Use of geomatics and multi-criteria methods to assess water erosion in the Tigrigra watershed (Azrou region, Morocco)

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Abstract. In Morocco, the capacity of dam reservoirs has decreased in recent years due to water erosion. This study aims to identify the sub-watersheds most vulnerable to soil erosion in the Tigrigra watershed by utilizing morphometric analysis of linear, landscape, and shape parameters and various multi-criteria decision models. These approaches allow for the prioritization of areas or sub-watersheds at high erosion risk. In the study area, erosion assessment is conducted using multi-criteria decision support models (MCDM) such as MOORA, VIKOR, TOPSIS, COPRAS, WASPAS, and SAW within a GIS environment. This approach highlights the significant role of morphometric parameters and multi-criteria methods in identifying sub-watersheds susceptible to erosion. Overall, the results indicate that morphometric parameters are highly effective in identifying erosion-prone areas. The Tigrigra watershed generally exhibits low to medium sensitivity to erosion, except for certain sub-watersheds. Subcatchment 28 showed significant erosion in most methods used.

1. *Introduction*

Worldwide, water erosion stands as the most severe form of soil erosion, prevailing predominantly in humid and sub-humid regions marked by frequent rainstorms. It also poses a significant challenge in arid and semi-arid areas, where rainfall is limited and often occurs in intense thunderstorms, resulting in bare ground devoid of vegetation cover.

In this study, MCDM has been utilized to estimate soil loss based on morphometric parameters. Morphometric parameters are derived from the analysis of various drainage features such as stream orders, basin area, perimeter, and length. These parameters have also been applied for several purposes such as identifying environmental hazards, determining potential groundwater regions, and verifying dam locations [1]. Additionally, various factors such as topo-hydrological, climatic, and environmental conditions were identified as significant contributors impacting erosion. Moreover, a range of factors including topo-hydrological, climatic, and environmental conditions were recognized as influential factors affecting erosion. However, there have been many studies that integrate these parameters for erosion susceptibility mapping of sub-watersheds [3, 4]. By assigning priority to sub-watersheds and assessing their erosion susceptibility through a variety of computed morphometric parameters, regions prone to erosion within watersheds can be identified. The methodology employed in this study includes the utilization of six MCDM models: SAW, COPRAS, TOPSIS, MOORA, WASPAS, and VIKOR. The Analytical Hierarchy Process (AHP) was employed to assign weights to each morphometric parameter. The ultimate ranking of the sub-watersheds was established by averaging the rankings obtained from the various MCDM models. This research leveraged morphometric parameters to implement this approach, aiming to reduce uncertainty in classifying sub-watersheds for prioritization. This method provides greater accuracy in prioritization compared to traditional methods, as it incorporates the combined results of various MCDM models. Consequently, it aids decision-makers in implementing soil and water conservation projects, especially when budget constraints are present.

2. *Study area*

The Tigrigra watershed, spanning 1029.4 km², is located in the eastern region of the central Middle Atlas (Figure 1). This mountainous watershed extends over the plateaus of the Tabular Middle Atlas and the Western Meseta, with altitudes ranging from 800 m to 2117 m. Remarkably, the Tigrigra watershed straddles the limestone plateau of the central Middle Atlas and the central massif of Hercynian schist.

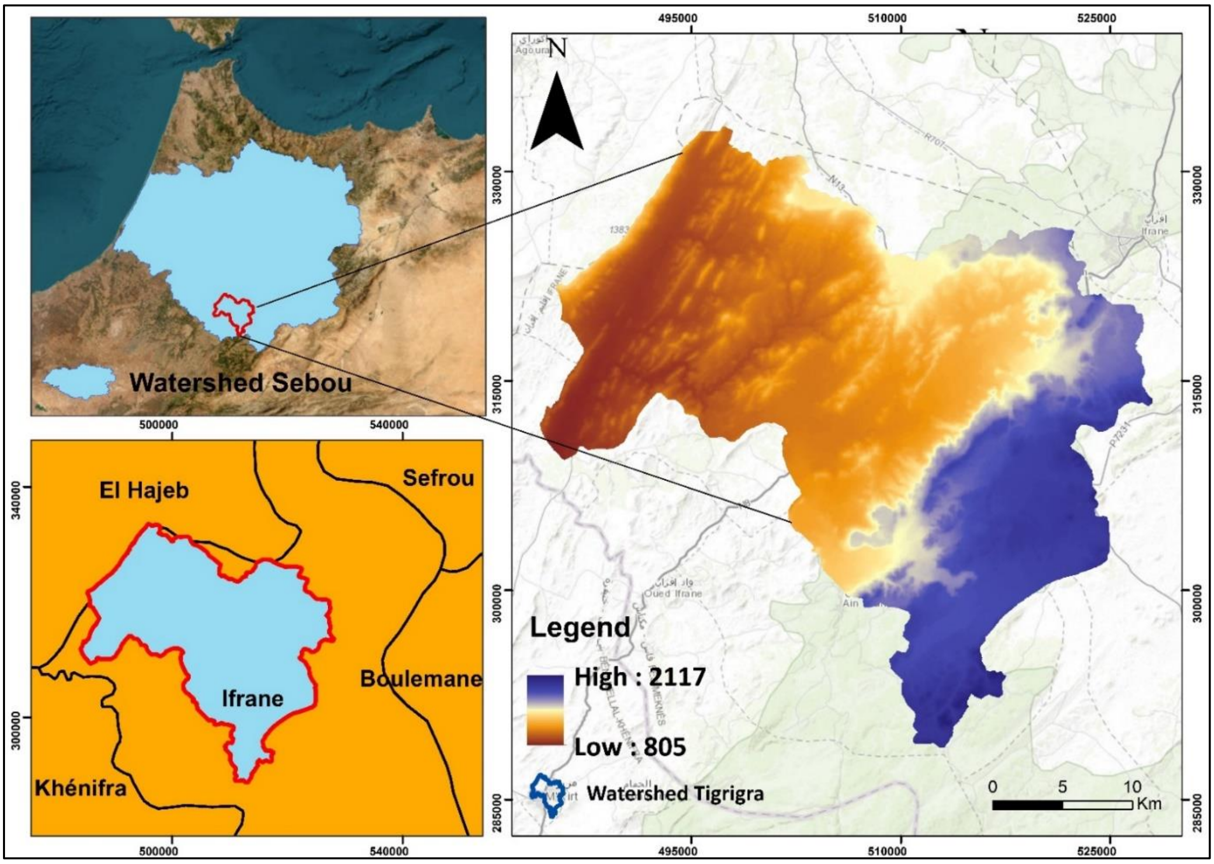

Fig. 1. Geographical location of Tigrira watershed.

3. *Material and methods*

Erodibility prioritization

This study introduces the prioritization of erodibility among the 40 sub-watersheds of the Tigrigra basin using a diverse array of MCDM techniques. The model clearly depicts the relative ranking and prioritization of sub-watersheds based on their susceptibility to erosion.

Multi-criteria decision-making (MCDM) techniques were employed to prioritize the 40 sub-watersheds based on morphometric characteristics, utilizing six MCDM models: SAW, COPRAS, WASPAS, VIKOR, TOPSIS, and MOORA. The Analytical Hierarchy Process (AHP) was employed to allocate weights to each morphometric parameter. The final ranking of the sub-watersheds was determined by averaging the rankings obtained from the different MCDM models. This approach minimizes uncertainty in sub-watershed classification for prioritization and enhances accuracy compared to traditional methods, as it amalgamates results from multiple MCDM models (Figure 2).

4. Results and Discussions

Morphometric analysis

- ***Linear parameters***

Dd, serves as an indicator of landscape dissection and the runoff potential of a basin. In the Tigrigra basin, sub-basin 10 exhibits the lowest stream density at 0.13 km, suggesting it has the highest infiltration capability among all sub-basins. Conversely, sub-watershed 37 shows a high stream density of 2.51 km, indicating lower infiltration (Figure 3).

Fu, the ratio of the number of rivers to the surface area of a basin, is a significant parameter [2]. Sub-watershed 37 demonstrates very high Fu values at 7.42, while sub-watersheds 11 and 5 have low values at 0.03 and 0.04, respectively (Figure 3).

Rbm. indicating basin infiltration, shows an inverse correlation in this study area, suggesting that the basins are structurally uncomplicated and possess high infiltration rates. Nonetheless, sub-waters 19, 28, and 34 display very high Rbm values at 11.04, 69.22, and 28.44, respectively (Figure 3).

T, influenced by various physical factors such as climate, precipitation, vegetation, and rock and soil type, reveals that sub-catchment 37 has the highest drainage texture at 0.76, making it the most sensitive sub-catchment. Conversely, sub-basin 11 exhibits the lowest sensitivity at 0.02 (Figure 3).

C, values vary from a minimum of 0.40 for sub-basin 37 to a maximum of 7.57 for sub-basin 10(Figure 3).

Lo, influences the hydrological assessment of the basin [4]. Lo values for the basin range from 3.79 in sub-basin 10 to 0.02 in sub-basin 37. Higher Lo values indicate a greater susceptibility to erosion (Figure 3).

If, they range from a minimum of 0.01 in sub-basin 35 to a maximum of 18.64 in sub-basin 37, making sub-basin 35 the most susceptible to erosion (Figure 3).

➢ *Shape Parameters*

Thus, **Re** demonstrates an inverse correlation with erosion susceptibility. In the study basin, Re ranges from 0.92 to 0.59, indicating steep slopes and high total relief (Figure 4).

A **Rc** value of 1 indicates a completely circular watershed [3]. Sub-catchment 10, with the highest Rc (0.39), is the least susceptible to erosion. Conversely, sub-watershed 38, with the lowest **Rc** (0.10), is the most sensitive to erosion due to its lower infiltration capacity (Figure 4).

The **Cc** values range from 3.12 to 1.59 across the sub-watersheds. Sub-watershed 10 exhibits the lowest **Cc** value, indicating it is the most prone to erosion among all the sub-watersheds. Conversely, sub-watershed 38, with the highest **Cc** value, shows the least sensitivity when only considering this parameter (Figure 4).

In the study basin, the highest **Rf** is found in sub-catchment 37 (7.42), and the lowest **Rf** is found in sub-catchment 11 (0.03) (Figure 4).

In the current area, the **Bs** value varies between 1.49 in sub-catchment 13 and 3.63 in sub-catchment 12, making them respectively the most and least sensitive sub-catchments to erosion (Figure 4).

➢ *Landscape parameters*

Slope (S) is a hydrological morphometric factor that reflects the runoff amount and concentration [5]. The highest slope among the sub-catchment basins is found in sub-catchment 27 (20.26°), indicating its high susceptibility to erosion. In comparison, the lowest slope is observed in sub-catchment 26 (3.19°), suggesting it is less prone to erosion (Figure 5).

Rn is employed to evaluate the flood potential of rivers [6]. **Rn** values for the sub-catchments of the Tigrigra basin range from a minimum of 0.00 in sub-catchment 24 to a maximum of 0.35 in sub-catchment 18. Consequently, sub-catchment 18, with the steepest slope, displays the highest sensitivity to erosion (Figure 5).

The highest **Rh** value is observed in sub-basin 23 (0.12), while the lowest value is in sub-basin 39 (0.03). Thus, sub-watershed 23 is more susceptible to erosion compared to other sub-watersheds (Figure 5).

Bh, is also correlated with erosion. In the Tigrigra catchment, Bh values vary, with SW37 having a minimum value of 40 and SW22 having a maximum value of 905 (Figure 5).

Erodibility prioritization

Following a thorough morphometric analysis, 16 parameters were chosen based on their significance in determining erosion susceptibility. MCDM methods were employed to prioritize the most erosion-prone watershed, utilizing the AHP which assigns weights to each criterion based on their importance. The AHP methodology commences with establishing the initial decision matrix comprising these 16 parameters, followed by standardizing the criteria, a common second step in most MCDM models (Table 1).

Table 1. The consistency ratio.

λmax	CI	RI	CR
17.7242	0.11494	1.7325	0.06635

Table 2. The range of methods used

	Very low	Low	Moderate	High	Very high
COPRAS	0.118-0.137	0.137-0.159	0.159-0.171	0.171-0.208	0.208-0.319
VIKOR		0-0.25	0.25-0.5	0.5-0.75	0.75-1
SAW	0-0.25	0.25-0.5	0.5-0.75	0.75-1	
WASPAS	0.118-0.137	0.137-0.159	0.159-0.171	0.171-0.208	0.208-0.319
MOORA		0.05-0.059	0.06-0.069	0.07-0.079	0.08-0.09
TOPSIS		0-0.25	0.25-0.5	0.5-0.75	0.75-1

Standardization is essential due to the diverse units of measurement used for different morphometric parameters. Subsequently, the weight of each morphometric parameter was determined using the AHP method (Figure 9). The consistency ratio of the matrix was 0.06, which is deemed acceptable as it is below 0.1[2]. The outcomes of the AHP method indicated that drainage density, seepage number, and average bifurcation ratio, scoring 0.14, 0.152, and 0.132 respectively, contributed the most to subsurface soil erosion. This finding aligns with the results obtained [3].

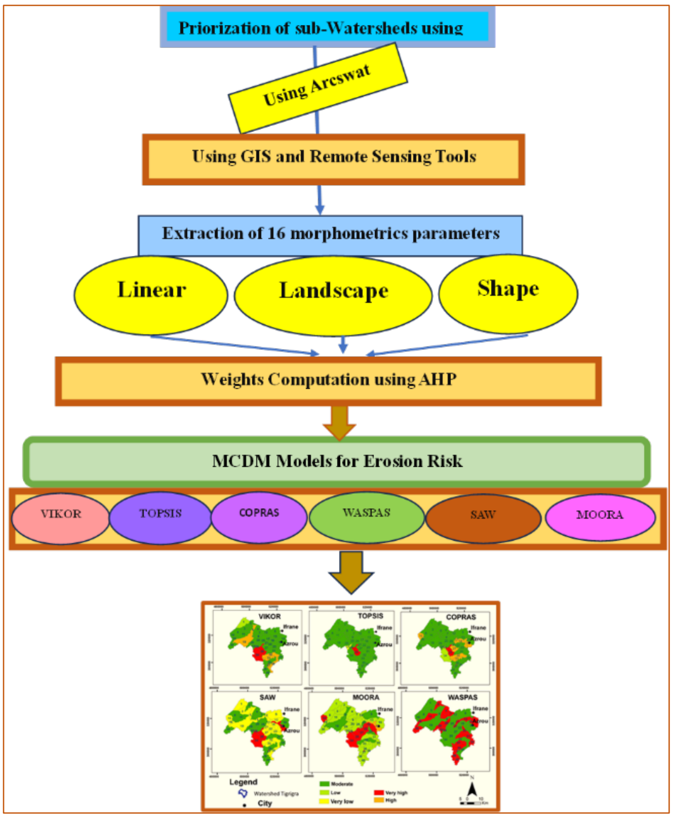

Fig.2. Flowchart outlines the process employed to prioritize the erodibility of sub-watersheds.

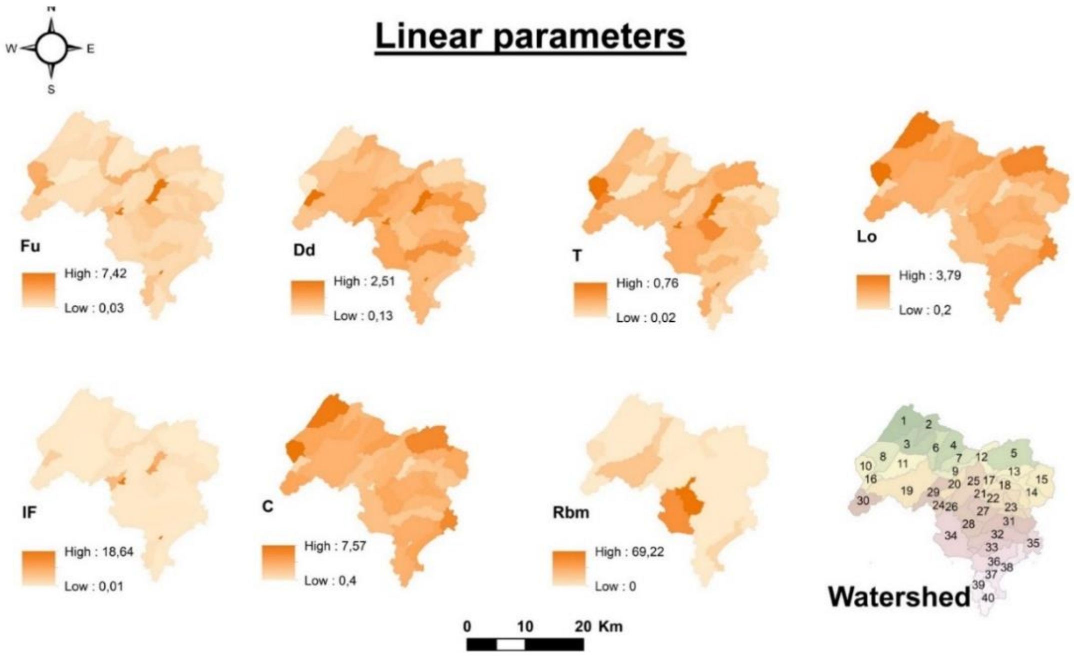

Fig.3. Linear parameters map for 40 sub-watersheds of Tigrigra including: Stream frequency (Fu), Drainage density (Dd), Length of overland Flow (Lo), Texture ratio (T), Infiltration number (If), Constant of channel maintenance (C) and Mean bifurcation ratio (Rbm).

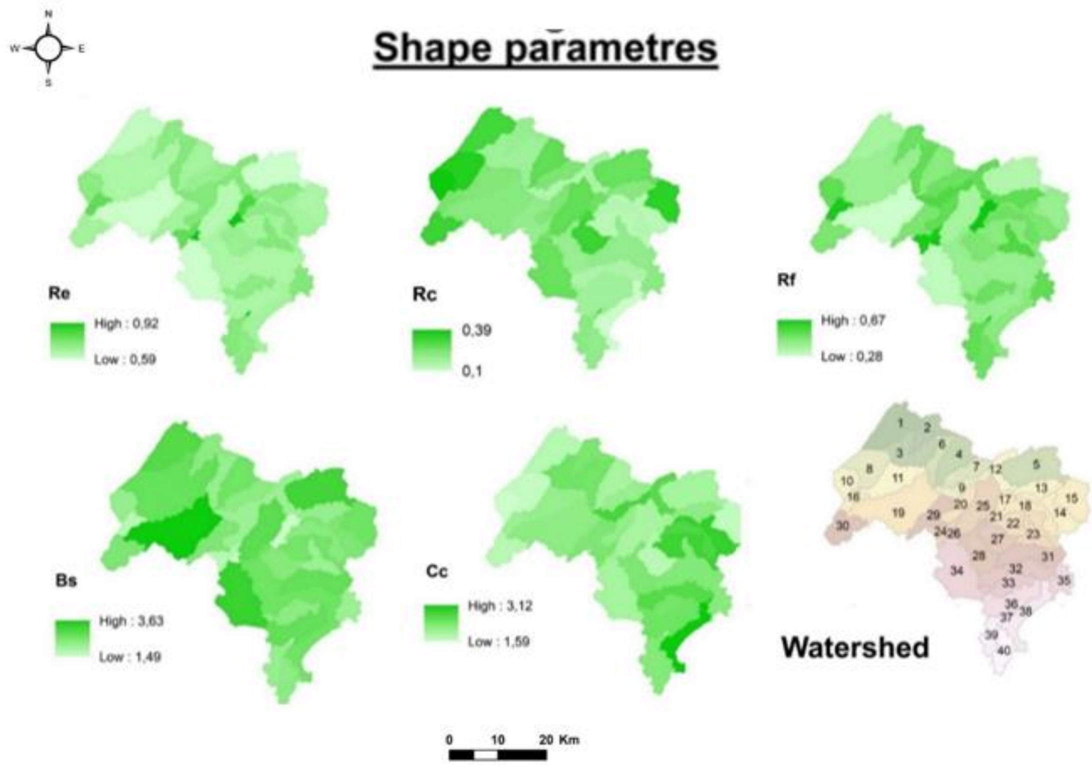

Fig.4. Shape parameters map for 20 sub-watersheds of Tigrigra including Elongation ratio (Re), Circularity ratio (Rc), Form factor (Rf), Shape factor (Bs), and Compactness coefficient (C)

- **COPRAS**

The scores obtained for all 40 sub-basins using the COPRAS model ranged from a minimum of 0.07 to a maximum of 0.2960 and were categorized into five groups (Figure 14). Consequently, sub-basins 28 and 37 fall into the very high erosion class. Sub-basin 34 belongs to the moderate group, while the remaining sub-basins are classified into the low to very low group (Table 2 and Figure 6).

- **VIKOR**

The results of prioritizing sub-watersheds based on their sensitivity to erosion revealed that, according to the VIKOR model, sub-watersheds 28, 34, and 37 had the highest scores and were the most susceptible to erosion. In contrast, sub-watershed 1 scored 0.87, indicating low sensitivity to erosion, while the others exhibited moderate erosion sensitivity (Table 2 and Figure 6).

- **SAW**

The prioritization results of the sub-watersheds in terms of their sensitivity according to the SAW model showed that sub-watersheds 14, 34, 26, 28, 37, and 34 had the highest scores (0.61, 0.89, 0.91, 1.39, 3.51, and 0.327 respectively), making them the most sensitive to erosion. In contrast, the other sub-watersheds were mixed between high and medium sensitivity. After ranking the sub-watersheds based on erosion and loss of natural resources (Table 2 and Figure 6).

- **MOORA**

The results of the MOORA model indicated that sub-watersheds 10, 18, 22, 27, 28, 34, and 37 have very high scores, ranking them as most sensitive to erodibility. In contrast, sub-watersheds 14 and 26, with scores of 0.077 and 0.078 respectively, show high sensitivity to erosion. After ranking the sub-watersheds based on erosion and loss of natural resources (Table 2 and Figure 6).

- **TOPSIS**

Finally, according to the TOPSIS model, sub-watershed 28, with a high score of 0.55, is the most susceptible to erosion. In contrast, sub-watershed 24, with a score of 0.25, is the least sensitive to erosion, while the other sub-watersheds fall into the moderate category. After classifying the sub-watersheds in terms of erosion and loss of natural resources. However, the sub-watersheds in the study area were ultimately divided into three categories: low, moderate, and high (Table 2 and Figure 6).

- **WASPS**

The scores obtained for all 26 sub-basins using the WASPAS model varied from minimum (0.11) to maximum (0.47). In the study area, there is a mixture of only low and medium classes throughout the basin (Table 2 and Figure 6).

Discussion

Soil erosion is widely recognized as one of the most perilous environmental hazards globally, exerting a significant impact on the sustainable development of agriculture and natural resources, encompassing land and water. Based on the application of six multi-criteria methods, our study area is generally divided into four classes, with each method showing variations ranging from two to four classes. According to the VIKOR method, sub-catchments 28 and 34 exhibit very high erosion, while SW 6, SW19, SW32, SW33, SW37, and SW38 are categorized as high erosion areas. The TOPSIS method places sub-basin 28 in the high class, with others classified as medium. Results from the COPRAS method suggest that SW28 falls into the very high erosion class, while the remaining sub-basins range from very low to low erosion. The application of the SAW method reveals that SW28, SW34, and SW12 are classified as very high erosion areas. Conversely, the MOORA method identifies SW10, SW18, SW22, SW27, SW28, and SW34 as falling into the very high erosion class. Finally, the WASPAS Methods present an erosion between moderate and moderate (Figure 6).

From these findings, it's evident that SW28 and SW34 consistently exhibit severe erosion across the majority of cases. This can be attributed to the Rbm parameter, with exceptionally high values of 69.22 and 28.44 in sub-watersheds 28 and 34 respectively, and a significant influence of 13.25% according to the AHP method, elucidating the enduringly severe erosion in these watersheds. Additionally, it is noteworthy that the MOORA method places several sub-watersheds in the high erosion class compared to other methods. This can be explained by the fact that MOORA does not differentiate between positively and negatively correlated values with erosion but assigns equal consideration to all values (Figure 8).

Another study utilizing MCDM methods indicates that TOPSIS, SAW, and CF yield unsatisfactory results due to limitations such as lacking datasets for all decision-making problems and assigning relative weights based on assumptions in each variable[4]. On the contrary, the VIKOR method demonstrated superior performance compared to other MCDM methods, as confirmed by the SWAT model validation. This can be attributed to its benefits, including hierarchical problem formulation, pairwise comparison utilizing quantitative and qualitative expert knowledge, and decision evaluation regarding compatibility and incompatibility [2]. Furthermore, research employing MCDM methods demonstrates that VIKOR is more effective in identifying areas prone to erosion compared to WASPAS and TOPSIS [5].

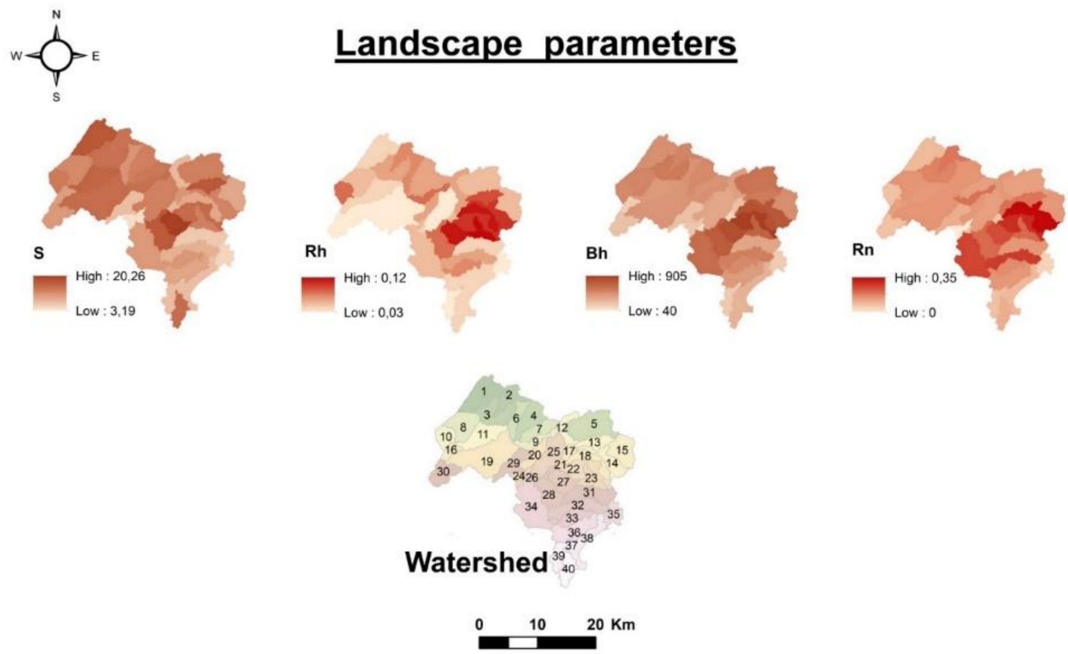

Fig.5. Landscape parameters map for 40 sub-watersheds of Tigrigra including Basin relief (Bh), Slope (S), Ruggedness number (Rn), and Relief ratio (Rh).

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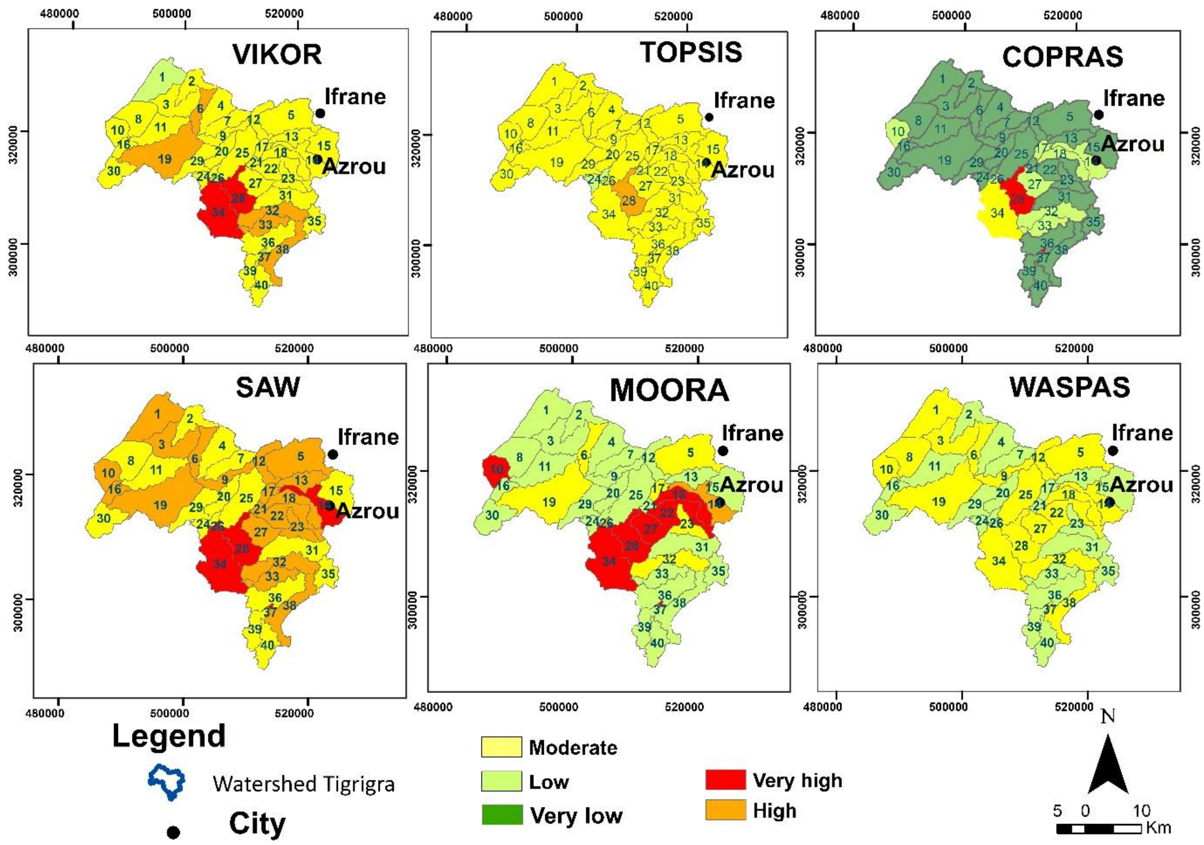

Fig.6. Four MCDM models used to prioritize 20 sub-watersheds.

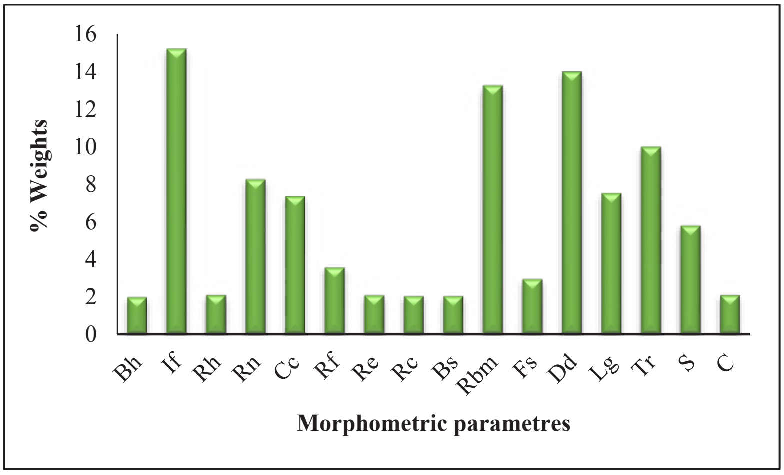

Fig.7. Analytical Hierarchy Process (AHP) calculates parameter weights.

5. Conclusion

The current study demonstrates that the integration of geographic information systems with MCDM methods and statistical techniques offers a more precise approach to prioritizing sub-watersheds compared to conventional methods.

The quantitative analysis of morphometric parameters, such as linearity, landscape, and shape using GIS, proves highly beneficial in evaluating river basins and prioritizing watersheds for soil conservation and water management. The morphometry of a river basin's drainage reflects the hydrogeological maturity of the watercourse,

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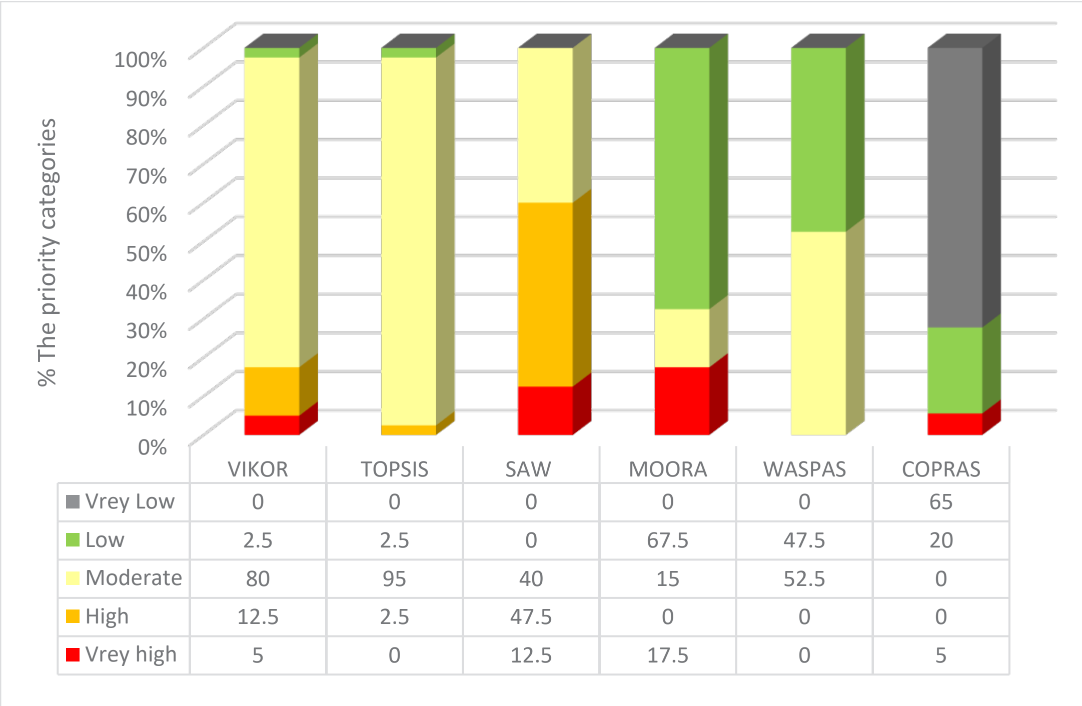
allowing for the establishment of various relationships between the watershed and hydrogeological parameters. Validation of the results through non-parametric tests indicates that, among the MCDM models, the SAW method demonstrates greater prediction accuracy compared to VIKOR, TOPSIS, MOORA, COPRAS, and WASPAS for watershed prioritization. The COPRAS method assigns 65% to the very low class, while the MOORA method assigns 67.5% to the low class and 15% to the very moderate class. Conversely, TOPSIS and VIKOR assign 95% and 80% respectively to moderately erodible health classes. The SAW method assigns 47.5% to the high class. Sub-watersheds SW28 and SW34 exhibit higher susceptibility to erosion (Figure 8).



	VIKOR	TOPSIS	SAW	MOORA	WASPAS	COPRAS
Vrey Low	0	0	0	0	0	65
Low	2.5	2.5	0	67.5	47.5	20
Moderate	80	95	40	15	52.5	0
High	12.5	2.5	47.5	0	0	0
Vrey high	5	0	12.5	17.5	0	5

Fig.8. Level priority of four MCDM models.

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