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Research article

The combination of Multi-Criteria Decision-Making (MCDM) and morphometric parameters for prioritizing the erodibility of sub-watersheds in the Ouljet Es Soltane basin (North of Morocco)

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ABSTRACT

Preserving water and soil resources ranks among the top priorities outlined in the national water strategy. Indeed, the integrated management of water resources in vulnerable territories, particularly in Morocco, requires a deep knowledge of the hydrological functioning and use of water resources in these regions. The diverse hydroclimatic and morphological features within the Ouljet Es Soltane watershed, which is a sub-basin of the extensive Oued Sebou watershed, present significant challenges in managing its water and soil resources. Identifying areas susceptible to soil erosion is crucial for implementing preventive measures in the Ouljet Es Soltane basin and ensuring its sustainable development. Morphometric analysis plays an important role in the effective management and sustainable utilization of the basin's resources. This study used four MCDM models, including the CF (Compound Factor), VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), and SAW (Simple Additive Weighing), to prioritize 20 sub-watersheds of the Ouljet Es Soltane watershed.

Based on the sub-watershed prioritization results obtained from the VIKOR, TOPSIS, and SAW models, sub-watershed 16 achieved scores of 0, 0.59, and 0.8, respectively, positioning it as the first rank. These findings highlight that sub-watershed 16 exhibits a high susceptibility to erosion and is classified as one of the most vulnerable areas in terms of erosion risk.

Based on the results obtained from the VIKOR, TOPSIS, and SAW models, the susceptibility of the sub-watersheds to erosion can be classified into four categories: low, moderate, high, and very high. On the other hand, the CF model only has two categories: low and moderate susceptibility. Overall, the findings suggest that morphometric parameters are highly effective in identifying areas at risk of erosion. Furthermore, the VIKOR, TOPSIS, and SAW methods exhibit greater

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predictive accuracy compared to the CF model. The comparison of these models involved the use of Spearman correlation coefficient test (SCCT).

The findings of this study can provide valuable insights for making informed decisions in developing an effective framework for soil erosion control strategies.

1. Introduction

Soil and water are essential natural resources that play a critical role in supporting human life. However, Morocco faces significant challenges related to soil degradation and erosion, compounded by the unpredictable patterns of rainfall and recurring droughts. The issue of water erosion affects almost all areas of land in the country, leading to the erosion of a substantial agricultural land area of over 2 million hectares.

The average rate of soil degradation in Morocco has been reported to range from 23 to 55 tons per hectare per year, according to studies conducted by Refs. [1–3]. However, extreme values have been observed, ranging from 115 to 524 tons per hectare per year [4–6]. These variations in soil degradation rates can be attributed to various environmental factors, including geology, lithology, topography, soil characteristics, climate, vegetation, and human activities.

Some research has been conducted in Morocco to examine water erosion using diverse methodologies and models. The Universal Soil Loss Equation (USLE) and its revised version (RUSLE) are prominent empirical models that have been widely employed in these studies. These quantitative models take into consideration various factors including rainfall erosivity, soil erodibility, slope length, and land cover. By incorporating these variables, they provide valuable insights into erosion patterns and contribute to the identification of areas prone to erosion [7–9]. In addition to these quantitative approaches, qualitative methods such as the Activity Program/Regional Activity Center (PAP/CAR) have also been utilized in the assessment of water erosion in Morocco [10,11]. These qualitative methods complement the quantitative models by considering a broader range of socio-economic and environmental factors. By incorporating aspects such as land management practices, human activities, and policy frameworks, these methods provide a comprehensive understanding of the complex dynamics of water erosion. Furthermore, many studies have been conducted on watersheds and sub-watersheds in order to assess erosion-prone regions based on morphometric analysis [12–15], and machine learning approaches [16–18].

In recent decades, there has been a growing trend in research studies that utilize remote sensing (RS) techniques, Geographic Information System (GIS) tools, and Multi-Criteria Decision-Making (MCDM) models for morphometric analysis. The main focus of these studies has been to prioritize sub-watersheds, with the overarching goal of improving agricultural productivity and ensuring the sustainable utilization of natural resources. By integrating these advanced technologies and analytical methods, researchers have aimed to gain a deeper understanding of sub-watershed characteristics, identify areas requiring attention, and make well-informed decisions to effectively manage resources and foster sustainable land use practices.

Various types of Multi-Criteria Decision-Making (MCDM) methods have been extensively used in the literature for sub-watershed prioritization. These include CF (Compound Factor) [19], SAW (Simple Additive Weighting) [20–22], WPM (Weighted Product Method), AHP (Analytic Hierarchy Process) [23,24], FAHP (Fuzzy Analytical Hierarchy Process) [25,26], TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution [20,27,28], VIKOR (Vlšekriterijumsko KOmpromisno Rangiranje) [21,29], ELECTRE (ELimination Et Choix Tradusiant la Reality) [30], and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) [31]. These Methods evaluate and prioritize sub-watersheds using multiple criteria, identifying erosion-prone areas and allocating resources effectively, improving erosion control measures and reducing vulnerability.

Previous research has aimed to compare various MCDM-based sub-watershed prioritization approaches using morphometric analysis, considering different spatial scales and morphometric parameters. For instance Ref. [21], conducted a study comparing four MCDM methods: SAW, TOPSIS, VIKOR, and CF models. Their results revealed that VIKOR outperformed TOPSIS, SAW, and CF in terms of performance. Likewise [32], conducted a comparison of four multi-criteria decision-making (MCDM) models (VIKOR, TOPSIS, SAW, and CF) for prioritizing sub-watersheds based on morphometric parameter. Their findings showed that VIKOR and CF methods are more favorable compared to TOPSIS and SAW. Moreover [33], compared three MCDM models (VIKOR, CF, and ELECTRE) to evaluate their susceptibility to erosion. The results of this study indicated that the VIKOR performs better than the CF and ELECTRE models.

[28] conducted a study to assess the performance of MCDM models in prioritizing erosion susceptibility of sub-catchments. They compared four MCDM models: WASPAS-AHP, TOPSIS, VIKOR, and AHP. The results showed that the VIKOR model performed the best in identifying water erosion-prone sub-watersheds.

In a study conducted by Ref. [34], the susceptibility of sub-watersheds to erosion was evaluated using five different Multi-Criteria Decision-Making (MCDM) models: SAW, COPRAS, TOPSIS, MOORA, and ARAS. The objective of the study was to assess the effectiveness of these models in predicting erosion susceptibility. The results indicated that the COPRAS model exhibited the highest level of accuracy in predicting erosion susceptibility among the five models. This suggests that the COPRAS model can be a valuable tool for assessing and prioritizing sub-watersheds based on their vulnerability to erosion.

Furthermore [35], employed MCDM techniques such as AHP and TOPSIS for the erodibility prioritization of sub-watersheds. Their findings indicated that the AHP approach showed greater predictability compared to other models when analyzing morphometric parameters of each sub-basin.

Recent studies use multi-criteria decision-making (MCDM) methods on a GIS platform to prioritize sub-basins and develop effective management plans for land degradation mitigation and conservation. Four techniques, CF, VIKOR, TOPSIS, and SAW, are employed to assess sub-watersheds and rank them for conservation and management interventions.

The research has two main objectives: (1) analyzing the morphometric parameters of the sub-watersheds in the Ouljet Es Soltane using ASTER GDEM data to understand their hydrological characteristics, and (2) prioritizing the sub-watersheds based on their susceptibility to soil erosion using four MCDM models (CF, VIKOR, TOPSIS, and SAW). This comprehensive assessment will provide valuable insights into water flow, drainage patterns, and erosion risks, allowing for the identification of critical sub-watersheds that require immediate attention and effective erosion control measures.

2. Materials and methods

2.1. Description of the study area

The study area for this research is a micro-catchment located in the northwestern region of Morocco. It spans an area of around 2541 km^2 and is situated in the southwestern part of the Sebou basin. The geographic coordinates of the study area range from approximately 33°10′N to 33°40′N in latitude and 5°W to 5°55′W in longitude.

The study area has a Mediterranean climate that ranges from semi-arid to humid. Frequent summer droughts and intense rainfall events define this climate. The rainfall in the region shows annual fluctuations. The highest point within the basin is situated in the southeastern part, reaching an elevation of 2171 m above sea level (asl), while the lowest point is located in the northwestern part, with an altitude of 300 m asl. The study area experiences a Mediterranean climate, which exhibits a range from semi-arid to humid conditions. The mean annual precipitation in the study area is 700 mm, and the average annual temperature is 20.6 °C (Fig. 1).

Similar to other semi-arid regions in Morocco, this area is susceptible to climate change, leading to concerns such as soil degradation, loss of vegetation cover, and water resource challenges. The increasing population and the growing demand for these resources exacerbate these issues. Additionally, knowing the priority areas with their classification and assisting decision-makers in the planning of these priority areas will help in the sustainable management of soil, water, and vegetation resources (ecosystems). Moreover, the significance of this type of study in this region lies in the presence of several large and medium-sized dams (El Kansera, Ouljet Essoltane) and hillside dams that require protection against siltation issues.

2.2. Morphometric parameters

The morphometric analysis of the Ouljet Es Soltane watershed and its sub-basins was conducted using a combination of topographic maps (1:50,000) and ASTER GDEM data. The ASTER GDEM data, with a resolution of 30 m, was particularly useful for deriving various parameters for each sub-watershed. These parameters include basin area, basin perimeter, stream order, number of streams, basin length, stream length, and mean stream length.

Linear parameters such as mean bifurcation ratio, drainage density, stream frequency, texture ratio, length of overland flow, infiltration number, and constant of channel maintenance are also derived from the ASTER GDEM data. These parameters provide insights into the connectivity and flow patterns of the drainage network. Shape parameters are used to assess the geometric properties and overall shape characteristics of the basins. These parameters include: form factor, shape factor, elongation ratio, compactness

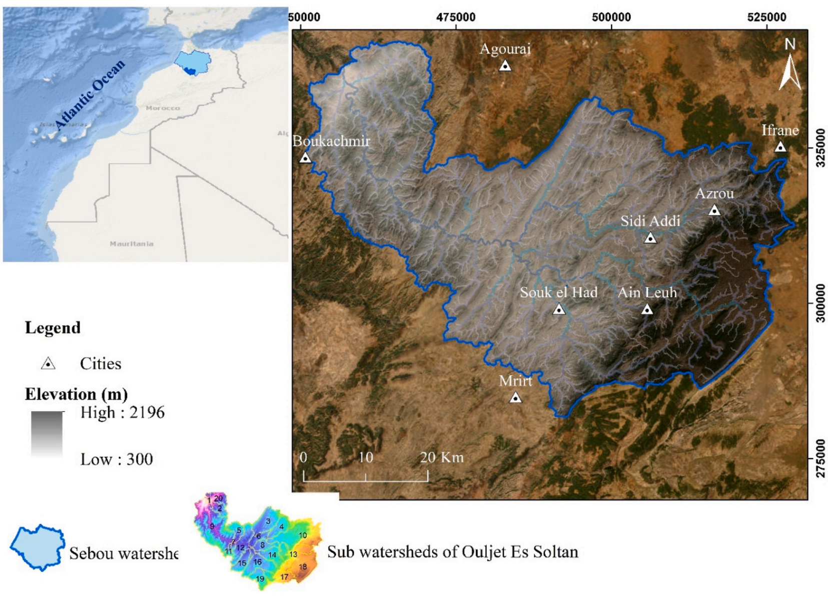


Fig. 1. Location map of Ouljet Es Soltane watershed.

coefficient, and circularity ratio, are calculated to assess the geometric properties and overall shape characteristics of the basins. Furthermore, landscape parameters such as ruggedness number, basin relief, relief ratio, and slope degree are derived to analyze the terrain ruggedness and elevation variations within the watershed.

Table 1 presents the computed morphometric parameters using the Arc SWAT (Soil and Water Assessment Tool) tools within the ArcGIS software. These tools offer a convenient and efficient way to calculate various morphometric parameters based on the available spatial data.

Table 1
The equations used to calculate morphometric parameters.

Morphometric parameters	Formula	Reference
Basin Area (A)	Plan area of the watershed (km^2) GIS software analysis	[36]
Basin perimeter (P)	Perimeter of watershed (km) GIS software analysis	[36]
Stream order (U)	Hierarchical rank	[36]
Number of streams (Nu)	Total stream number of all orders GIS software analysis	[37]
Basin length (Lb)	Length of basin (km)/GIS software analysis Lb = 1.321 × $A^{0.568}$ A = area of the basin (km^2)	[38]
Stream length (Lu)	Length of the stream (km)	[36]
Mean stream length (Lsm)	$Lsm = \frac{Lu}{Nu}$ Lu = total stream length of all orders Nu = total no. of all stream segments of order "u" GIS software analysis	[36]
Bifurcation ratio (Rb)	$Rb = \frac{Nu}{Nu+1}$ Nu +1 = no. of segments of the next higher order	[39]
Drainage density (Dd) (km/km2)	$Dd = \frac{Lu}{A}$ Lu = total stream length of all orders (km) A = area of the watershed (km^2)	[36]
Stream frequency (Fu) (no./km2)	$Fu = \frac{Nu}{A}$ Nu = total no. of streams of all orders A = area of the basin (km^2)	[36]
Mean bifurcation ratio (Rbm)	Rbm = average of bifurcation ratio of all orders	[37]
Texture ratio (T) (no./km^2)	$T = \frac{Nu}{P}$ Nu = total no. of streams of all orders P = perimeter (km)	[36]
Length of Overland Flow (Lo) (km)	$Lo = \frac{1}{2Dd}$ Dd = drainage density	[36]
Infiltration number (If)	If = Fu × Dd Fu = Stream frequency, Dd = drainage density	[40]
Constant of channel maintenance (C)	$C = \frac{A}{\sum_{i=n}^{i=1} Lu}$ A = area of the basin (km^2) Lu = total stream length of all orders (km)	[36]
Form factor (Rf)	$Rf = \frac{A}{Lb^2}$ A = area of the basin (km^2) Lb^2 = square of the basin length	[36]
Shape factor (Bs)	$Bs = \frac{Lb^2}{A}$	[38]
Elongation ratio (Re)	$Re = 1.128\sqrt{A/Lb}$ A = area of the basin (km^2) Lb = basin length	[39]
Compactness coefficient (*Cc*)	$Cc = \frac{P}{2\sqrt{\pi A}}$ P = perimeter of the basin (km) A = area of the basin (km^2)	[36]
Circularity ratio (Rc)	$Rc = 4 \times \pi \times \frac{A}{P^2}$ A = area of the bain (km^2), P = perimeter (km)	[41]
Ruggedness number (Rn)	$Rn = Dd \times \left(\frac{Bh}{100}\right)$ Bh = basin relief; Dd = drainage density	[42]
Basin relief (Bh)	$H = h - h1$ h = Maximum height; h1 = minimum height	[36]
Relief ratio (Rh)	$Rh = \frac{Bh}{Lb}$ Bh = basin relief; Lb = basin length	[39]
Slope (S)	$S = \frac{Bh}{N\sqrt{A}} \times 100$ Bh = basin relief; A = area of the basin (km^2)	[43]

2.3. Erodibility prioritization of sub-watersheds using MCDM methods

Fig. 2 presents the erodibility prioritization of the 20 sub-watersheds of the Ouljet Es Soltane basin, employing a diverse set of MCDM techniques.

This model provides a clear depiction of the relative rankings and prioritization of the sub-watersheds based on their erodibility. This visualization aids in better understanding the distribution of erosion risks across the study area and supports effective decision-making regarding erosion control and management strategies.

The study uses multi-criteria decision-making (MCDM) techniques to prioritize 20 sub-watersheds in the Ouljet Es Soltane basin based on morphometric characteristics. This approach improves informed decision-making and understanding of erosion susceptibilities.

2.3.1. AHP technique

The Analytic Hierarchy Process (AHP) is a robust methodology developed to tackle intricate decision problems. It employs a hierarchical structure with multiple levels that incorporate various decision criteria, sub-criteria, objectives, and alternatives. A key aspect of the AHP is the use of consistent matrices and corresponding eigenvectors to effectively calculate or approximate weights for the criteria [44]. AHP is a versatile and resilient decision-making methodology that can be utilized for a wide range of multi-criteria problems, such as evaluating the risk of soil erosion [45,46].

The AHP prioritized sub-watershed ranking in this study was determined using the following procedures.

a. First step: Creation of a pairwise comparison matrix

The AHP prioritization process uses a pairwise comparison matrix to compare morphometric parameters based on their importance or relevance to erosion. The matrix is constructed using a scale of 1–9, with 1 representing equal importance, 9 indicating more importance, and 1/9 indicating less importance. The most influential parameter is assigned a value of 9, while the least influential parameter is assigned a value of 1. This method helps in prioritizing parameters and determining their significance in evaluating and ranking sub-watersheds based on erodibility [47]. Assessing the importance of factors based on field experience and Saaty's guidelines aids in determining their priority and significance, as presented in Table 2.

The pairwise comparison matrix provides a systematic way to quantify the importance of each parameter relative to others,

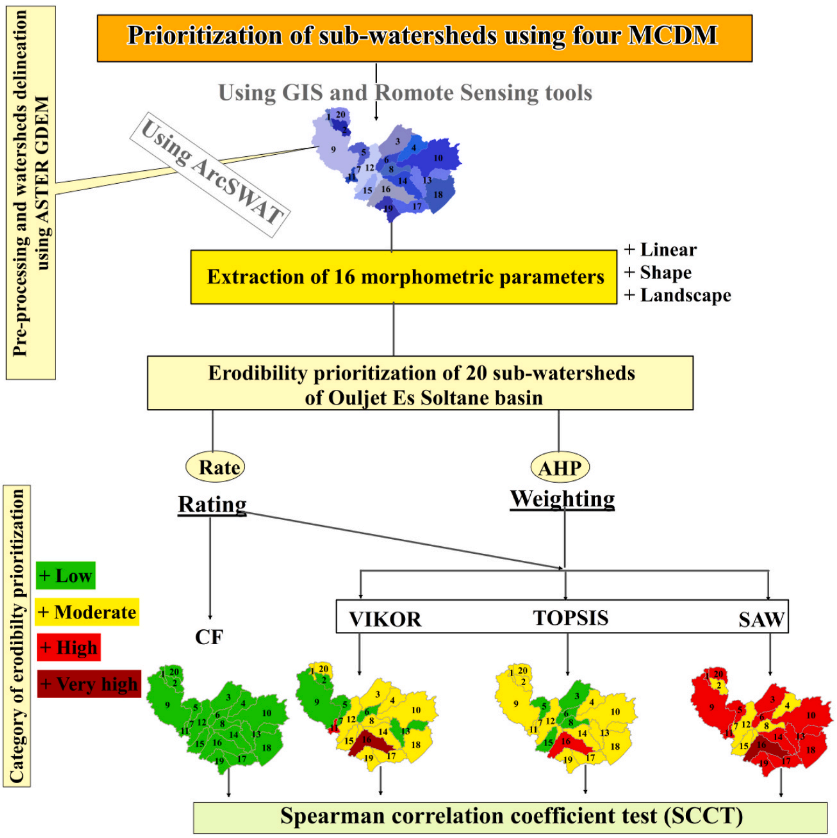


Fig. 2. Flowchart outlines the process employed to prioritize the erodibility of sub-watersheds.

Table 2
Intensity of importance according to Saaty's scale [47].

1	Equal importance	Two factors contribute equally to the objective
2	Weak	
3	Somewhat more important	Experience and judgment slightly favor one over the other
4	Moderate plus	
5	Much more important	Experience and judgment strongly favor one over the other
6	Strong plus	
7	Very much more important	Experience and judgment very strongly favor one over the other
8	Very, very strong	
9	Absolutely more important	The evidence favoring one over the other is one of the highest possible validities

allowing for the calculation of weights for each parameter in the subsequent analysis. It helps in prioritizing the parameters and determining their significance in the overall evaluation and ranking of sub-watersheds based on erodibility. Therefore, the pairwise comparison matrix is created using the following criteria (Eq. (1)):

$$\text{Matrix} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \tag{1}$$

b. Second step: Calculate the weights for the morphometric parameters

The weights of the criteria are determined through the utilization of a comparison matrix. To achieve the normalized pairwise matrix, each element in the column of the pairwise matrix is divided by the sum of the column. This normalization procedure guarantees that the values in each column reflect the relative significance or weights of the criteria [47].

c. Third step: Verify consistency

Compute consistency ratio (CR) to assess decision sufficiency and weight consistency using equation (Eq. (2)):

$$CR = \frac{CI}{RI} \times 100 \tag{2}$$

where: CR is the consistency ratio; CI is the consistency index; RI is the random index given in Table 3.

The consistency index is a dimensionless value that depends on the size of the matrix (number of parameters) and the consistency in judgment [47]. It can be evaluated using the equation provided below (Eq. (3)):

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

where: CI is the consistency index; λ_{max} is the maximum eigenvalue of the pairwise comparison matrix; n is the number of criteria (or parameters).

If the consistency ratio (CR) or consistency index (CI) is found to be less than 10 %, it indicates that the qualitative decision of factors can be considered as consistent.

d. Fourth step: Priority assessment and factors' significance

The normalized comparison matrix is multiplied by criterion weight values to determine the overall priority of sub-watersheds. The highest aggregated score is considered the most prioritized, indicating more attention and focus on soil and water conservation measures. Sub-watersheds with lower scores are ranked accordingly.

2.3.2. Compound Factor (CF)

This method is based on the principles of knowledge-driven modeling, as proposed by Ref. [48], which allows the conversion of qualitative insights into quantitative estimates using scientific knowledge. In this approach, the ranks assigned to each parameter

Table 3
Random Index (RI) values [47].

N° of parameters	3	4	5	6	7	8	9	10
RI	0.58	0.89	1.12	1.24	1.32	1.41	1.45	1.49

correspond to the available options. The composite value, also referred to as the mean of the ranks assigned to all parameters, represents the combined influence of these parameters. The computation of the CF model is represented by the following equation [49,50] (Eq. (4)):

$$CF = {}^{1}\!/_{n} \sum_{i=1}^{n} R \tag{4}$$

where: CF is the Compound value, R is the rank of options, and n is the number of parameters.

2.3.3. *VIKOR technique (VIšekriterijumsko Kompromisno Rangiranje)*

The VIKOR method, originally developed by Ref. [51], is an important ranking technique used in Multi-Criteria Decision Making (MCDM). It addresses the challenge of managing inconsistent criteria within complex systems. By assessing the proximity of alternatives to ideal solutions, the VIKOR method assigns weights and ranks to each alternative. The step-by-step procedure for implementing the VIKOR method, as outlined [52], involves the following stages Fig. 3.

2.3.4. *TOPSIS technique (Technique for Order of Preference by Similarity to Ideal Solution)*

The TOPSIS method is a multi-criteria decision analysis approach that aims to identify the alternative with the shortest distance to the positive ideal solution (PIS) and the longest distance to the negative ideal solution (NIS).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a Multiple Criteria Decision Making (MCDM) method that was initially proposed by Ref. [53]. The result is quantified using the approximation coefficient, where a higher value indicates a more preferred alternative [54,55].

The TOPSIS method is a Multiple Criteria Decision Making (MCDM) approach that was initially proposed by Ref. [53] (Fig. 4). The steps involved in the TOPSIS method can be described as follows.

2.3.5. *SAW model (Simple Additive Weighing)*

The SAW method is extensively utilized in Multi-Criteria Decision-Making, as demonstrated by its application in various studies [53,56].

This method calculates the score of each option by combining its values across multiple criteria, considering the assigned weight for each criterion. The decision maker directly assigns the relative weight of each criterion [57,58].

In this study, the score of each sub-watershed is computed by summing the weighted values assigned to all the criteria.

The steps followed in the SAW process are presented in Fig. 5.

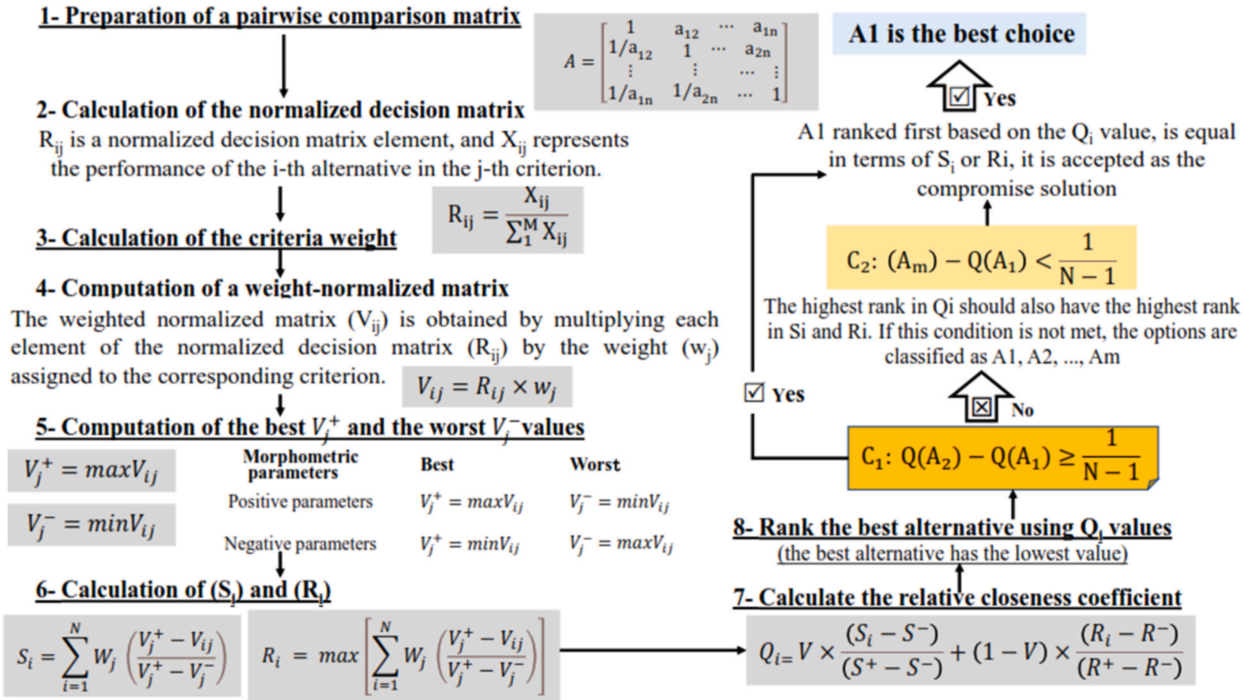


Fig. 3. Step for implementing the VIKOR method.

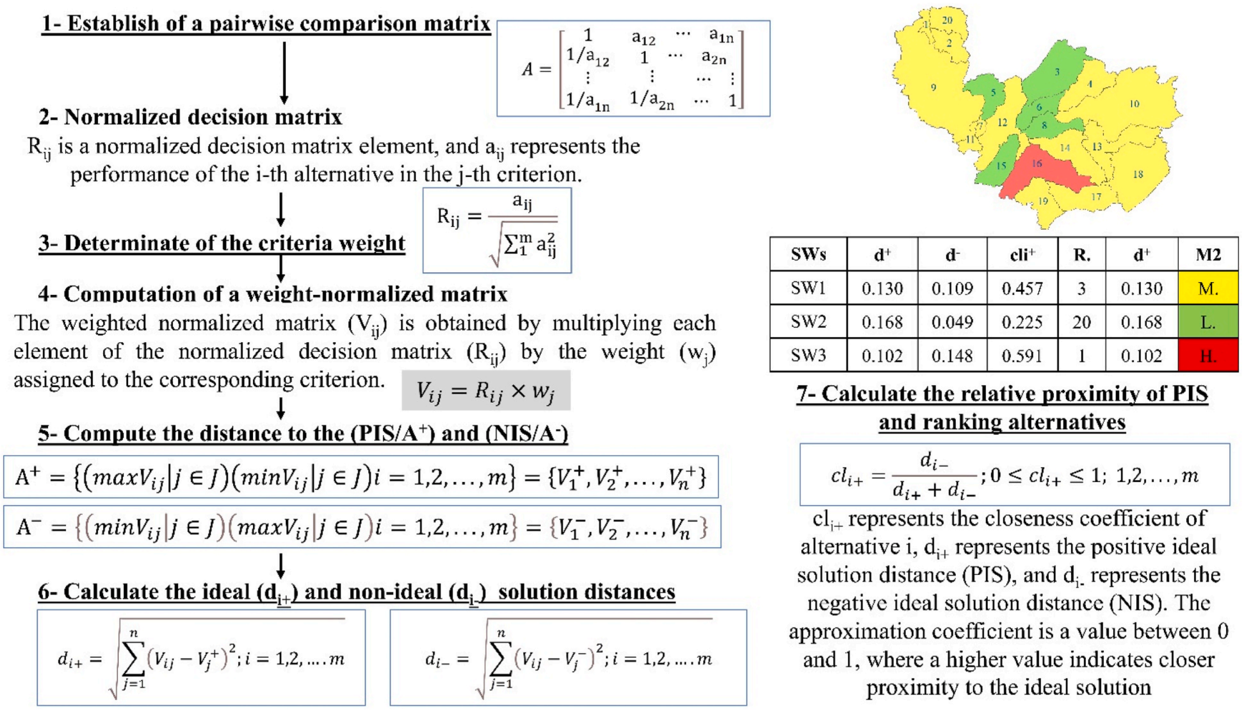


Fig. 4. Flowchart of the TOPSIS method.

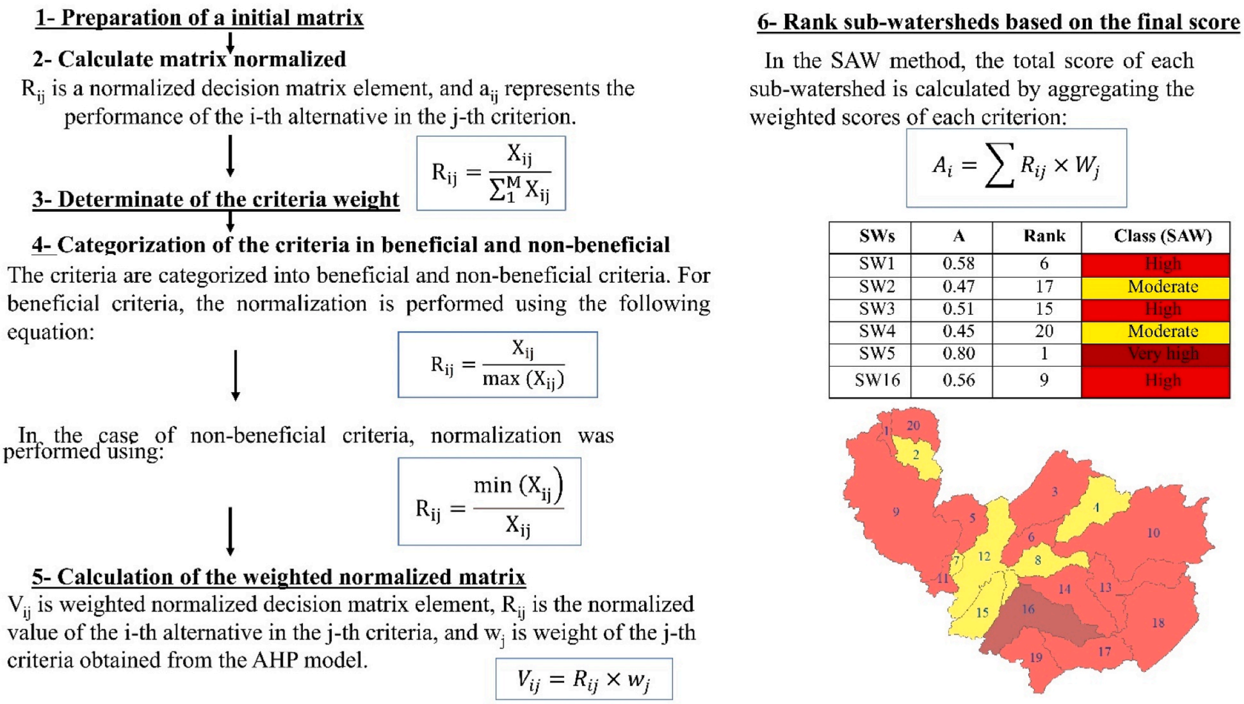


Fig. 5. SAW method implementation.

2.4. Multivariate analysis and validation for sub-watershed ranking

In this research, Principal Component Analysis (PCA) and Cluster Analysis (CA) were employed to classify sub-watersheds within the Ouljet Es Sotlane basin according to their soil erosion characteristics. In this research, Principal Component Analysis (PCA) and Cluster Analysis (CA) were employed to classify sub-watersheds within the Ouljet Es Sotlane basin according to their soil erosion characteristics.

The PCA method was applied to analyze extensive data matrices and condense the variables into composite variables or principal components [59], which exhibit correlations with erosion risk morphometric parameters [60].

Furthermore, Cluster Analysis was used to statistically evaluate the validity of the derived sub-basin priority classes based on morphometric analysis, aiming to determine if significant differences exist among them. This analysis helped to account for spatial variations between sub-catchments in terms of prioritization, providing guidance for managing and addressing erosion-related concerns in different areas of the basin.

In this research, we employed two specific indices to assess and compare the outcomes of the models in question, aiming to provide a comprehensive evaluation. These indices are the Percentage of Changes (Eq. (5)) and the Intensity of Changes (Eq. (6)). The utilization of these indices for model evaluation and comparison aligns with established methodologies in the field, as discussed by Refs. [21,61], and allows for a rigorous and comprehensive analysis of the model results.

$$\Delta P = \frac{N - N_{constant}}{N} \times 100 \tag{5}$$

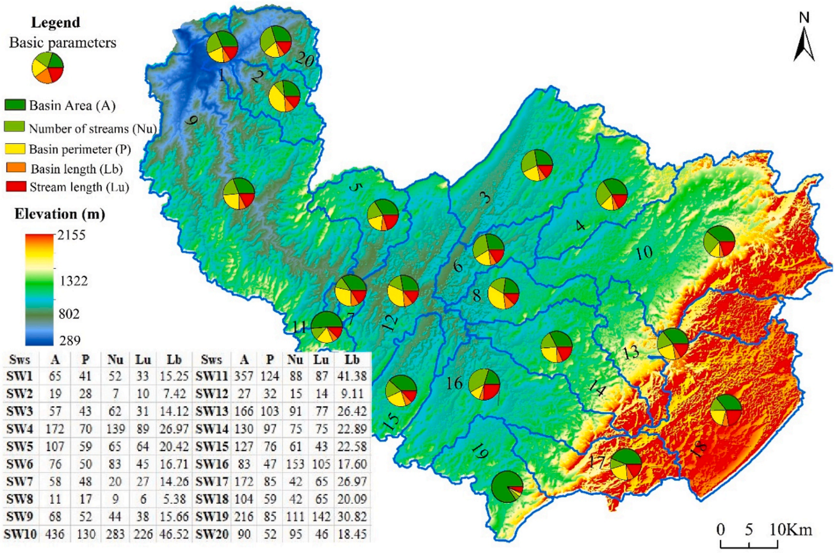
$$\Delta I = \frac{\sum_{i=1}^{N} \frac{rank(r1)}{rank(r2)}}{N} \tag{6}$$

where: ΔP is percentage of changes, N is number of alternatives, $N_{canstant}$ is number of alternatives with the same rank, and ΔI is intensity of changes, rank i (r1) is rank of alternative in the first method, rank i (r2) is rank of alternative in second method.

In addition, the non-parametric Spearman correlation coefficient test (SCCT), or Spearman rank correlation coefficient, was used to evaluate the connection between two variables by examining whether their relationship follows a monotonic trend. This approach accommodates both linear and non-linear relationships, making it versatile in analyzing various types of data associations [62]. The Spearman correlation calculates the covariance between two variables, reflecting their shared variance. Subsequently, it normalizes this measure within the range of −1 to 1. In this range, a value of −1 indicates a perfect negative relationship, while a value of 1 signifies a perfect positive relationship. The formula for the Spearman Correlation is as follows (Eq. (7)):

$$\rho = 1 - \frac{6^* \sum d_i^2}{n(n^2 - 1)} \tag{7}$$

Where: ρ is the coefficient and n is the number of points in the data set. For each point (x_i, y_i), the square of the difference in the ranks of the two coordinates is represented by d_i^2.



Sws	A	P	Nu	Lu	Lb	Sws	A	P	Nu	Lu	Lb
SW1	65	41	52	33	15.25	SW11	357	124	88	87	41.38
SW2	19	28	7	10	7.42	SW12	27	32	15	14	9.11
SW3	57	43	62	31	14.12	SW13	166	103	91	77	26.42
SW4	172	70	139	89	26.97	SW14	130	97	75	75	22.89
SW5	107	59	65	64	20.42	SW15	127	76	61	43	22.58
SW6	76	50	83	45	16.71	SW16	83	47	153	105	17.60
SW7	58	48	20	27	14.26	SW17	172	85	42	65	26.97
SW8	11	17	9	6	5.38	SW18	104	59	42	65	20.09
SW9	68	52	44	38	15.66	SW19	216	85	111	142	30.82
SW10	436	130	283	226	46.52	SW20	90	52	95	46	18.45

Fig. 6. Computation of basic parameters for the sub-watersheds of the Oujelt Es Soltane basin.

3. Results

3.1. Morphometric analysis

Watershed morphometric provides a complete description of the relationships between various processes at the Earth's surface and various components of the Earth system such as hydrology, geomorphology, and geology [63].

The morphometric analysis is conducted to quantitatively assess the catchment area and aid in water resource planning and management. Morphometric parameters can be categorized into two groups based on their geomorphometric characteristics and potential influence on soil erosion risks.

The first category (C1) encompasses parameters that show a positive correlation with soil erosion, indicating that higher values of these parameters correspond to an increased risk of erosion, as documented in studies by Refs. [21,64]. On the other hand, category 2 (C2) includes morphometric parameters that exhibit a negative correlation with soil erosion. Higher values of these parameters indicate a lower risk of erosion. Parameters in Category 1 (C1) include drainage density, drainage frequency, bifurcation ratio, drainage texture, length of overland flow, and basin relief. Conversely, Category 2 (C2) consists of basin form factors, such as the form factor, circulatory ratio, and elongation ratio. This analysis takes into account three main aspects: the linear aspect, form aspect, and landscape aspect.

Moreover, specific morphometric parameters directly act as indicators for soil erosion, referred to as erosion risk assessment parameters. In this research, 16 morphometric parameters were investigated, representing the fundamental, linear, shape, and landscape characteristics of the watershed (Fig. 6).

3.1.1. Linear parameters

The linear parameters, including Drainage density (Dd), Stream frequency (Fu), Mean bifurcation ratio (Rbm), Texture ratio (T), Constant of channel maintenance (C), Length of overland Flow (Lo), and Infiltration number (If), play a crucial role in influencing the volume and intensity of water flow within the watershed. As a result, these parameters exhibit a positive correlation with soil erosion, signifying that higher values of these parameters are indicative of an elevated risk of erosion (Fig. 8).

Drainage density (Dd) is defined as the total length of streams of all orders within a given drainage area [36,65]. It has potentially affected both the time of concentration and the magnitude of the flow. Essentially, drainage density serves to increase the proximity of existing channels within a basin and provides a measure of the time it takes water to traverse the entire basin.

The value of drainage density is subject to a range of factors that govern the characteristic dimensions of the watershed. Dd serves as a gauge of the network's texture and reveals the equilibrium between the erosive force of overland flow and the resistance of surface soils and rocks. Key influences on drainage density include geological composition and the density of vegetation. The lithology of the area has a notable impact on drainage density. Highly permeable rocks with a substantial infiltration rate tend to reduce overland flow, resulting in low drainage density [66]. In contrast, low drainage density leads to a coarser drainage texture, while high drainage density results in a finer drainage texture, increased runoff, and a higher potential for erosion in the basin area [65].

Several studies [67–69], have classified drainage density into various classes, very coarse/highly permeable ($Db < 2$), coarse/-permeable ($2 < Db < 4$), moderately coarse/moderately permeable ($4 < Db < 6$), fine/impermeable ($6 < Db < 8$), and very fine/highly

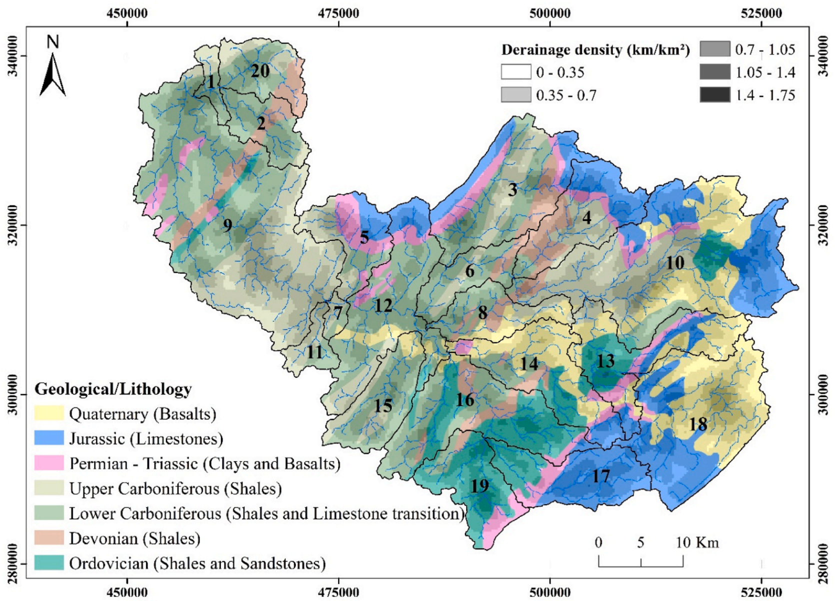


Fig. 7. Superposition of geological map and drainage density map in Oujelt Es Soltane basin.

impermeable (Db > 8).

In the case of this region, the drainage density is equal to 0.75 km/km2. This value is lower than 1.5 km/km2, indicating that the Oujelt Es Soltan basin is generally poorly drained (Fig. 7). The predominance of Paleozoic shale formations partly explains this low value. Additionally, apart from lithological criteria, the extensive low-altitude areas in the basin, its gentle slope, and low relief energy contribute to a low drainage density [70].

In the context of the Ouljet Es Soltane sub-watersheds, it is observed that SW16 exhibits the highest drainage density value (Dd = 1.27 km/km^2), indicating a greater resistance to erosion. Moreover, there is a noticeable cluster of sub-watersheds with Dd values ranging from 0.34 to 0.66, suggesting a moderate level of erosion resistance. On the other hand, SW11 displays the lowest drainage density value (Dd = 0.24 km/km^2), signifying the lowest resistance to erosion.

The lithological unit map used in this study was acquired from the Geological Map of Morocco (Fig. 7).

The Oujelt Es Soltane basin exhibits diverse geohydrological characteristics, leading to variations in morphometric attributes. Geologically, Paleozoic shales and quartzites are predominant in the lower part and central Beht River. Meanwhile, the upper part of the Beht River system is characterized by Mesozoic (Jurassic) rock formations.

Stream frequency (Fu) is the ratio of the total number of streams to the basin area [36,71]. It is also termed channel frequency (Fc) or drainage frequency (Fd). It forms a close positive correlation with Dd [72–74]. In addition, it forms a direct relationship with Nu per unit area of the basin [71]. According to Ref. [75], Fu can be categorized as very high (20.0–25.0), high (15.0–20.0), moderately high (10.0–15.0), moderate (5.0–10.0), and low (0.0–5.0). The high Fu values indicate a watershed characterized by a rocky surface and low permeability, which subsequently increases its susceptibility to erosion. Conversely, lower stream frequency values suggest higher permeability and reduced erosion risk. In the case of the Ouljet Es Soltane basin, stream frequency varies between 0.24 for SW11 and SW17 and 1.84 for SW16. This indicates that SW11 and SW17 have the lowest permeability capacity, making them highly susceptible to erosion. Conversely, SW16 exhibits the highest resistance to erosion due to its superior permeability. It is important to highlight that the erosion intensity within a watershed typically rises with stream frequency, as it exhibits a positive correlation with drainage density.

The mean bifurcation ratio, typically represented as (Rmb), is a geomorphic parameter used in the analysis of river and drainage basin networks [37,65]. The bifurcation ratio for a particular stream order is determined by dividing the number of streams of that order by the number of streams in the next higher order. In essence, the mean bifurcation ratio provides insights into the branching or hierarchical pattern of the drainage network. It exhibits a similar relationship to erosion susceptibility as drainage density and stream frequency. In the case of the Ouljet Es Soltane watershed, the mean bifurcation ratio (Rbm) ranges from 1.08 for SW6 to 83.78 for SW16. Based on the results, sub-watershed 16 displays the highest susceptibility to erosion within the study area.

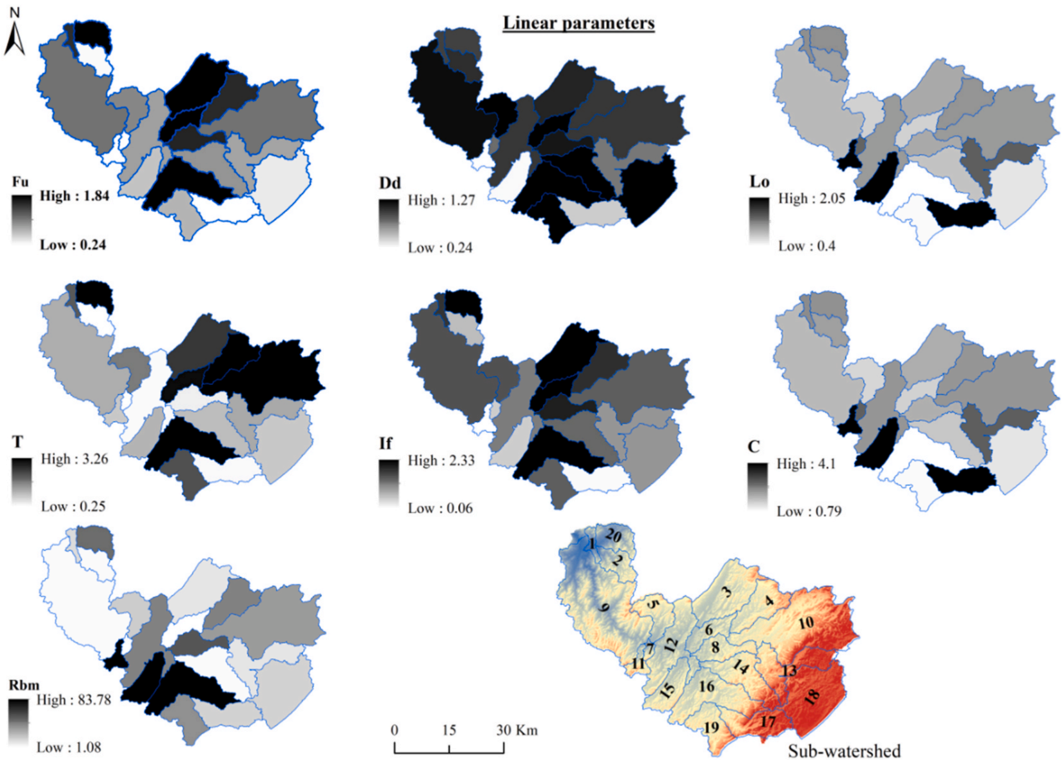


Fig. 8. Linear parameters map for 20 sub-watersheds of Ouljet Es Soltane including: Stream frequency (Fu), Drainage density (Dd), Length of overland Flow (Lo), Texture ratio (T), Infiltration number (If), Constant of channel maintenance (C) and Mean bifurcation ratio (Rbm).

Texture ratio (T) is a metric that represents the ratio between the first-order stream and the perimeter of the basin [36,39]. This ratio is influenced by various factors such as relief, geology, structure, rainfall, and infiltration capacity of the area. It holds significant importance in drainage morphometric analysis due to its correlation with the underlying lithology, infiltration capacity, and relief characteristics of the terrain.

The value of the texture ratio is influenced by lithological factors such as soil type, the rate of infiltration, and relief parameters within the basin [76]. In general, smaller values of T are indicative of a relatively flat basin with fewer variations in slope. Conversely, a higher value suggests a low infiltration rate and a greater tendency for runoff. According to a study [77], categorized T into five classes: very high (>6.0), high (5.0–6.0), moderately high (4.0–5.0), moderate (3.0–4.0), and low (<3.0). Among the sub-watersheds, SW16 exhibits the maximum texture ratio value of 3.26, indicating its highest sensitivity to erosion. On the contrary, SW2 possesses the lowest sensitivity to erosion with a texture ratio of 0.25.

The constant of channel maintenance (C) is essentially the reciprocal of drainage density [36,78–80]. According to Ref. [39], this constant helps determine the minimum land area required for the development of a drainage channel with a length of 1 km. It serves as a measure of the relative size of landform units in the watershed. It is directly correlated with erodibility, where a higher C value signifies a higher infiltration rate and a lower runoff rate [39]. initially introduced this concept. Lower values of this parameter suggest structural instability in the catchment, characterized by reduced permeability and increased runoff conditions. It is influenced by various factors, such as relief features, geological attributes, climate parameters, vegetation cover, duration of erosion, and the climatic history of the region.

In this study, SW11 exhibits a higher constant of channel maintenance (4.10) compared to SW16, which has a lower constant of channel maintenance (0.79). These results indicate that SW11 is more prone to erosion due to its higher erodibility compared to other sub-watersheds.

The term "length of overland flow" (Lo) represents the distance water travels across the ground surface before it converges into stream channels. Horton (1945) as half the reciprocal of drainage density (Dd) defined this factor. Lo values are closely related to the average slope of the channel, where lower values indicate steep slopes, and higher values indicate gentler slopes. The length of Overland Flow (Lo) is categorized into three classes: high (>0.3), moderate (0.2 < Lo < 0.3), and low (<0.2) [81]. Smaller values of Lo imply a higher proportion of surface runoff entering the streams. Even a small amount of rainfall can contribute a substantial volume of surface runoff to stream discharge when Lo is small. Within the Ouljet Es Soltane basin, SW11 exhibits the highest Lo value of 2.05, indicating a higher susceptibility to erosion. Conversely, SW16 displays the lowest Lo value of 0.40, suggesting a reduced vulnerability to erosion in this sub-watershed.

The infiltration number (If) is defined as the result of multiplying drainage density by Drainage Frequency [40]. It exhibits an inverse relationship with the rate of infiltration. When the Infiltration Number is higher, it implies a lower rate of infiltration and consequently, a greater amount of runoff. In the Oujelt Es Soltane basin, the infiltration number varies from 0.06 for SW11 to 2.33 for SW16. Consequently, SW16, with the highest infiltration number, exhibits the most susceptibility to erosion due to its characteristics of high infiltration and low runoff.

3.1.2. Shape parameters

The morphology of a basin is a crucial factor in influencing the hydrography of stream flow and peak flows. Several essential factors associated with basin shape encompass the elongation ratio (Re), circularity ratio (Rc), form factor (Rf), shape factor (Bs), and

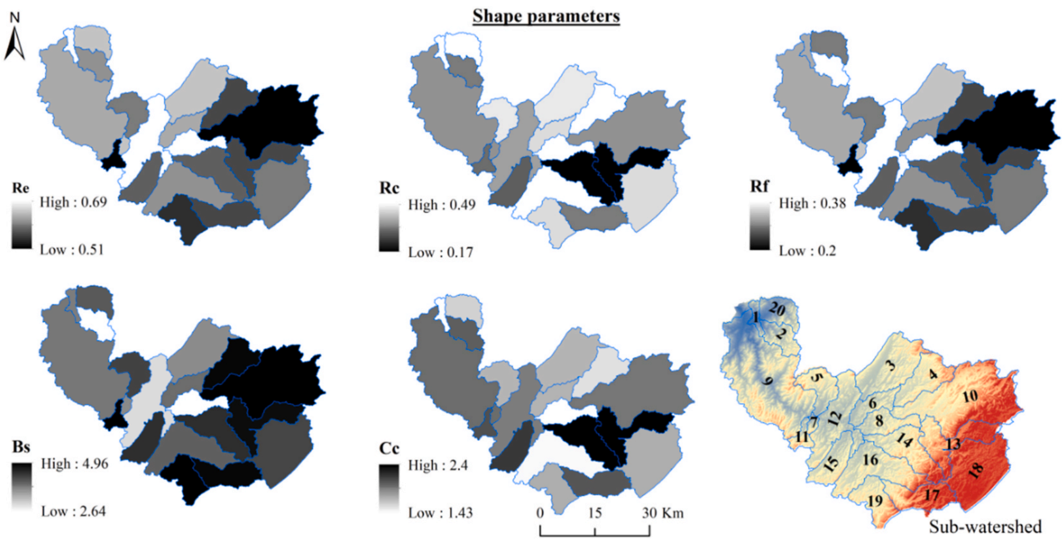


Fig. 9. Shape parameters map for 20 sub-watersheds of Ouljet Es Soltane including: Elongation ratio (Re), Circularity ratio (Rc), Form factor (Rf), Shape factor (Bs), and Compactness coefficient (C).

compactness coefficient (C) (Fig. 9). The elongation ratio (Re) gauges the length of the basin relative to its width.

The elongation ratio (Re) quantifies the relationship between the length and width of the basin. Values approaching 1.0 suggest areas with very low relief, while values falling between 0.6 and 0.8 are often associated with high relief and steep slopes in relation to the widespread disparity in climatological and geological properties [65,82].

[83] further classify watershed shapes based on their elongation, ranging from highly elongated (Re < 0.5), elongated (0.5 < Re < 0.7), less elongated (0.7 < Re < 0.8), oval (0.8 <Re < 0.9), to circular (0.9 < Re < 1.0).

In this research, SW10 demonstrated the lowest elongation ratio (Re) of 0.51, signifying its heightened vulnerability to erosion. Conversely, SW8 exhibited the highest Re value of 0.69, indicating its relatively lower susceptibility to erosion. The remaining sub-basins displayed Re values ranging from 0.51 to 0.69, suggesting different degrees of elongation or oval shape. These shapes are commonly linked with high relief, steep slopes, ample infiltration capacity, and low runoff.

The Compactness Coefficient (C) is a measure expressed as the ratio between the perimeter of a watershed and the perimeter of a circular area with an equivalent area [36,83,84]. It is closely associated with assessing erosion risk. Lower C values indicate a reduced vulnerability to erosion, while higher values suggest higher vulnerability, necessitating the implementation of conservation measures. A lower C value reflects a more elongated basin shape and lower erosion potential, whereas a higher C value indicates less elongation and higher erosion risk [23]. In the study area, C values range from 1.43 in SW1 to 2.40 in SW14.

The form factor (Rf) is a ratio calculated by dividing the catchment area by the square of the catchment length [36,71]. This form factor serves as an indicator of flow intensity within a catchment and reflects its overall shape.

In a perfectly circular basin, the form factor (Rf) value is always less than 0.7854 [85]. A smaller Rf value suggests a more elongated basin shape. Basins with higher form factor values tend to have higher peak flows of shorter duration, while those with lower form factor values have lower peak flows of longer duration [86]. In watersheds with a high value of Rf, there is a more significant peak in the hydrograph, but it occurs over a shorter duration. Conversely, watersheds with lower values can exhibit prolonged water flow with a flatter or lower peak [87]. This parameter is interconnected with various other parameters related to catchment geometry, drainage texture, and relief characteristics.

In this study, the Rf values varied from a minimum of 0.20 for SW10 to a maximum of 0.38 for SW8. As such, SW8, with the lowest form factor value, exhibits the highest sensitivity to erosion.

The shape factor (Bs) is expressed as a ratio of the square of basin length to the watershed area [36,71]. It influences sediment and runoff production rates, drainage length, and roughness. Hence, in terms of erosion response, the behavior of Bs (shape factor) is similar to that of Rf. Among the sub-basins, SW8 has the lowest Bs value of 2.64, indicating the highest erodibility and therefore the highest susceptibility to erosion. Conversely, SW10 has the highest Bs value of 4.96, indicating the least susceptibility to erosion.

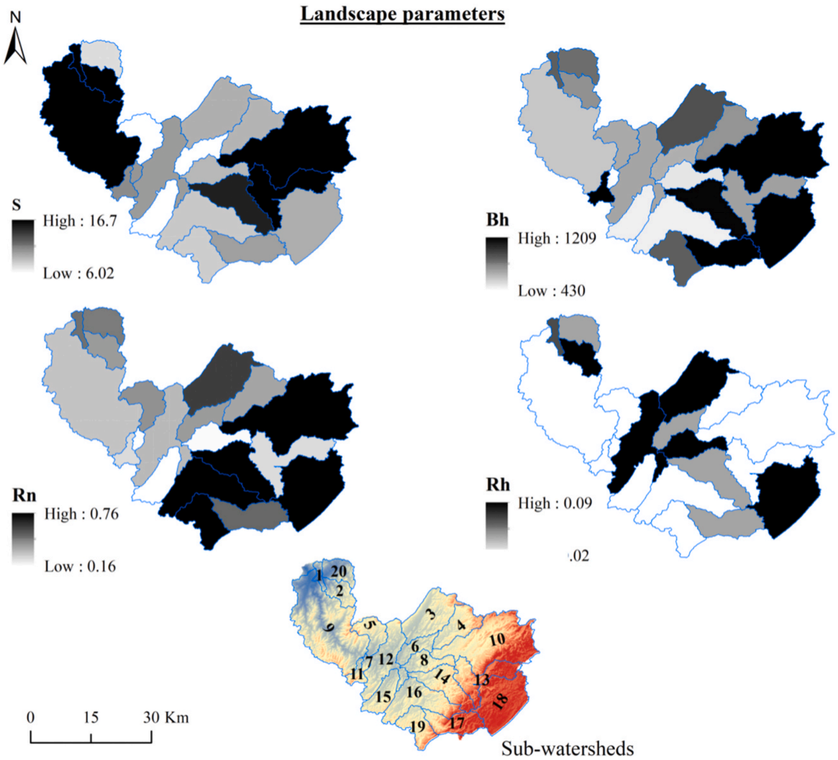


Fig. 10. Landscape parameters map for 20 sub-watersheds of Ouljet Es Soltane including: Basin relief (Bh), Slope (S), Ruggedness number (Rn), Relief ratio (Rh).

[41] originally introduced the circularity ratio, a measure similar to the elongation ratio. It is defined as the ratio of the area of the basin to the area of a circle with the same circumference as the basin's perimeter. Miller identified Rc as a significant metric that reveals the dendritic stage of a watershed, primarily influenced by the diverse slope and relief patterns in the basin. Different values of Rc (low, medium, high) indicate the various stages of development of a tributary watershed, categorizing them as young, mature, or old [88].

This parameter is influenced by various characteristics of a watershed, including stream length, stream frequency, geological structure, climate, roughness, and slope. Lower values of Rc indicate an elongated watershed with low roughness and an impermeable surface. Conversely, higher values of Rc suggest a circular watershed with high roughness and surface permeability. In this study, SW14 displayed the lowest Rc value of 0.17, signifying its lower susceptibility to erosion owing to its high infiltration capacity. Conversely, SW1 had the highest Rc value of 0.49, indicating its higher vulnerability to erosion.

3.1.3. Landscape parameters

Basin relief (Bh) represents the variation in elevation between the highest and lowest points within a drainage basin [37,39,78,80]. It is closely related to the hydrological characteristics of the basin. Similar to factors like drainage density (Dd) and stream frequency (Fu), Bh is also correlated with erosion. A low value for basin relief indicates limited runoff, reduced sediment transport, and the dispersal of water within the basin. This parameter is a significant factor in comprehending the geomorphic processes at play, the characteristics of landforms, and in gaining insights into the denudational features of the basin [89,90]. In the Ouljet Es Soltane watershed, Bh values vary, with SW7 having the minimum value of 430 and SW18 having the maximum value of 1209 (Fig. 10).

The slope (S) of a watershed is a critical hydrological morphometric factor that significantly influences erosion severity [91]. It is an important morphometric parameter controlled by morpho-climatic processes of any area underlain by varying resistance of rock surface. It indicates the extent of runoff and runoff concentration within the watershed. There exists an inverse relationship between infiltration and the slope of the basin. Steep slopes are linked to increased surface runoff and decreased infiltration rates [21,27]. In the studied sub-watersheds, the highest slope value is observed in SW1 (16.70), indicating its high sensitivity to erosion. Conversely, SW6 has the lowest slope value (6.02), suggesting that it is less prone to erosion.

The Ruggedness number (Rn) can be computed as the product of basin relief and drainage density [65,92,93]. It is a parameter used to assess the flood potential of streams [92,93]. It also characterizes the geometrical properties of the watershed and is directly related to its erodibility. Extremely high values of ruggedness number occur when slopes of the basin are not only steeper but long, as well [94]. In the Ouljet Es Soltane watershed, Rn ranges from 0.157 for SW15, which exhibits low sensitivity to erosion, to 0.756 for SW18, indicating high sensitivity.

According to Ref. [95], the relief ratio is defined as the maximum relief to horizontal distance along the longest dimension of the basin parallel to the principal drainage line. The relief ratio (Rh) is a significant index that affects both hydrological processes and watershed erosion.

In general, the relief ratio tends to increase as the drainage or stream area and the size of the watershed decrease. It indicates the overall slope of the watershed area and is instrumental in understanding the relationship between steepness and erosion in the basin. Numerous studies have noted a strong correlation between sediment loss per unit area and the relief ratio [39,91,96]. Higher values of this parameter signify a steeper slope and high relief of the basin. In basins with steeper slopes, there is an increased potential for runoff and erosion. In regions characterized by steeper slopes, the runoff enhances the possibility of erosion. Conversely, lower values of the relief ratio indicate a lower degree of slope and reduced relief in the basin [97]. Among the sub-watersheds, SW2 has the highest Rh value (0.090), while SW15 has the lowest value (0.021).

3.2. Prioritization of sub-watersheds using MCDM methods

3.2.1. CF method using for prioritizing erodibility

In the CF model, linear and relief attributes are assigned higher rankings due to their positive correlation with soil erodibility. Conversely, shape attributes receive lower rankings as they have a negative relationship with erodability. By combining the values of linear, shape, and landscape parameters, a compound factor (CF) ranking is calculated for each watershed in this study using Eq. (4).

The compound factor (CF) approach [49] used in this study takes into account the total number of sub-watersheds (SWs) in the Ouljet Es Soltane watershed. Each assessed parameter was assigned a rank from 1 to 20 for the SWs. For Group 1 parameters, the SW with the highest value was ranked 1, while the SW with the lowest value received a rank of 20. Conversely, for Group 2 parameters, the SW with the lowest value was ranked first, and the SW with the highest value was ranked 20th. The rankings of each SW across all parameters were then averaged by adding them and dividing them by the total number of parameters, resulting in the CF. The CF represents the combined influence of all parameters on the erosion susceptibility of each SW.

In conclusion, the sub-watersheds (SWs) were classified into four priority categories based on their compound factor (CF) values: very high sensitivity (CF range: 5–5.9), high sensitivity (CF range: 6–6.9), moderate sensitivity (CF range: 7–7.9), and low sensitivity (CF range: 8–8.9) [38].

The prioritization results of the 20 sub-watersheds using the CF method revealed that SW10 and SW11 obtained the lowest CF values (8.06 and 8.56) and were ranked 1st and 2nd, respectively. On the other hand, SW6 and SW7 had the highest CF values (12.06 and 13.19) and were placed at the 19th and 20th ranks, respectively. The classification of sub-watersheds based on erodibility indicated that the entire study area falls under the category of low sensitivity to erosion (Table 4).

Table 4
Prioritizing erodibility of sub-watershed by combination factor method (CF).

	Group1												Group 2						
SWs	**S**	**Bh**	**Rh**	**Rn**	**Rbm**	**Fu**	**If**	**Dd**	**Lo**	**T**	**C**	***Cc***	**Bs**	**Rf**	**Re**	**Rc**	**CF**	Rank	**Priority**
SW1	1	8	6	8	5	7	7	15	6	13	6	1	15	15	15	20	9.3	5	Low
SW2	5	10	1	12	13	17	16	10	11	1	11	15	19	19	19	6	11.6	15	Low
SW3	12	6	5	6	16	3	3	9	12	15	12	6	17	17	17	15	10.7	11	Low
SW4	13	11	17	13	6	6	6	13	8	18	8	4	4	4	4	17	9.5	6	Low
SW5	19	14	13	10	10	10	8	4	17	12	17	7	9	9	9	14	11.4	14	Low
SW6	20	15	10	11	20	2	2	5	16	16	16	8	13	13	13	13	12.1	19	Low
SW7	8	20	12	19	19	18	18	16	5	2	5	13	16	16	16	8	13.2	20	Low
SW8	14	17	2	18	4	5	5	8	13	5	13	2	20	20	20	19	11.6	15	Low
SW9	4	16	11	15	18	9	9	7	14	10	14	14	14	14	14	7	11.9	18	Low
SW10	2	3	19	4	9	8	11	12	9	19	9	12	1	1	1	9	8.1	1	Low
SW11	7	2	14	17	3	19	20	20	1	6	1	17	2	2	2	4	8.6	2	Low
SW12	9	13	3	14	7	12	13	11	10	3	10	11	18	18	18	10	11.3	13	Low
SW13	3	12	18	16	14	13	14	17	4	11	4	19	6	6	6	2	10.3	9	Low
SW14	6	5	7	3	17	11	12	6	15	8	15	20	7	7	7	1	9.2	4	Low
SW15	18	18	20	20	2	15	17	19	2	9	2	18	8	8	8	3	11.7	17	Low
SW16	15	19	15	2	1	1	1	1	20	20	20	3	12	12	12	18	10.8	12	Low
SW17	10	4	9	7	11	20	19	18	3	4	3	16	5	5	5	5	9	3	Low
SW18	11	1	4	1	12	16	15	3	18	7	18	10	10	10	10	11	9.8	7	Low
SW19	16	7	16	5	8	14	10	2	19	14	19	9	3	3	3	12	10	8	Low
SW20	17	9	8	9	15	4	4	14	7	17	7	5	11	11	11	16	10.3	9	Low

3.2.2. TOPSIS, VIKOR, SAW models prioritize erodibility in sub-watersheds

The study calculates linear, shape, landscape morphometric parameters for 20 sub-watersheds, and then constructs a decision matrix using normalized data. The weights of each criterion are determined using the Analytic Hierarchy Process (AHP) method (Fig. 11). The inconsistency ratio is 0.066, acceptable, below 0.1 [44].

The AHP method was employed to determine the relative importance of various morphometric parameters in relation to erodibility. The results indicated that Basin relief (Bh), Drainage density (Dd), Mean bifurcation ratio (Rbm), and Texture ratio (T) were the most influential parameters, with scores of 0.152, 0.140, 0.132, and 0.1, respectively. These parameters exhibited the greatest impact on the erodibility of the sub-watersheds. On the other hand, Elongation ratio (Re), Constant of channel maintenance (C), Relief ratio (Rh), Circularity ratio (Rc), and shape factor (Bs) had similar and relatively low scores of 0.020, suggesting that they had the least influence on erodibility in the study area.

In this study, the data underwent normalization using the linear method (Fig. 4) for the TOPSIS model with the vector method for the VIKOR method (Fig. 3), and using the steps detailed in Fig. 5 for the SAW model. Following that, the weights of the criteria were determined using the AHP method to create the weighted normalized decision matrix for the MCDM models (Fig. 12).

In addition, the utility index, regret index, and ranking of sub-watersheds based on the VIKOR model were calculated (Fig. 3). Furthermore, the TOPSIS model was used to determine the distance from the positive and negative ideals as well as the proximity coefficient of alternatives to the ideal solution, which were computed using Fig. 4. Additionally, the final weights of each sub-watershed were obtained using the SAW approach by summing the weighted normalized matrix rows, as described in Fig. 5 and Table 9.

The sub-watersheds were categorized into four priority levels based on their Qi values as follows (Fig. 13).

1. Very High priority: Sub-watersheds with a Q_i value ranging from 0 to 0.25;
2. High priority: Sub-watersheds with a Q_i value ranging from 0.25 to 0.5;
3. Moderate priority: Sub-watersheds with a Q_i value ranging from 0.5 to 0.75;
4. Low priority: Sub-watersheds with a Q_i value ranging from 0.75 to 1.

This classification scheme is based on the research conducted by Ref. [21].

Based on the findings of the VIKOR model, the sub-basins SW11 and SW16 obtained the highest scores of 0.32 and 0.001, respectively. They were ranked as the second and first most susceptible to erosion, indicating a higher susceptibility. Conversely, the sub-basins SW5, SW6, SW7, SW9, and SW13 obtained scores of 0.79, 0.89, 0.95, 0.85, and 0.79, respectively, placing them in the lowest ranks. These sub-basins exhibited the least sensitivity to erosion, indicating a lower susceptibility (Fig. 14b).

The TOPSIS model classified all sub-watersheds into four priority categories, taking into consideration their sensitivity to soil erosion (Fig. 14c).

The categorization of sub-watersheds was based on the range of the closeness coefficient (cli+), as follows: very high priority (0.75–1), high priority (0.5–0.75), moderate priority (0.25–0.5), and low priority (0–0.25), following the approach used in previous studies [21,27].

The categorization was determined using the range of the closeness coefficient (cli+) as follows: very high priority (0.75–1), high priority (0.5–0.75), moderate priority (0.25–0.5), and low priority (0–0.25), as described in previous studies [21,27]. The TOPSIS model results revealed that SW16 scored the highest with a value of 0.591, indicating it as the most susceptible to erosion. Conversely, sub-watersheds 5, 6, 8, and 15 exhibited the least sensitivity to erosion, obtaining the lowest scores of 0.231, 0.225, 0.247, and 0.249, respectively. The remaining sub-watersheds displayed moderate susceptibility to soil erosion. Based on the rankings of erosion susceptibility, the study area was categorized into four clusters: Low (0–0.25), Moderate (0.25–0.50), High (0.50–0.75), and Very high (0.75–1).

The results of the TOPSIS model revealed that SW16 had the highest score of 0.591, indicating it to be the most vulnerable to erosion. Conversely, sub-watersheds 5, 6, 8, and 15 exhibited the least sensitivity to erosion, obtaining the lowest scores of 0.231, 0.225, 0.247, and 0.249, respectively. The remaining sub-watersheds displayed a moderate susceptibility to soil erosion. Based on the rankings of sub-watersheds in terms of erosion susceptibility, the study area was divided into four clusters: Low (0–0.25), Moderate (0.25–0.50), High (0.50–0.75), and Very high (0.75–1)

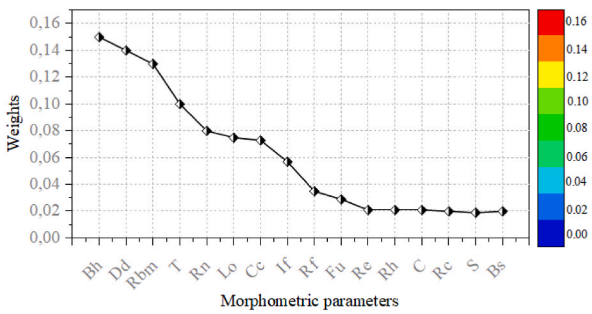


Fig. 11. Analytical Hierarchy Process (AHP) calculates parameter weights.

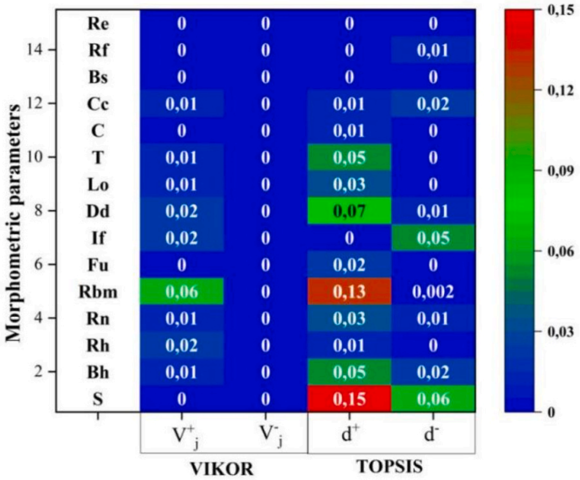


Fig. 12. Computation of the best and worst values in VIKR, and positive and negative ideal solutions in TOPSIS model.

Table 5
Percentage of changes.

	CF	VIKOR	TOPSIS	SAW	Average of percentage of changes
CF	0	75	90	95	65
VIKOR	75	0	90	85	63
TOPSIS	90	90	0	90	68
SAW	95	85	90	0	68

Table 6
Intensity of changes.

	CF	VIKOR	TOPSIS	SAW	Sum
CF	1	1.352	1.337	1.207	4.896
VIKOR	1.695	1	1.373	1.228	5.297
TOPSIS	1.655	1.314	1	1.204	5.173
SAW	1.522	1.141	1.192	1	4.855

Table 7
Total variance explained of Ouljet Es Soltane watershed.

Dim (PC)	Eigenvalue	Variance	Accumulated variance
Dim1	7.2	36	36
Dim2	5.72	28.6	64.6
Dim3	2.15	10.8	75.4

The results obtained from the SAW model (Fig. 14d) revealed that sub-watersheds SW2, SW7, SW8, SW12, and SW15 obtained scores of 0.47, 0.45, 0.46, 0.47, and 0.48, respectively, placing them at the lower ranks and indicating their lower sensitivity to erosion. Conversely, the remaining sub-watersheds were ranked higher, suggesting their greater susceptibility to erosion.

By employing diverse multi-criteria decision-making (MCDM) techniques for sub-watershed prioritization, it is evident that most of the study area shows moderate to low levels of erosion. The application of the FC model results in classifying all watersheds as low priority, indicating their relatively lower susceptibility to erosion.

The MCDM models' prioritization levels can be summarized as follows.

a. VIKOR Model:
   - High Priority: SW11 and SW16 (10 % of the study area);
   - Medium Priority: Thirteen sub-watersheds (65 % of the total area);
   - Low Priority: Five sub-watersheds (25 % of the Ouljet Es Soltane watershed).
b. TOPSIS Model:
   - High Priority: 5 % of sub-watersheds;

Table 8
Average morphometric parameter values as well as values for four MCDM models by cluster.

Cluster	1	2	3
Rbm	5.81	5.33	83.78
Fu	0.45	0.72	1.84
Dd	0.49	0.52	1.27
Lo	1.12	0.98	0.40
T	1.01	1.05	3.26
If	0.24	0.38	2.33
C	2.24	1.97	0.79
Cc	1.91	1.65	1.46
Rf	0.23	0.29	0.27
Re	0.54	0.60	0.58
Rc	0.29	0.38	0.47
Bs	4.36	3.53	3.73
S	11.17	9.63	7.87
Bh	989.14	617.50	464.00
Rh	0.03	0.05	0.03
Rn	0.48	0.32	0.59
CF	**9.28**	**11.19**	**10.75**
VIKOR	**0.61**	**0.74**	**0.00**
TOPSIS	**0.35**	**0.29**	**0.59**
SAW	**0.58**	**0.51**	**0.80**

Table 9
Use of the VIKOR, TOPSIS, and SAW models to prioritize 20 sub-watersheds.

SWs	S_i	R_i	Q_i	R.	M1	d^+	d^-	cli^+	R.	d^+	M2	A	R.	M3
SW1	0.70	0.16	0.61	6	M.	0.130	0.109	0.457	3	0.130	M.	0.58	6	H.
SW2	0.71	0.16	0.75	14	M.	0.142	0.090	0.387	6	0.142	M.	0.47	17	M.
SW3	0.67	0.17	0.74	13	M.	0.153	0.056	0.267	14	0.153	M.	0.59	5	H.
SW4	0.73	0.16	0.68	11	M.	0.150	0.059	0.282	11	0.150	M.	0.52	13	H.
SW5	0.76	0.16	0.79	17	L.	0.166	0.050	0.231	19	0.166	L.	0.52	12	H.
SW6	0.73	0.17	0.89	19	L.	0.168	0.049	0.225	20	0.168	L.	0.51	15	H.
SW7	0.82	0.17	0.95	20	L.	0.161	0.056	0.259	15	0.161	M.	0.45	20	M.
SW8	0.75	0.16	0.65	7	M.	0.155	0.051	0.247	18	0.155	L.	0.46	19	M.
SW9	0.76	0.17	0.85	18	L.	0.141	0.093	0.398	5	0.141	M.	0.51	14	H.
SW10	0.60	0.16	0.55	4	M.	0.128	0.110	0.462	2	0.128	M.	0.61	2	H.
SW11	0.63	0.15	0.32	2	H.	0.145	0.074	0.339	8	0.145	M.	0.61	3	H.
SW12	0.73	0.16	0.67	10	M.	0.153	0.056	0.267	13	0.153	M.	0.47	18	M.
SW13	0.73	0.16	0.79	16	L.	0.140	0.095	0.405	4	0.140	M.	0.53	11	H.
SW14	0.60	0.17	0.65	9	M.	0.142	0.080	0.360	7	0.142	M.	0.56	8	H.
SW15	0.80	0.14	0.50	3	M.	0.160	0.053	0.249	17	0.160	L.	0.48	16	M.
SW16	0.42	0.14	0.00	1	Vh.	0.102	0.148	0.591	1	0.102	H.	0.80	1	Vh.
SW17	0.69	0.16	0.71	12	M.	0.155	0.064	0.291	10	0.155	M.	0.56	9	H.
SW18	0.58	0.16	0.59	5	M.	0.152	0.070	0.315	9	0.152	M.	0.59	4	H.
SW19	0.70	0.16	0.65	8	M.	0.152	0.058	0.276	12	0.152	M.	0.58	7	H.
SW20	0.70	0.16	0.75	15	M.	0.158	0.054	0.255	16	0.158	M.	0.53	10	H.

L.: Low; M.: Moderate; H.: High; Vh.: Very high; R.: Rank.
M1: VIKOR.
M2: TOPSIS.
M3: SAW.

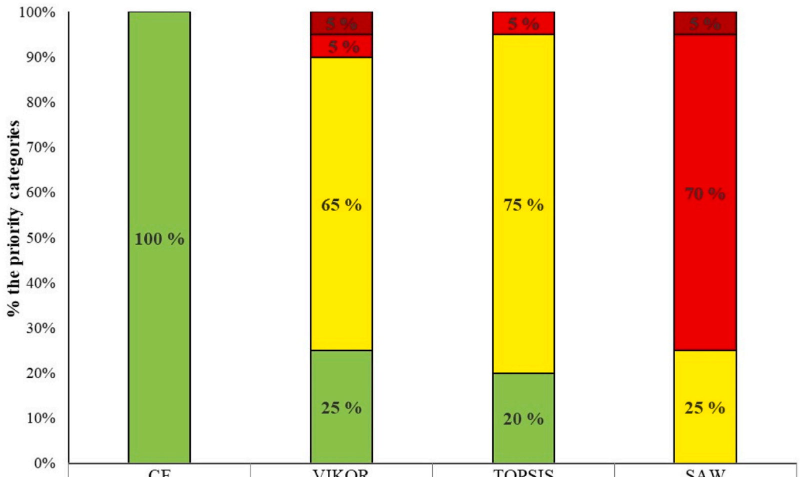
- Moderate Priority: Fifteen sub-watersheds (75 % of the study area);
- Low Priority: Four sub-watersheds (20 % of the study area).

c. SAW Model:
- Highest Priority: 80 % of the study area;
- Moderate Priority: 20 % of the study area.

The results show that the majority of the study region exhibits moderate to low levels of erosion. The FC model categorizes all watersheds as low priority, indicating their lower sensitivity to erosion (Fig. 14a).

In addition to the similarities, there are contradictions in the results. For example, for SW7, SW9, SW11, SW13, and SW16, relatively unstable rankings are observed in different methods.

The inherent qualities of the approaches and the unique values given to the criteria employed in each of them can be utilized to explain why the rankings derived from each multi-criteria decision-making method are incompatible with one another [98]. Their various attitudes are what cause these strategies to differ from one another. According to the study's findings, all ranking techniques



	CF	VIKOR	TOPSIS	SAW
Very high	0	5	0	5
High	0	5	5	70
Moderate	0	65	75	25
Low	100	25	20	0

Fig. 13. Level priority of four MCDM models.

can be applied. There is little doubt that none of these techniques will yield the same rankings.

Two different evaluation methods of percentage change and intensity change were used to determine the MCDM model's efficiency. Percentage change results showed the best efficiency of the TOPSIS method with high accuracy value (68) and SAW (68) than CF (65), and VIKOR methods (63) (Table 5). In contrast, intensity change denoted that the VIKOR method is more efficient with high accuracy (5.297) than TOPSIS (5.173), CF (4.896) and SAW methods (4.855), respectively (Table 6).

According to the percentage change and intensity change of MCDM validation test, it is the point that TOPSIS and VIKOR have the best efficiencies with high accuracy values than other methods.

3.3. Sub-watershed prioritization based on multivariate analysis

The first three main components were found to be the most significant in explaining the variation in the data by the Principal Component Analysis (PCA), which was run on the 16 parameters. According to the values of the correlation matrix's eigenvectors (Fig. 15 and Table 7), the most significant parameter was chosen based on how much it contributed to the principal component. For 75.36 % of the database's overall variance, the first three main components were responsible.

Most linear factors, including Drainage Density (Dd), Stream Frequency (Fu), Mean Bifurcation Ratio (Rbm), Texture Ratio (T), Infiltration Number (If), Circularity Ratio (Rc), TOPSIS, and SAW techniques, have a positive correlation with the first component (Dim1). The Compactness coefficient (*Cc*), Length of overland Flow (Lo), Constant of channel maintenance (C), and VIKOR technique are in opposition to these factors.

Basin relief (Bh) and Shape factor (Bs) have a positive correlation with Dim2 (the vertical axis), the second component. Elongation ratio (Re), Form factor (Rf), relief ratio (Rh), and CF on this axis all have a negative correlation with it (Dim2).

The erodibility prioritization of the sub-watersheds of the Ouljet Es Soltane basin was carried out using a variety of methods, and the correlation matrix of the 16 morphometric parameters (Fig. 16) shows that there are strong correlations (correlation coefficient greater than 0.7) between Rn and SAW, CF and Basin relief (Bh), TOPSIS and Slope (S), and SAW and CF. More moderately correlated parameters (correlation coefficient greater than 0.5) also exist between SAW and Texture ratio (T), Shape factor (Bs), Basin relief (Bh), Form factor (Rf), and Elongation ratio (Re); between CF and Shape factor (Bs); Ruggedness number (Rn), Form factor (Rf), and Elongation ratio (Re); between VIKOR and Ruggedness number (Rn); and between TOPSIS and SAW and CF.

The 20 watersheds were subjected to a Cluster Analysis (CA), which classified the data into various clusters based on their morphometric characteristics. The results are shown in Fig. 17. Following were the three distinct clusters found.

1. Cluster 1 consists of seven watersheds (SW10, SW11, SW13, SW14, SW17, SW18, and SW19) exhibiting low values for the shape parameter but high values for Mean bifurcation ratio (Rbm), slope (S), Constant of channel maintenance (C), CF, and VIKOR.
2. Cluster 2 comprises 12 watersheds characterized by high values in Drainage density (Dd), stream frequency (Fu), Texture ratio (T), Infiltration number (If), relief ratio (Rh), and CF. Conversely, this cluster demonstrates lower values for elongation ratio (Lo), slope (S), Mean bifurcation ratio (Rbm), TOPSIS, and SAW.

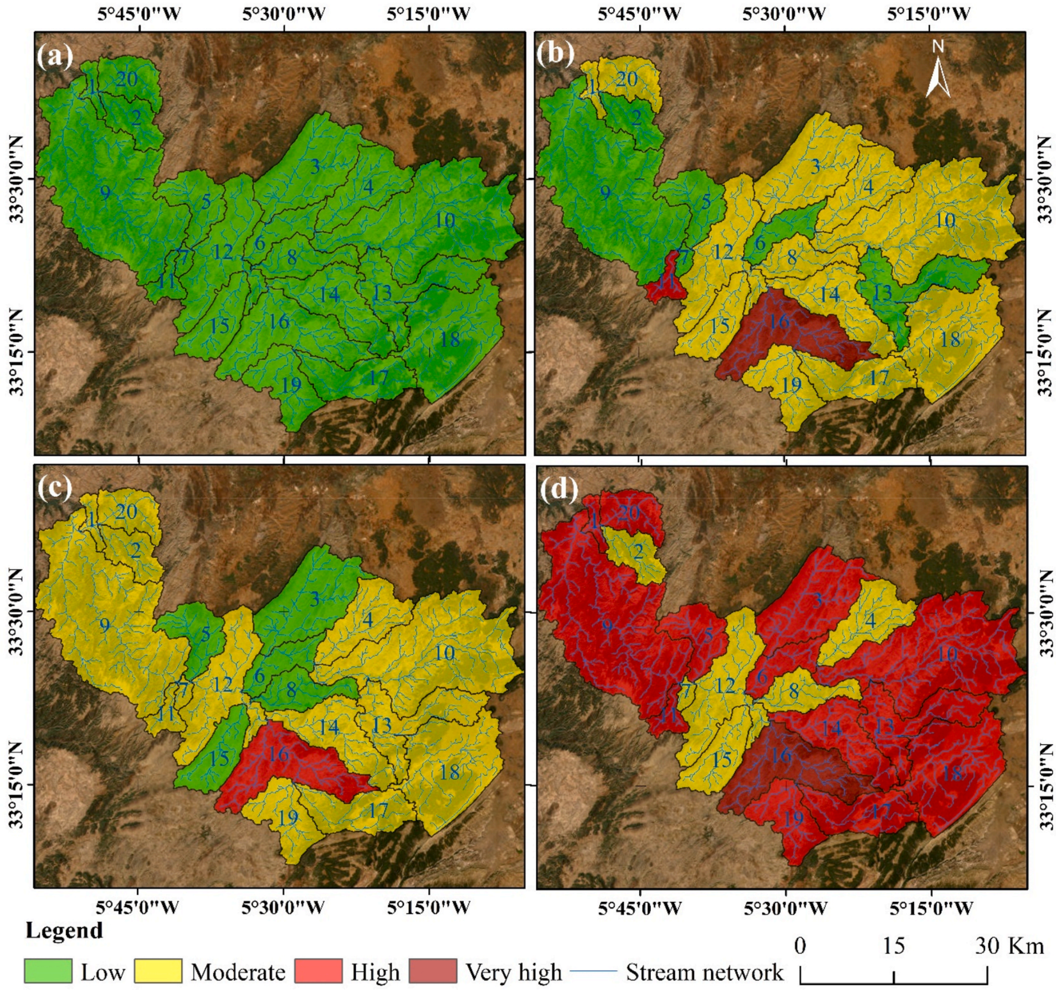


Fig. 14. Four MCDM models using for prioritize 20 sub-watersheds, (a): CF; (b): VIKOR; (c): TOPSIS; (d): SAW models.

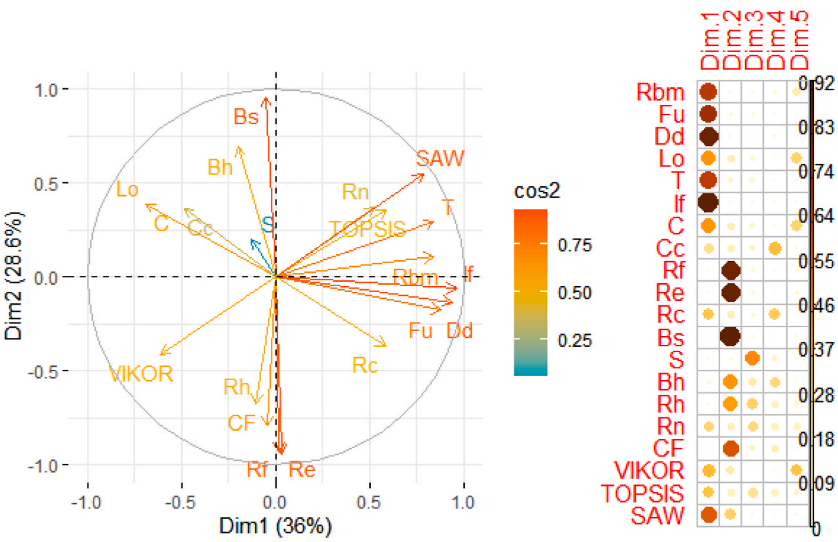


Fig. 15. Projection of the variables on the Dim1-Dim2 and factor coordinates of the variables, based on correlations.

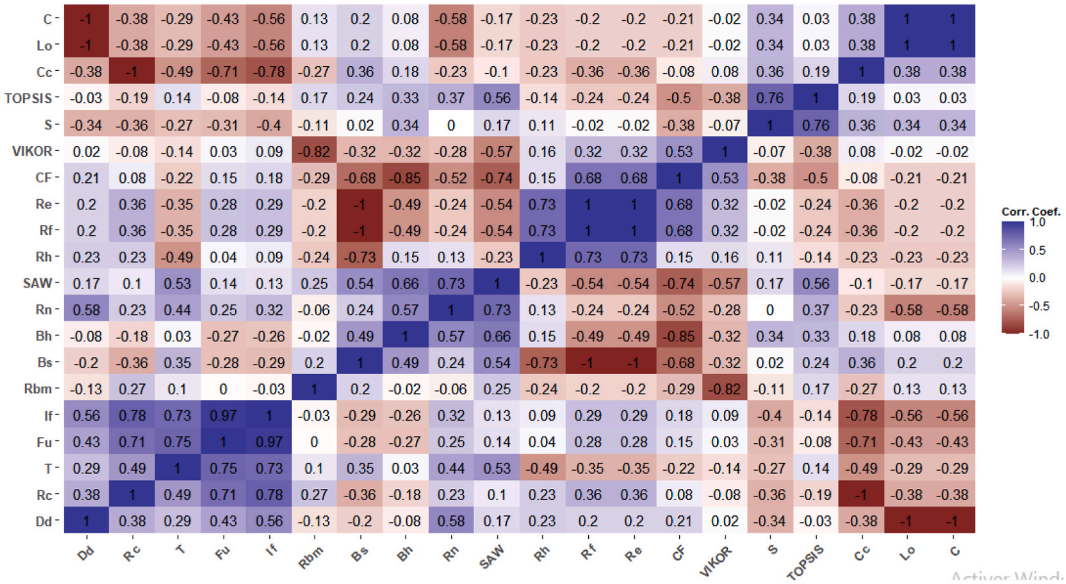


Fig. 16. Correlation coefficient values of morphometric parameters and four method erodibility prioritizations (CF, VIKOR, TOPSIS and SAW).

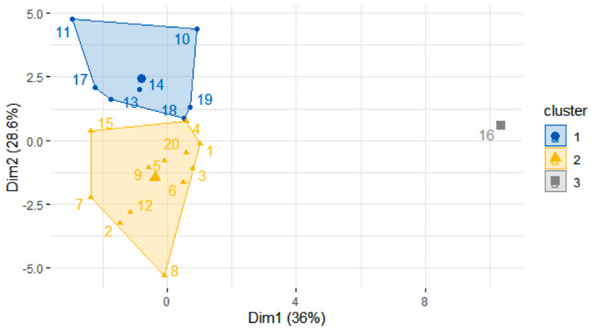


Fig. 17. Three clusters of 20 watersheds by Cluster Analysis.

3. The only watershed (16) in Cluster 3 showed the greatest values for the characteristics related to linearity, form, and landscape. Additionally, among all the watersheds, it has the highest values of CF, TOPSIS, and SAW (Table 8).

4. Discussions

The Ouljet Es Soltane watershed has a significant influence on agricultural productivity and serves as a vital water source for residential and irrigation purposes, among various other applications. However, it must make concentrated efforts for conservation and restoration to ensure sustainable development because of the problem of soil erosion and degradation. Planners and decision-makers must prioritize their interventions and allocate resources wisely in light of time and resource constraints. This process's crucial first step is to rank sub-watersheds according to their susceptibility to soil erosion. This prioritization of actions for soil and water conservation has been addressed using various techniques.

Whereas MCDM methods are widely recognized as reliable for prioritizing watersheds, their applicability may be limited in certain areas like the Ouljet Es Soltane basin, where comprehensive data on climate, sediment yield, soil loss, and surface runoff are scarce. In such cases, indirect evaluation methods that leverage morphometric analysis in conjunction with multi-criteria decision-making have emerged as suitable alternatives for establishing priorities and devising feasible solutions. This study employed an MCDM approach utilizing sixteen morphometric parameters to identify sub-watersheds that are more susceptible to erosion.

This research has also demonstrated the role of morphometric analysis in understanding the hydrological functioning and soil erosion susceptibility within the Ouljet Es Soltane basin. The morphometric parameters we analyzed played a key role in characterizing the unique features of the watershed and identifying areas at risk of erosion (Table 9).

However, some of these morphometric parameters are highly important in relation to the inter-correlation (strong either positive or negative, good and moderately good) among them for a better understanding of the watershed morphometry.

This study reveals that the lower shape parameter values (i.e. Rf < 0.78, Re < 0.8, and Rc < 0.50) indicate a basin having an elongated shape and flatter peak for an extended period and higher erodibility due to their inverse relationship with erodibility. Whereas Rf > 0.78, Re > 0.8, Rc > 0.50, and C≥1 indicate a basin having a circular shape and a higher peak for a smaller period, and the drainage yields the shortest Tc before the occurrence of peak flow.

A relatively higher Rb value designates an early-peak hydrograph with a huge possibility of flash flood during rainstorm events.

The runoff conditions and erosion potential of a watershed are more aptly conveyed through factors such as Circularity ratio Rc, Texture ratio T, Compactness coefficient *Cc*, Bifurcation ratio Rb, Drainage density Dd, Stream frequency Fu, Constant of channel maintenance C, and Length of overland flow Lo.

Hence, greater values of Dd, Fu, and Rb indicate a higher propensity for erosion due to their direct correlation with soil erodibility. Conversely, lower values of C and Lo signify conditions conducive to increased surface runoff, rendering the area susceptible to flooding and gully erosion, primarily stemming from structural disturbances, low infiltration rates, and steep terrain. On the contrary, smaller values of Rb, Rmb, Dd, and Fu denote low runoff conditions, typically associated with a relatively flat basin, a sparse number of stream segments, coarse terrain, high infiltration rates, abundant vegetation, and gentle terrain. Such basins are less prone to erosion.

The results from the application of MCDM models to prioritize sub-watersheds revealed variations in erosion susceptibility across the study area depending on the specific models used. In the CF model, all sub-watersheds were classified as having low erosion susceptibility. In contrast, the VIKOR model identified 10 % of the sub-watersheds as being highly susceptible to erosion, while the TOPSIS model indicated that only 5 % of the sub-watersheds were vulnerable to erosion. Notably, the SAW method categorized 75 % of the sub-watersheds as having a high erosion potential. Sub-watersheds with higher values of morphometric parameters, which exhibit a positive correlation with soil erosion, demonstrated increased erodibility in certain cases. Specifically, sub-watersheds SW11 and SW16 were identified as highly erodible according to the VIKOR model, while SW16 stood out in the TOPSIS model. Additionally, the SAW model identified 14 sub-watersheds with elevated erodibility. These sub-watersheds exhibited higher values for linear parameters (Dd, Fu, Rbm, T, C, Lo, and If) and landscape parameters (Bh, S, Rn, and Rh).

The findings of this study align with those reported by Ref. [99]. The study indicates that the total area characterized by very high soil erosion severity is relatively low, accounting for less than 10 % in the VIKOR and TOPSIS models. However, in contrast, the SAW model reveals a significantly larger extent, with 75 % of the study area being classified as having very high soil erosion severity. These results were compared to similar studies conducted in different regions [21] reported a 5 % coverage of very high soil erosion susceptible zones based on the VIKOR method, while [100] reported that 36 % of the total area exhibited very high soil erosion susceptibility. The comparison of results from these MCDM models highlights a high level of soil erosion risk and emphasizes the need for immediate action, particularly in watershed SW16, followed by watershed SW11.

The results of the study unequivocally demonstrate that sub-watershed 16 (SW16) is highly susceptible to erosion, primarily due to its distinctive characteristics, including severe soil degradation and a notable absence of vegetation. This assessment is underpinned by a comprehensive analysis of a detailed land use and land cover (LULC) map specifically created for the year 2022, utilizing Sentinel-2 satellite images with a resolution of 30 m. These findings clearly highlight the adverse conditions that contribute to erosion within this particular basin (Fig. 18).

The non-parametric Spearman correlation coefficient test (SCCT) was employed to evaluate the consistency of the rankings of 20 sub-watersheds within the models. This test suggests that, relative to the CF, VIKOR, TOPSIS, and SAW models, all models exhibited a

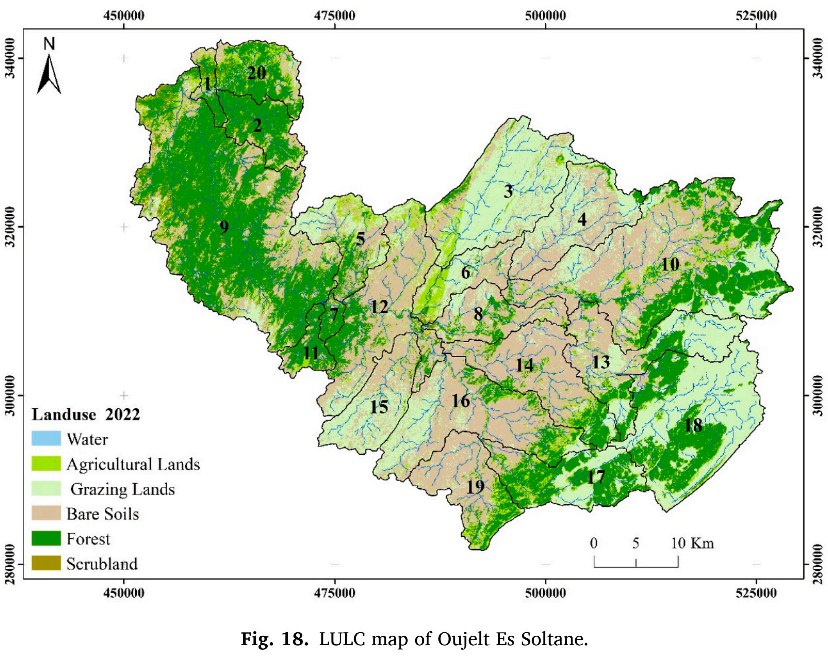


Fig. 18. LULC map of Oujelt Es Soltane.

significant positive rank correlation. It is observed that a high correlation exists between the four MCDM models of CF-VIKOR, CF-TOPSIS, VIKOR-SAW, and TOPSIS-SAW. However, the CF-SAW models demonstrated the very high positive rank correlation. Their Spearman's rank correlation coefficients were 0.74. It is also derived that moderate Spearman's correlation is exhibited between the pair VIKOR-TOPSIS equal to 0.38. The ranks of the sub-watersheds are highly correlated, but there might be some variability in the exact order (Fig. 19). Excluding the particular analysis, the sub-watershed classification from Ref. [38] using the CF model indicates that the entire study area is marked by low to moderate sensitivity to erosion (Table 4 and Fig. 14a). However, when factoring in the Spearman's rank correlation coefficients with the SAW model, which identifies sub-watersheds as exhibiting moderate to high susceptibility to erosion (Table 9 and Fig. 14d), there arises an evaluation of the erosion sensitivity among the 20 sub-watersheds based on their order. This highlights the reason behind the strong correlation observed between CF-SAW models.

5. Conclusion

The prioritization of sub-watersheds plays a crucial role in the long-term conservation, improvement, and maintenance of watersheds. This study employs various tools such as GIS, remote sensing, and morphometric analysis to address this issue.

In this study, several methods were employed to assess and prioritize sub-watersheds in terms of erosion susceptibility. The results of the different methods are as follows (Table 10).

1. CF Model:
   - All 20 sub-watersheds were classified as having low erosion susceptibility.
2. VIKOR Model:
   - 10 % of the sub-watersheds were classified as having high erosion severity.
   - The remaining 90 % were distributed among moderate and low erosion susceptibility categories.
3. TOPSIS Model:
   - 5 % of the sub-watersheds were identified as vulnerable to erosion.
   - The majority (95 %) fell into the moderate and low erosion susceptibility categories.
4. SAW Model:
   - 75 % of the sub-watersheds were classified as having high erosion susceptibility.
   - The remaining sub-watersheds were distributed among moderate and low erosion susceptibility categories.
5. The Spearman correlation coefficient test (SCCT) suggests that the CF-SAW models demonstrated a strong correlation for the prioritization of the 20 sub-watersheds.

These findings emphasize the variation in erosion susceptibility assessments depending on the methodology employed. The SAW model identified a large proportion of the study area as highly susceptible to erosion, while the CF model classified all sub-watersheds as having low erosion susceptibility. The VIKOR and TOPSIS models provided intermediate results, with a portion of the sub-watersheds falling into the high erosion severity and vulnerability categories.

This research displays the effectiveness of remote sensing (RS), geographic information systems (GIS), and multi-criteria decision-making (MCDM) in prioritizing sub-watersheds through morphometric analysis. The findings from the MCDM models and multivariate

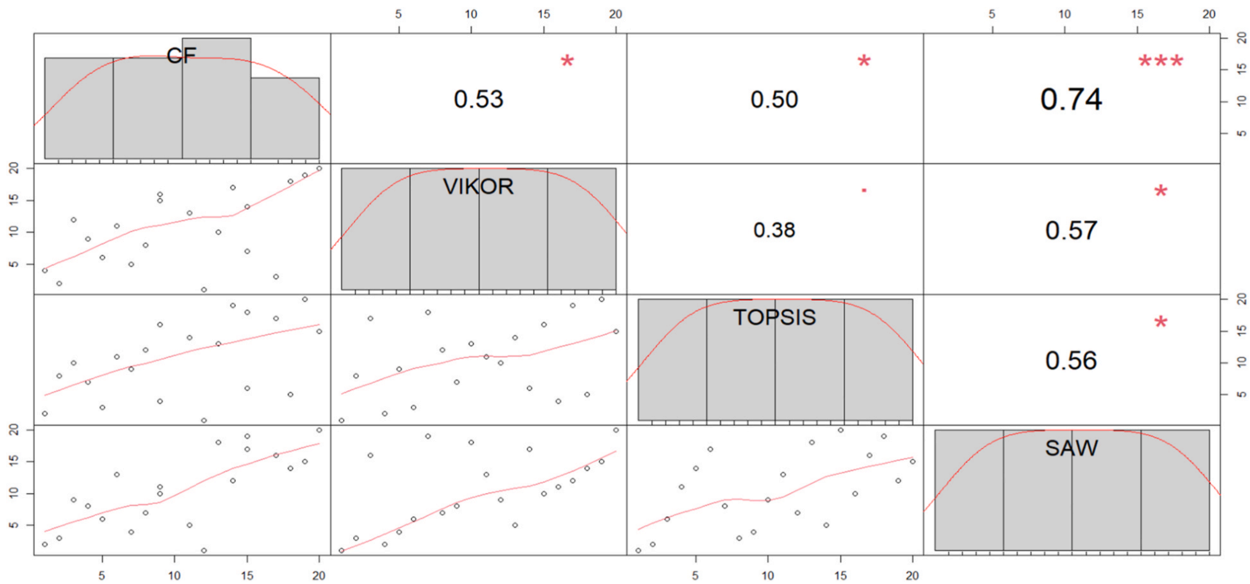


Fig. 19. Comparison of models using Spearman correlation coefficient test (SCCT).

Table 10
Study results summarized for various methods.

SWs	CF	VIKOR	TOPSIS	SAW
SW1	Low	Moderate	Moderate	High
SW2	Low	Moderate	Moderate	Moderate
SW3	Low	Moderate	Moderate	High
SW4	Low	Moderate	Moderate	High
SW5	Low	Low	Low	High
SW6	Low	Low	Low	High
SW7	Low	Low	Moderate	Moderate
SW8	Low	Moderate	Low	Moderate
SW9	Low	Low	Moderate	High
SW10	Low	Moderate	Moderate	High
SW11	Low	High	Moderate	High
SW12	Low	Moderate	Moderate	Moderate
SW13	Low	Low	Moderate	High
SW14	Low	Moderate	Moderate	High
SW15	Low	Moderate	Low	Moderate
SW16	Low	Very high	High	Very high
SW17	Low	Moderate	Moderate	High
SW18	Low	Moderate	Moderate	High
SW19	Low	Moderate	Moderate	High
SW20	Low	Moderate	Moderate	High

techniques highlight that sub-watershed SW16 is highly susceptible to erosion. Consequently, it is crucial to implement appropriate soil erosion control measures within this watershed to mitigate erosion and decrease sedimentation in the reservoir. This research displays the effectiveness of remote sensing (RS), geographic information systems (GIS), and multi-criteria decision-making (MCDM) in prioritizing sub-watersheds through morphometric analysis.

Furthermore, these findings underscore the critical importance of implementing targeted soil conservation and re-vegetation strategies in SW16 to mitigate erosion risks effectively. The presence of effective erosion control measures, such as reforestation, terracing, or vegetation restoration, can play a pivotal role in preserving soil integrity and minimizing the potential for erosion. Additionally, collaborative efforts involving local communities, policymakers, and environmental organizations may be essential to address these pressing environmental challenges and promote sustainable land management practices in the region.

In forthcoming articles and projects, we will systematically employ a diverse array of models and methodologies to prioritize and assess Oujlet Es Soltan watershed management. These encompass a range of techniques, including hypsometric analysis, land use/land cover analysis, the Revised Universal Soil Loss Equation (RUSLE), the Programme d'Actions Prioritaires/Centre d'Activités Regionales (PAP/CAR), EPM and SWAT Models, as well as advanced approaches such as Machine Learning and Deep Learning. Our rigorous analysis involves a comprehensive evaluation of these methods, enabling us to make informed comparisons, and ultimately, to underscore the identification of the most effective and efficient strategies for watershed prioritization.

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Data will be available on request.

Additional information

No additional information is available for this paper.

Ethics approval/declarations

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Code availability

Not applicable.

CRediT authorship contribution statement

Mourad El Abassi: Writing – original draft, Software, Formal analysis. **Habiba Ousmana:** Writing – review & editing, Validation, Methodology. **Jihane Saouita:** Formal analysis. **Abdellah El-Hmaidi:** Supervision, Investigation, Conceptualization. **Zineb Iallamen:** Software, Data curation. **Hajar Jaddi:** Funding acquisition, Data curation. **My Hachem Aouragh:** Validation, Supervision, Methodology. **M'hamed Boufala:** Resources, Data curation. **Zahra Kasse:** Visualization, Supervision. **Anas El Ouali:** Visualization. **Abdelaziz Abdallaoui:** Software, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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