomas Saaty (Saaty 1977; Demir et al.

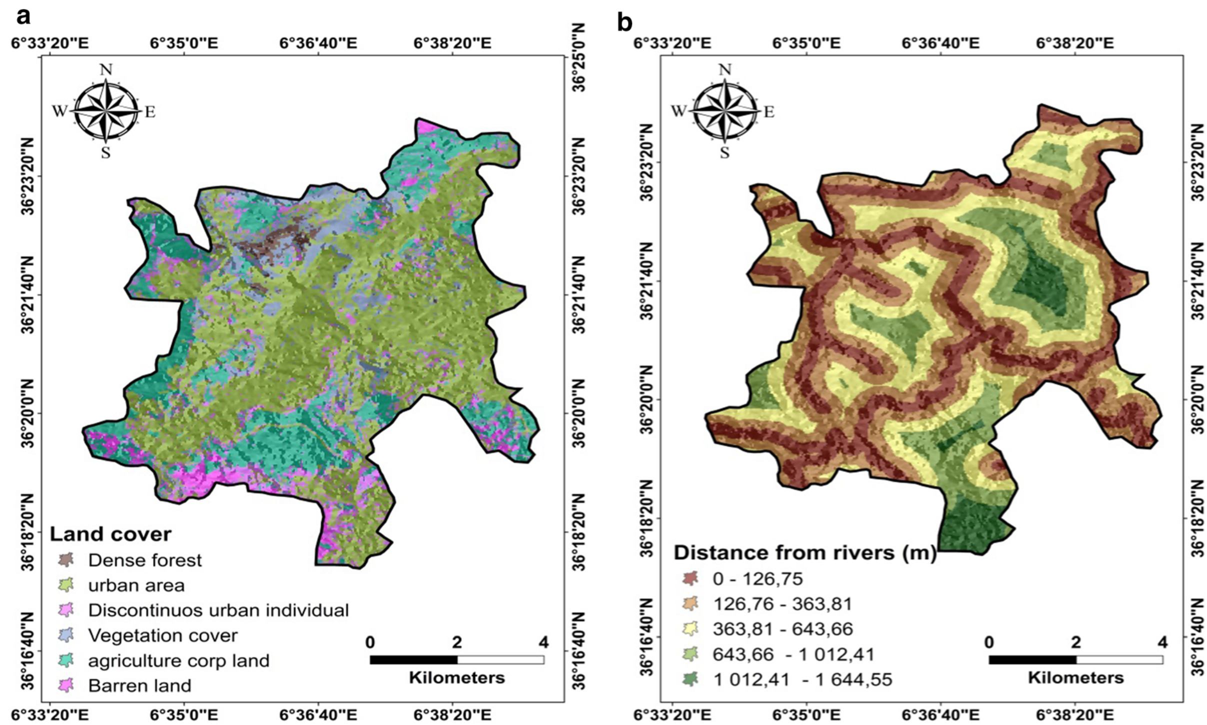

Fig. 6 Causative factor maps of the study area: **a** land cover, **b** distance from drainage

2013), is a semi-quantitative method that makes it possible to make the best decision among several, according to the needs and understanding of the problem to be addressed.

Step 1 Define and structure the problem and its objectives into factors.

Step 2 Prioritize the factors according to their importance.

This step involves prioritizing factors according to the principle of importance (Table 2). Let I_1, I_2, …, …, I_i…, be all the factors whose weight coefficient is sought. According to the principle of hierarchization, I_1 is more important than I_2 which is more important than I_{i-1} which is more important than I_i. In the end, I_n is the least important factor.

Step 3 Pair comparison of factors by importance.

To determine preferences, a scale of values must be chosen to specify the degree of importance of one factor in relation to another. The scale of values from 1 to 9 was adopted, which allows to introduce the decision-maker's assessments as closely as possible to reality. The comparison between all the factors gives the pairwise matrix (Table 3).

Step 4 Determine the weights associated with each factor.

In this step, the weights for each factor (w_1, w_2… w_n) were calculated. Each element of the matrix was divided by the sum of the values of the corresponding column and then averaged per line. At the end, the sum of the weights must be equal to 1. Table 3 shows the weights of the different factors.

Step 5 Check the consistency of the matrix.

One of the main advantages of the method is the possibility to evaluate the calculations made and to calculate a consistency index. In other words, it is possible to check whether the values of the scale (1–9) assigned by the decision-maker are consistent or not. For this purpose, the CI consistency index and the CR consistency ratio were calculated with the Eqs. 2 and 3.

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n - 1} \tag{2}$$

n: number of factors; $\lambda_{\max}$: is the largest eigenvalue

$$\mathrm{CR} = \frac{CI}{RI} \tag{3}$$

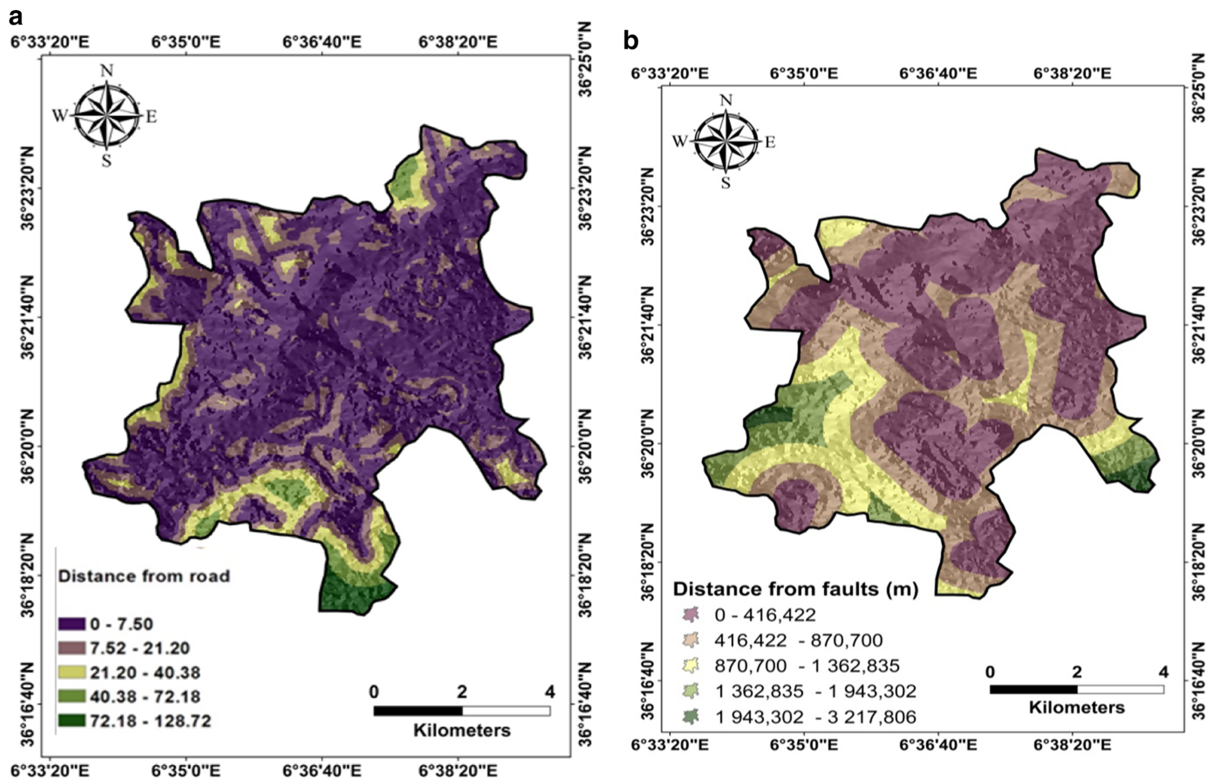

Fig. 7 Causative factor maps of the study area: **a** distance from roads, **b** distance from faults

RI: depending on the number of factors (Table 4).

3.3 Fuzzy AHP Model

In his article, Chang (1996) presented an approach based on the fuzzy AHP method by introducing triangular fuzzy numbers for the binary comparison between factors. For the first time, it proposes a method for calculating priorities for triangular fuzzy comparison matrices.

Step 1 Compare performance scores using odd fuzzy triangular numbers.

Step 2 Construct the fuzzy comparison matrix $\check{A}(a_{ij})$ (Eq. 4):

$$A = \begin{bmatrix} (1,1,1) & \cdots & (l_{1,n}m_{ln}u_{ln} \\ \vdots & \ddots & \vdots \\ (l_{n1}m_{n1}u_{n1} & \cdots & (1,1,1) \end{bmatrix} \quad (4)$$

Avec $a_{ij} = a_{ji}^{-1} eta_{ji}^{-1} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}}\right)$.

Step 3 Realize the sum (R_i) on the line ith (for all the rows) of the matrix $\check{A}(a_{ij})$ (Eq. 5):

$$R_i = \sum_{j=1}^{n} a_{ij} \quad (5)$$

R_i is obtained by the arithmetic of the fuzzy numbers (Eq. 6)

$$R_i = \sum_{j=1}^{n} a_{ij} = \sum_{j=1}^{n} \left(a_{ij}^{l}, a_{ij}^{m}, a_{ij}^{u}\right) = \left(\sum_{j=1}^{n} a_{j=1}^{l}, \sum_{j=1}^{n} a_{ij}^{m}, \sum_{j=1}^{n} a_{ij}^{u}\right)$$
$$R_i = (l_i, m_i, u_i) \quad (6)$$

Step 4 calculate the sum of the matrix (A) (Eq. 7)

$$A = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} \quad (7)$$

Step 5 The fuzzy synthetic extension for a factor i is defined by the Eq. 8

$$S_i = R_i \times A^{-1} \quad (8)$$

Step 6 The weight of a factor i is

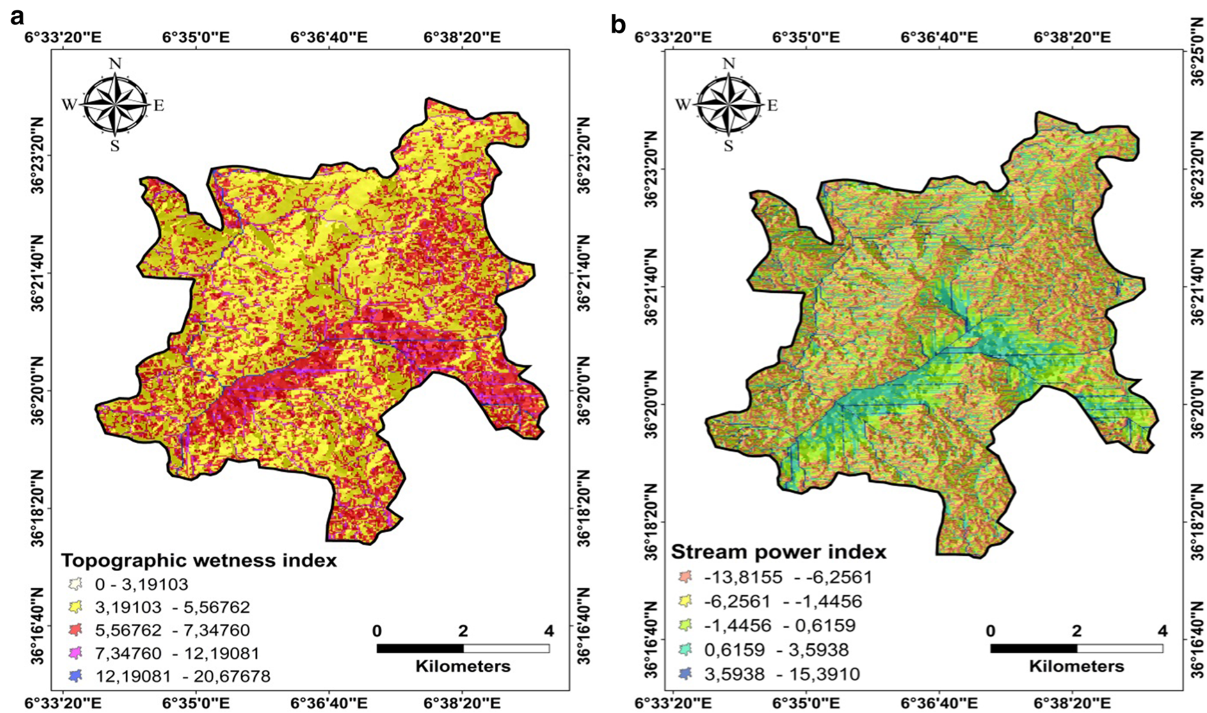

Fig. 8 Causative factor maps of the study area: **a** topographic wetness index, **b** stream power index

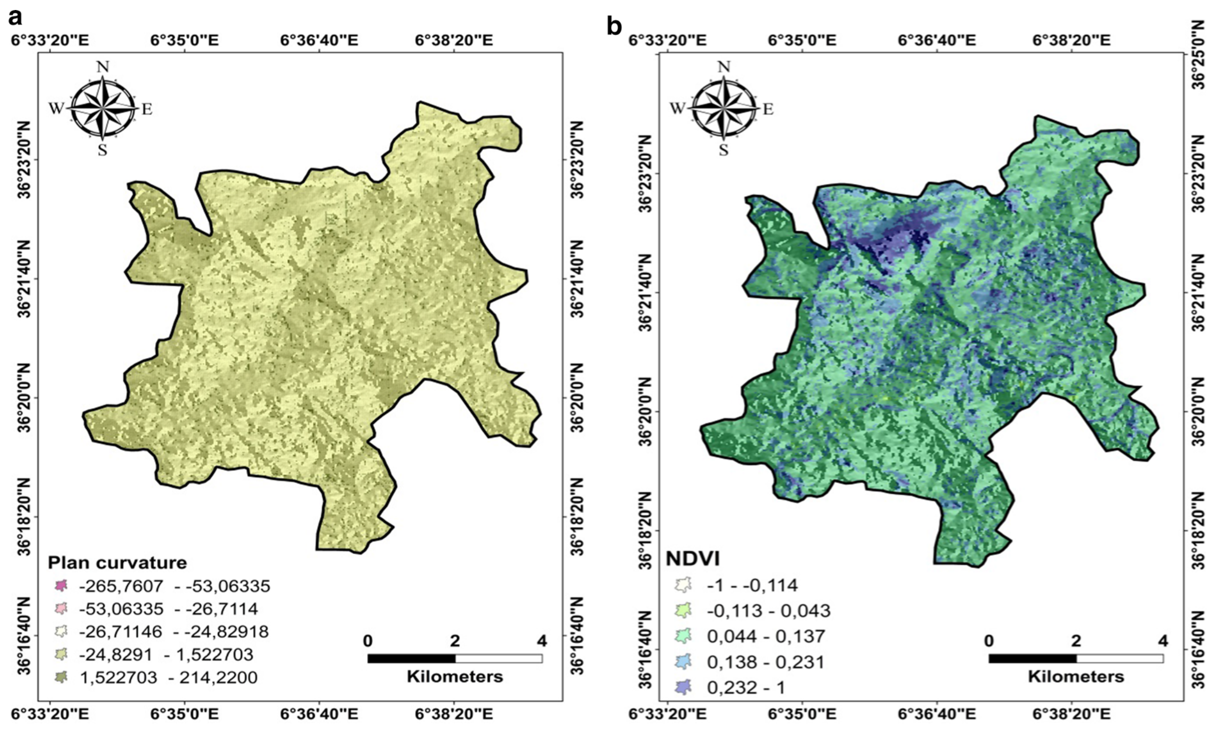

Fig. 9 Causative factor maps of the study area: **a** slope curvature, **b** distance from NDVI

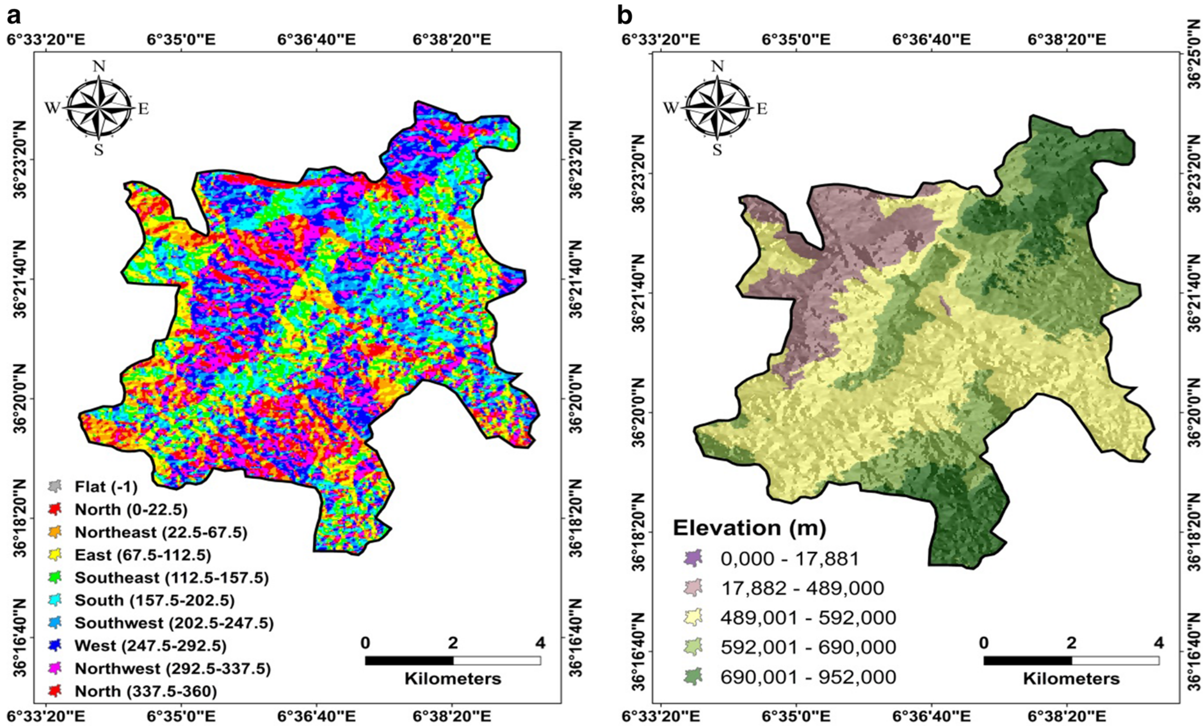

Fig. 10 Causative factor maps of the study area: **a** slope aspect, **b** elevation

$$W_i = minV(S_i \geq S_k) \quad where, \ \mathrm{k} = 1, \ldots \mathrm{n}; \ \mathrm{k} \neq \mathrm{i} \tag{9}$$

where V is the degree of possibility for S_i to be greater than S_k;

$$V(S_i \geq S_k) = \begin{cases} 1, & if \ S_i \geq S_k \\ 0, & if \ l_k m_i \\ \dfrac{l_k - u_i}{(m_i - u_i) - (m_k - l_k)} \end{cases} \tag{10}$$

Step 7 Normalize the weights of the factors, for a factor i:

$$W_i^{'} = \frac{W_i}{\sum_{i=1}^{n} W_i} \tag{11}$$

3.4 Standardization

The standardization technique is used to translate various inputs of a decision problem to a common scale, to allow comparison and overcome the incommensurability of data (Rahman et al. 2012). The standardization process allows the scaling of all evaluation dimensions between 0 and 1 the standardization of factors was established based on fuzzy logic. The new features of Arcgis10.2 in the operator (Fuzzy member ship) have been introduced in the spatial modelling of landslide risk to standardize the criteria on the same scale to measure them, on the one hand, and to convert the semantic description of landslide risk into a numerical model of spatial prediction, on the other hand.

3.5 Weighted Linear Combination

After calculating the factor weights for the AHP and FAHP models, landslide susceptibility maps were created using the weighted linear combination (WLC) on the GIS platform. The WLC concept consists of combining all the factor maps to determine the value of the landslide susceptibility coefficient using the following equation (Rodcha et al. 2019)

$$WLC = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{W_i X_i} \tag{12}$$

where n is the number of factors, W_i is the weight value of the i factor, and X_i is the score of the i factor.

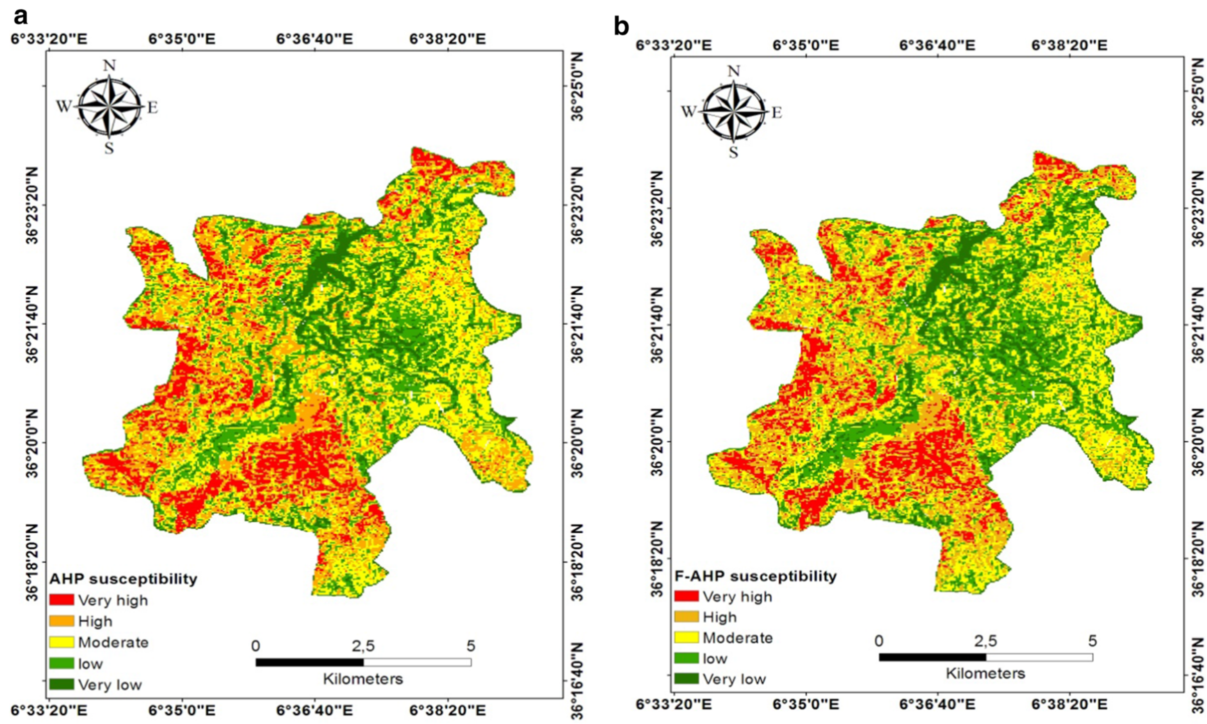

Fig. 11 Landslide susceptibility map created using: **a** the AHP model, **b** the FAHP model

3.6 Validation

The final and most essential step in the landslide assessment is to validate the accuracy of the model using known landslide locations. There are various methods available for this step, such as the Seed Cell Area Index (SACI) method, the spatially agreed areas approach and the Receiving Operating Characteristics (ROC) curve. The method used in this study is the ROC curve, which was first developed during the Second World War for the development of effective means of detecting Japanese airplanes.

It was then applied more generally in signal detection and then in medicine, where it is now widely used. The ROC curve is a graph representing the performance of a classification model for all threshold settings. This curve traces the real positive rate as a function of the false positive rate. The True Positive Rate (RPR) (Mohammady et al. 2012), the equivalent of the recall is defined by Equation X. The false positive rate (FPR) is defined as follows:

$$\mathrm{TPR} = \frac{TP}{TP + FN} \tag{13}$$

$$\mathrm{FPR} = \frac{FP}{TN + FP} \tag{14}$$

The AUC is a synthetic index calculated for the ROC curves. The performance of the model is evaluated by calculating the AUC, which varies between 0 and 1. For an ideal model AUC = 1; for a random model AUC = 0.5. The model is generally considered good if the AUC value is greater than 0.7. A discriminating model must have an AUC between 0.87 and 0.9. A model with an AUC greater than 0.9 is excellent.

4 Results

The objective of this study was to create a landslide susceptibility map, using the AHP model and the Fuzzy AHP model taking into account a set of factors triggering landslides, and to compare the results of the two models used.

4.1 AHP Model Results

The AHP model was obtained by following the steps described previously. The factors were ranked in order of importance, as shown in (Table 3). A pairwise comparison matrix (Table 3) was elaborated and used to determine the weight of each factor (Table 3). The last step is to check the consistency of the matrix, by calculating the consistency index (0.0252) and the consistency ratio (0.0165). The maps produced with the AHP model (Fig. 11a) show five degrees of susceptibility to landslides: very high, high, moderate, low and very low. Table 6 shows the percentage of each degree.

4.2 FAHP Model Results

The FAHP model was obtained by following the steps described previously. First prioritize the factors in order of importance, then a fuzzy comparison matrix was built. The weight of each factor (Table 5) was calculated using the fuzzy comparison matrix. The last step consists in checking the consistency of the comparison matrix by calculating the consistency index CI = 0.02112. The maps produced with the FAHP model (Fig. 11b) show five degrees of susceptibility to landslides: very high, high, moderate, low and very low sensitivity. Table 6 shows the percentage of each degree.

4.3 The Validation

The accuracy of the results was assessed using a prepared landslide inventory and analysis of the ROC curves. Figure 12 shows the ROC curve corresponding to the AHP model and the Fuzzy AHP model. The AUC calculated for the AHP model and the Fuzzy AHP model are 0.777 and 0.908 respectively.

5 Discussion

In this study, twelve conditioning factors from different origins were combined to map landslide susceptibility, using the AHP and Fuzzy AHP models. The result maps of the AHP and the Fuzzy AHP model show that large part of the study area was threat by the landslide hazards. The study region was divided into five zones of landslide susceptibility degree: very high, high, moderate, low and very low susceptibility degree.

The model's accuracy is validated using the ROC method, and its results show that both models can be used for this purpose. The comparison between the two models using AUC values shows that the results obtained are satisfactory (0.777 for the AHP model and 0.908 for the FAHP model). However, the fuzzy AHP model is more accurate than the AHP model, meaning that the fuzzy AHP model predicts landslide susceptibility with minimal subjectivity and imprecision in the process (Bouamrane et al. 2020).

Based on the results of the most accurate model, the high and very high susceptibility classes were dominated in the south-central, extreme west and extreme northeast. This part of the study area is characterized by complex topography with steep slopes. The most common lithological formations in this region class are Miocene marl clay, Miocene conglomerate and Quaternary colluviums, conglomerates and thick fill. These formations have poor geotechnical characteristics that favor landslides. The area under consideration is agricultural land with an intense network of rivers and faults. The TWI and SPI values are high due to the presence of water and the complex topography. Therefore, the combination of all these factors increases the risk of landslides.

Regarding the expected landslides predominated in the central-western and south-eastern regions, they were classified as moderately susceptible. They are characterized by Miocene conglomerates, Miocene marl clay and Quaternary ancient alluvial terraces lithological formation with steep slopes. This part of the region is an urban area with an intense road network. In this area, distances from faults and watercourses are small. Therefore, the combination of these two factors has led to the degradation of the mechanical characteristics of the soil. The TWI and SPI values are high due to the presence of water and the rugged topography in this region.

The zone of low and very low susceptibility degree full in the central eastern and some parts of the south western, the lithologic formations dominant in this part of the study area were: The Quaternary ancient alluvial terraces, Quaternary lacustrine calcareous formations, Tellian Calcareous marls (Cretaceous–Eocene) and the Neritic limestone (Cenomanian–Turonian). This region was characterized by gentle slopes and that minimize the impact of the hydrologic

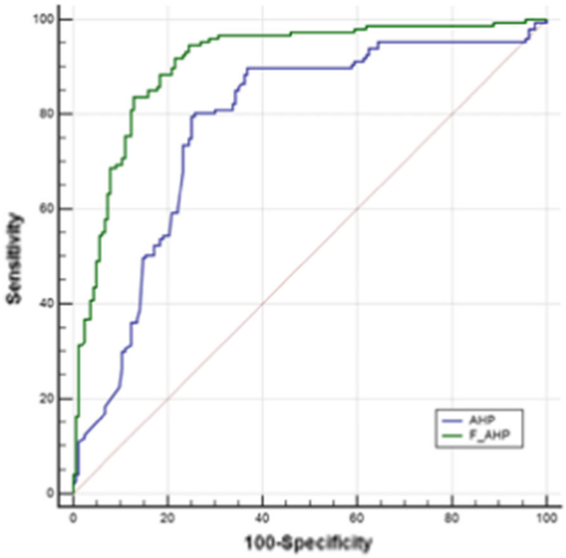

Fig. 12 The ROC curves of the AHP model and the FAHP model

conditioning factors such as the TWI and the SPI. This zone was considered as an urban area with intense traffic network. According to the relation between the variability map of the conditioning factors and the susceptibility maps, the most influencing factors were the slope degree, lithology, land use and the distance from drainage. Based on the results of these models, and the percentages of the study area in each degree, it can be concluded that the city of Constantine is exposed to the risk of landslides.

6 Conclusion

In this study, landslide susceptibility zoning was performed for the urbanized region of the city of Constantine in north-eastern Algeria, using the AHP and FAHP models. To this end, a set of natural and anthropogenic conditioning factors were considered for the development of the models such as slope gradient, lithology, land cover, distance from drainage, distance from the road, distance from faults, topographic wetness index, stream power index, slope curvature, NDVI, slope aspect and elevation. The landslide susceptibility zoning map created by the AHP model shows five zones with different degrees of susceptibility: very high (9.43%), high (26.27%), moderate (28.36%), low (23.41%) and very low (12.53%) in the study area. The map obtained with the FAHP model shows the five degrees with different percentages of the study area: very high (9.84%), high (19.93%), moderate (25.74%), low (23.41%) and very low (15.28%). The application of the ROC method shows that the models applied could be used to assess landslides susceptibility. Based on the AUC values of the AHP model (0.891) and the FAHP model (0.982), it can be concluded that the second model is more accurate than the first. The results of the study show that the city of Constantine is exposed to the risk of landslides, and to minimize the impacts and risks of this phenomenon, a susceptibility map was also created.

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