Prioritization of Sub-Watersheds Susceptible to Soil Erosion using Different Combinations of Objective Weighting and MCDM Techniques in an Ungauged River Basin

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Abstract

The identification of areas prone to soil erosion in ungauged river basins is crucial for timely preventive measures, as erosion causes significant damage by lowering soil productivity and filling reservoirs with sedimentation. This study proposes a novel approach to prioritize sub-watersheds (SWs) in Ponnaniyar river basin. It utilizes different combinations of five objective-based weighting methods and seven Multi-criteria Decision Making (MCDM) techniques under outranking and synthesis methods with soil loss, morphometry, land use/land cover (LULC), and topography parameters. The results obtained from different hybrid models are validated using metrics like percentage and intensity of change. The findings reveal that MW-PROMETHEE (53.85%) and CRITIC-WASPAS (8.31) perform best in prioritizing areas based on morphometry, while CRITIC-TOPSIS (48.35% and 7.58) is more effective in prioritizing areas based on land use/land cover (LULC) and topography. The grade average method is used to integrate the rankings from 71 models: 35 based on morphometry, 35 based on LULC, and 1 based on the RUSLE model. The analysis identifies SW2 with a grade value of 4.34 as severely affected by soil erosion, followed by SW11 (5.45), SW5 (5.56), and SW9 (5.68), all falling within the very high priority level. This study recommends implementing appropriate water harvesting structures, which might be helpful in mitigating soil degradation, promoting soil conservation, and ensuring sustainable agricultural productivity.

1 Introduction

Globally, an estimated 75 billion metric tons of soil is eroded annually by the combined impacts of water and wind, largely from agricultural regions (Myers 1994). According to India's Ministry of Environment and Forests (2001), the fertile topsoil is absent from almost 53% of the country's entire geographical area due to major erosion

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and degradation leading to a drop in the quality of soil. For effective watershed development and management, it is necessary to carry out an integrated quantifiable morphometric analysis, by taking LULC, topography parameters and soil loss into consideration. This analysis facilitates the understanding of interrelationships between various features in the selected study area (Chae et al. 2022).

Morphometric analysis quantitatively evaluates various factors like geography and landforms, aiding in understanding geohydrological properties of watersheds and their relationships with basin characteristics. LULC study and topographic analysis are vital tools used worldwide for evaluating changes in surface features, including rivers, croplands, and terrains. The key to effectively manage river basins is focusing research efforts at the SW level as it is challenging to assess entire basin extents. Prioritizing specific locations within basins allows for tailored development strategies, such as MCDM, aimed at managing and preserving soil resources (Meshram et al. 2022).

Approaches like outranking method, synthesis method and interactive methods under MCDM have been extensively researched and proven effective in various domains, showcasing their utility in decision-making processes (Jafary et al. 2018; Theochari et al. 2021). Determining criteria weights in MCDM is crucial, as it significantly impacts the decision-making process.

From the extensive literature review, it is observed that several studies have prioritized SWs based on soil erosion in different river basins and climates using only morphometric parameters (Dhanush et al. 2024; Meshram et al. 2022). Others have integrated both morphometric and LULC parameters for prioritization (Sinha and Eldho 2021; Shekar and Mathew 2022) while only one study has included the rate of soil loss in their analysis (Shivhare et al. 2018). The effectiveness of different objective weighting methods and their influence on MCDM techniques with multiple parameters in SW prioritization within ungauged basins remains largely unexplored. Improper selection of weighting and MCDM methods for specific parameters can compromise the accuracy of SW prioritization in river basins.

This study prioritizes SWs in an ungauged basin based on their vulnerability to soil erosion by adopting different combinations of objective weighting methods and MCDM techniques, utilizing data on soil loss, morphometry, LULC, and topography extracted from limited datasets. Additionally, the study seeks to identify suitable hybrid models for each parameter set (morphometry, LULC & topography) within the selected river basin. This integrated approach can offer valuable insights for soil resource managers and planners involved in implementing various conservation measures.

2 Study Area

Ponnaniyar river is a tributary of the Cauvery river in South India and its ungauged basin is selected as the study area (Fig. 1). The physical characteristics are examined and the SWs prone to erosion in the basin are identified. This river is non-perennial and mainly depends on rainfall from the northeast monsoon season from October to December. Geographically, the basin spans latitudes from 10°10′00″ N to 10°50″00″ N and longitudes from 78°10′00″ E to 78°50′00″ E, with relief ranging from -42 m to 674 m.
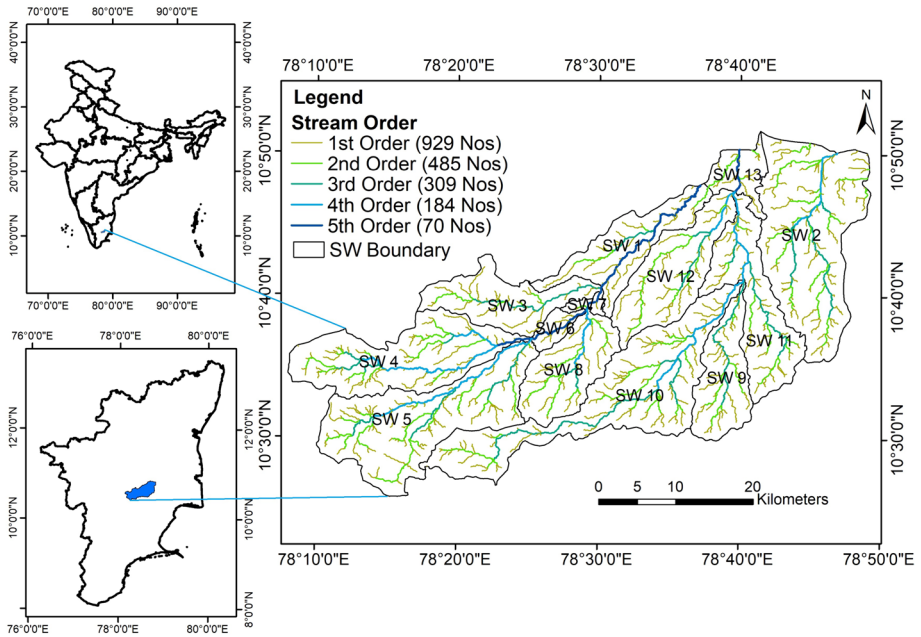
Fig. 1 Location Map of Ponnaniyar River Basin

3 Research Methodology and Methods

3.1 Research Methodology

The methodology of the research is represented as a flow chart (Fig. 2).

3.2 Data Acquisition, Source and Preprocessing

Due to limited or inadequate rainfall data in remote regions, satellite precipitation datasets have become essential for hydrological studies, these datasets are accessible in different resolutions. In this study, CHIRPS dataset having $0.05° \times 0.05°$ resolution is acquired from www.ucsb.edu. Utilizing ArcGIS software, the CHIRPS data is transformed into point data. Subsequently, the rainfall and erosivity values (R_factor) are computed and appended to the point dataset, followed by interpolation using the Inverse Distance Weightage (IDW) technique. Soil texture data acquired from www.fao.org is used for erodibility analysis (K_factor). Cartosat-1 DEM acquired from www.bhuvan.nrsc.gov.in is used for extraction of morphometric parameters and topography parameters, to determine length and steepness (LS_factor) and extent of agriculture practices (P_factor). Landsat-8 data acquired from www.earthexplorer.usgs.gov is used for LULC classification of the basin at SW level and to determine land management factor (C_factor).
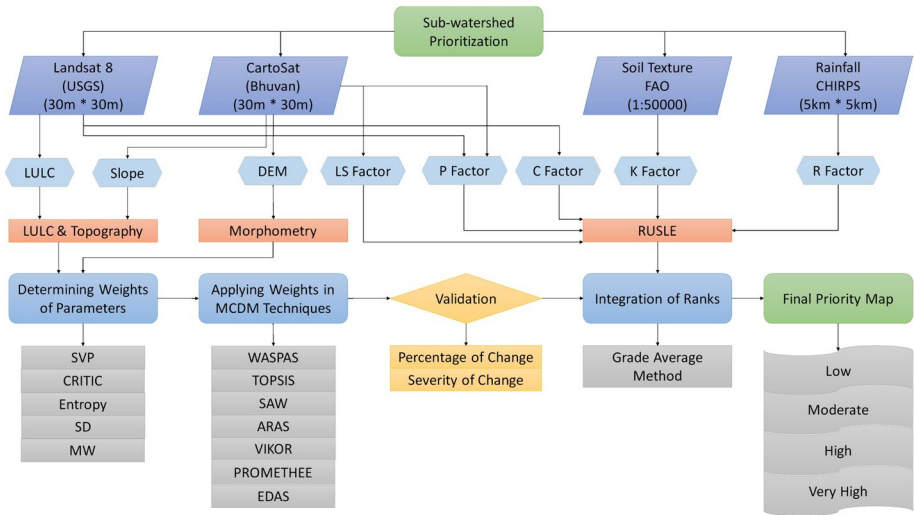
Fig. 2 Flow Chart of Research Methodology

3.3 Morphometric Parameters

Morphometric characteristics provide a detailed understanding of various flow conditions, including drainage, geomorphology, and land surface processes. In this study, ArcSWAT tool is employed to segment the sub-watershed in three steps: Data preparation, Preprocessing, and Watershed delineation. In data preparation, Digital Elevation Model (DEM) data is projected to Universal Transverse Mercator (UTM) 44N for the selected study area and formatted for analysis. In preprocessing, the coherent surface is created by filling sinks, eliminating spikes or depression, and interpolating the missing data point followed by watershed delineation, which segments the basin into 13 smaller sub-watersheds using the drainage network and topographic features as criteria. The Strahler method is utilized to hierarchically organize the stream network within the chosen basin (Strahler 1964). Subsequently, shape, relief, areal, linear, hypsometry under morphometric parameters are accessed following formulas outlined in Table 1. In morphometry, 18 parameters (3-linear, 6-real, 4-shape, 4-relief, 1-hypsometry) are considered to prioritize SWs in the selected river basin.

3.4 Land Use/Land Cover (LULC) and Topography Parameters

Land use/land cover and topography are crucial factors to be considered in prioritizing sub-watersheds. Landsat-8 imagery is used to categorize the land cover classes: barren land as BL (scrub land, sandy area, barren rocky, ravenous land), forests as F (deciduous, evergreen, swamp, scrub forest), agricultural lands as A (cropland, plantation, fallow), settlements as S (mining, urban and rural), vegetation as V (includes monocots in grasslands and herbs in non-grasslands), and water bodies as WB (rivers, tanks, lakes, canals) under Level-1 classification for the Ponnaniyar river basin using Random trees classifier (RTC) (Sampath and Radhakrishnan 2023). Recent research studies used high spatial resolution data for improved accuracy, often sourcing imagery from platforms like

Table 1 Equation for calculation of Morphometric Parameters

S. No	Parameter	Equation	Units	References
	Basic Parameter			
1	Area	ArcGIS	km^2	-
2	Perimeter (P)	ArcGIS	km	-
3	Basin Length (L_b)	$1.312 * (A)^{0.568}$	km	Schumm (1956)
	Linear Parameter			
4	Stream Number (N_u)	Total number of stream orders	Nos	ArcGIS
5	Stream Length (L_u)	Total stream length Length of all orders	km	Horton (1945)
6	Mean Length Ratio (R_l)	Mean of all stream length ratios	No unit	Strahler (1964)
7	Mean Bifurcation Ratio (R_b)	Mean of all bifurcation ratios	No unit	Strahler (1964)
8	RHO Coefficient (RHO)	R_l / R_b	No unit	Horton (1945)
	Areal Parameter			
9	Compactness Constant (C_c)	$0.2821 * P / A^{0.5}$	No unit	Horton (1945)
10	Constant Channel Maintenance (C)	$1 / D_d$	km	Schumm (1956)
11	Length of Overland Flow (L_o)	$1 / (2 * D_d)$	km	Horton (1945)
12	Drainage Density (D_d)	L_u / A	km / km^2	Horton (1932)
13	Drainage Texture (D_t)	N_u / P	$1 / km$	Horton (1945)
14	Stream Frequency (F_s)	N_u / A	$1 / km^2$	Horton (1932)
	Shape Parameter			
15	Elongation Ratio (R_e)	$(2 / Lb) * (A / pi)^{0.5}$	No unit	Schumm (1956)
16	Circulatory Ratio (R_c)	$4 * pi * A / P^2$	No unit	Miller (1953)
17	Form Factor (R_f)	A / L_b^2	No unit	Horton (1932)
18	Shape Factor (R_s)	L_b^2 / A	No unit	Horton (1945)
	Relief Parameter			
19	Relief (R)	$E_{max} — E_{min}$	m	Schumm (1956)
20	Relief Ratio (R_h)	R / L_u	m	Schumm (1956)
21	Relative Relief (R_r)	R / P	No unit	Melton (1958)
22	Ruggedness Number (R_n)	$R * D_d / 1000$	No unit	Chorley and Dale (1972)
23	Basin Slope (S_a)	$tan^{-1} (R/L_b)$	No unit	Verstappen (1983)
	Hypsometry Parameter			
24	Hypsometric Integral (HI)	$(E_{mean} – E_{min}) / (E_{max} — E_{min})$	No unit	Pike and Wilson (1971)

Google Earth, which provide free, detailed satellite images and aerial photos. Google Earth, developed by Google Inc. in June 2005, delivers a virtual globe experience by overlaying high-resolution satellite imagery, to offer users a more realistic view of the world (Tilahun and Teferie 2015). Following LULC classification, a set of 100 points representing various land cover types is generated, and their values are determined using Google Earth. These points are then used to create a theoretical error matrix, which is employed to evaluate the

classification accuracy using Eqs. (1) and (2), overall accuracy (OA) and kappa coefficient (K). Using Cartosat-1, the topography, i.e. slope is extracted by surface analysis in the geospatial platform and classified into five groups for each SW, namely SL1–Slope($<5°$), SL2–Slope($5°–10°$), SL3–Slope($10°–15°$), SL4–Slope($15°–20°$), SL5–Slope($>20°$). To prioritize the SWs, 10 parameters (5 from LULC classes and 5 from topography) are considered. Water bodies are neglected for the analysis due to absence of erosion.

$$OA = \frac{Total\ Number\ of\ Corrected\ Classified\ Pixels\ (Diagonal)}{Total\ Number\ of\ References} * 100 \tag{1}$$

$$K = \frac{(TS * TCS) - \sum Column\ Total * Row\ Total}{TS^2 - \sum Column\ Total * Row\ Total} \tag{2}$$

where, TS-Total Samples, TCS-Total Corrected Samples.

3.5 Revised Universal Soil Loss Equation (RUSLE)

The annual soil loss in the Ponnaniyar river basin at the SW scale is determined for the year 2021 by multiplying factors with a 30 m x 30 m resolution in the RULSE model, as given in Eq. (3).

$$A = R * K * LS * C * P \tag{3}$$

where, A denotes the annual soil loss (tons/ha/yr), R denotes the rainfall erosivity (mm. ha^{-1} h^{-1}y^{-1}), K denotes the soil erodibility (tons.ha.h^{-1} MJ^{-1} ha^{-1} mm), LS denotes Length and steepness, C denotes land management and P denotes agriculture practice. LS, C, and P are dimensionless.

3.6 Weight Determination

Various methods exist for calculating weights, categorized as subjective, objective, or integrated, depending on the consideration of preferences and data used. Based on studies by Odu (2019), Mahmood et al. (2023), five objective-based weighting techniques which are Statistical Variance Procedure (SVP), Mean Weighting method (MW), CRiteria Importance Through Intercriteria Correlation (CRITIC) method, entropy method and Standard Deviation (SD) method are used in the present research to assign the weight of morphometric parameters, LULC and topographic parameters. These objective weighting approaches do not consider human involvement and estimate parameter weights from data collected for each parameter using various mathematical models (Odu 2019). The relative relevance of each parameter is assessed after determining the value of each assessment factor for the 13 sub-watersheds. The five objective-based weighting methods and their highlights are presented in Table 2.

3.7 Multi-Criteria Decision Making (MCDM) Techniques

The seven most common MCDM approaches based on outranking and synthesis methods are adopted in the present study to identify the SWs that are severely affected by soil erosion (Şahin 2021; Teja et al. 2023). Determined weights of morphometric parameters, LULC and topographic parameters from different objective-based weighting methods are applied in

Table 2 Objective Weighting methods, their formulas and highlights

Method	Equation	Highlights
SVP	$\omega_j = \frac{1}{n}\sum_{i=1}^{n}\left[(y_{ij} - \overline{y_{ij}})^2\right]$ $i \in [1\ldots n], j \in [1\ldots m]$ ω_j denotes the statistical variance, $\overline{y_{ij}}$ denotes the mean value of the dataset $w_j = \frac{\omega_j}{\sum_{i=1}^{n}\omega_j}$ w_j denotes the weight of the parameter	1. This method uses variance to produce the objective weight of each parameter 2. This assessment procedure operates based on value of parameters
CRITIC	$c_j = \sigma_j \sum_{i=1}^{m} 1 - r_{ij}$ c_j denotes the information of the parameter, σ_j denotes the standard deviation of each parameter, r_{ij} denotes the linear correlation between i and j indicators $cw_j = \frac{c_j}{\sum_{j=1}^{m}c_j}$ cw_j denotes the weight of the parameter	1. This method employs statistical analysis to derive raw data from decision parameters and incorporates correlation-based techniques 2. It addresses value conflicts in MCDM techniques, offering objective weights for ranking SWs 3. This assessment procedure operates without the need for manual input
Entropy	For beneficiary parameter, $r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m}a_{ij}}$ For non-beneficiary parameter, $r_{ij} = \frac{1/a_{ij}}{\sum_{i=1}^{m}1/a_{ij}}$ r_{ij} denotes the normalized value in the i-th and j-th indicators, a_{ij} denotes the i-th alternative value of j-th parameter $e_j = -(\ln m)^{-1}\sum_{i=1}^{m}r_{ij}\ln r_{ij}$ Where, e_j denotes the entropy values, m denotes the total number of SWs $w_j = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)}$ w_j indicates the weight of the parameter	1. This method is utilized to assign weights in a particular scenario, especially when selecting materials from a group 2. It involves a decision matrix with a specific dataset, and the entropy value is calculated from the normalized decision matrix 3. Entropy measures the uncertainty of a discrete probability density function, with a wider distribution indicating more ambiguity compared to a tightly packed one 4. This method uses material-specific information for each parameter to determine its relative importance
SD	$\sigma_j = \sqrt{\dfrac{\sum_{i=1}^{m}(X_{ij}-\overline{X_{ij}})^2}{m}}$ σ_j denotes the standard deviation of each parameter, $\overline{X_{ij}}$ denotes the mean value of the parameter $w_j = \frac{\sigma_j}{\sum_{j=1}^{n}\sigma_j}$ w_j indicates the weight of the parameter	1. This technique incorporates the solution in the equation used to calculate the weights of parameters according to standard deviation of the SWs 2. This process is almost similar to standard variance procedure 3. The weights of parameters depend on the value of each alternative

Table 2 (continued)

Method	Equation	Highlights
MW	$w_j = \frac{1}{n}$ n denotes the number of parameters	1. It works based on the premise that all criteria carry equal weight 2. It is mostly used when data is unavailable or data is insufficient to take decisions 3. Based on the assumption that each parameter is equally important, the mean weight is determined

Where, *SVP* Standard Variance Procedure, *CRITIC* Criteria Importance Through Intercriteria Correlation, *SD* Standard Deviation, *MW* Mean Weight

seven MCDM techniques to identify the severely affected SWs in the study area. The unique characteristics of each MCDM are provided in Table 3.

3.8 Evaluation of Ranks

3.8.1 Percentage of Changes

It indicates the relative relevance between two approaches, for instance, the percentage of change between SVP-WASPAS and SVP-TOPSIS methods. This measure evaluates the extent to which there is fluctuation or alteration in the methods, in percentage terms. To compare the outcomes of the seven MCDM techniques from each weighting technique and to evaluate the success of the validation process, the percentage of change is used to study the variation and is calculated using Eq. (4) (Badri 2003).

$$\Delta P = \frac{N - NN_{Constant}}{N} * 100 \tag{4}$$

where, ΔP indicates the percentage of change, N indicates the total number of sub-watersheds and $NN_{constant}$ indicates the number of sub-watersheds. A comparison is done between the two techniques to determine the percentage of change.

3.8.2 Severity of Changes

In the absence of any shifts, the degree of significance between the two approaches should be equal to '1'. The rate of change between two approaches is seen to be increasing, resulting in higher numeric values. The degree of difference between two approaches based on the priority of the SW in each MCDM method from each weighting technique is determined using Eq. (5) (Badri 2003).

$$\Delta I = \frac{\sum_{i=1}^{N} \frac{r_1}{r_2}}{N} \tag{5}$$

where, ΔI indicates the severity of change, r_1 indicates the first method of sub-watershed priority (for instance, SVP-WASPAS) and r_2 indicates the second method (for instance, SVP-TOPSIS) of sub-watershed priority.

3.9 Integration of Ranks

In this study, the grade average technique is applied to integrate the ranks obtained from morphometry, LULC and RUSLE model parameters. For each sub-watershed, the final rating is derived as the arithmetic median of the ranks acquired using several approaches. It follows that a selection is given first priority if its ranking average is lower (Şahin 2021).

Table 3 MCDM methods and their highlights

Method	Highlights
WASPAS	1. It is recognized as one of the most precise and consistent methods in MCDM
	2. It is developed from the Weighted Sum Model (WSM) and Weighted Product Model (WPM)
	3. It offers improved accuracy in calculating the optimum value by considering variance
	4. This approach reduces uncertainty errors associated with defining starting values for criteria
	5. It ensures minimal variation in the relative importance of each option while achieving the lowest ranking with the optimal value
	6. It effectively addresses MCDM limits with its accuracy in estimation, thereby improving ranking precision
TOPSIS	1. It identifies the best alternative by measuring its proximity to two solutions: the positive ideal solution (PIS) and the negative ideal solution (NIS)
	2. The PIS represents the optimal values of each beneficiary parameter, while the NIS represents the worst values of each non-beneficiary parameter
	3. SWs are ranked based on their similarity to PIS and dissimilarity to NIS, with higher values indicating superior choices
	4. Unlike the NIS, which focuses on minimizing non-beneficiary criteria, the PIS optimizes beneficiary criteria
	5. The PIS represents the optimal criteria values, while the NIS denotes the worst achievable criteria values
	6. It enables the evaluation and normalization of the choice matrix based on specific parameter scores
	7. The final solution ranking is determined by considering the distance coefficient of each option
SAW	1. It remains one of the simplest and commonly used MCDM strategies
	2. In this method, non-cost parameters are transformed into non-beneficiary parameters, while cost parameters are converted into beneficiary parameters
	3. This involves normalizing parameters so that the highest parameter becomes the lowest and vice versa
	4. Finally, the alternative overall score is multiplied by the weight assigned to each parameter
VIKOR	1. This method is used to resolve difficulties with parameters that are incompatible and ambiguous
	2. A discrete decision-making issue with quasi and opposing parameters is solved using this method which is a MCDM technique
	3. In order to find a compromise solution for an issue with competing parameters, i.e. non-beneficiary parameters of morphometry, LULC and topography, this strategy focuses on ranking and selection from a group of possibilities and offers a complete solution
	4. It presents the ranking index for multiple parameters based on specific indicator of proximity of solutions to the optimal solution
ARAS	1. It is based on utility theory and quantitative measures are used to rank and evaluate the optimal solution function scores in order to pick the best option
	2. Its broad adoption and popularity are due to its simple, precise and quick processes
	3. It produces acceptable and mostly correct results when ranking different alternatives according to their performance based on chosen weighted assessment criteria
PROMETHEE	1. It is a contemporary method which is capable of ranking a limited number of constrained solutions, enabling both alternative ranking and criteria-based selection
	2. It offers several advantages, including the use of fundamental arithmetic for ease of understanding and application
	3. It assigns weights to parameters and computes Φ coefficients to rank sub-watersheds
	4. It determines alternatives with subsequent updates

Table 3 (continued)

Method	Highlights
EDAS	1. It evaluates alternatives by measuring Positive Distance from Average (PDA) and Negative Distance from Average (NDA)
	2. This provides a comprehensive assessment of competing criteria, identifying favorable alternatives based on their overall distance from the average solution
	3. These calculations quantify how much each solution deviates from the typical one
	4. A higher PDA score and lower NDA value indicate a superior alternative compared to the old solution
	5. This method is particularly helpful in cases with incompatible standards
	6. This method offers the analytical advantage of generating a robust and precise ranking of the SWs

Where, *WASPAS* Weighted Aggregated Sum Product Assessment, *TOPSIS* Technique of Order Preference Similarity to the Ideal Solution, *SAW* Simple Additive Weighting, *VIKOR* Vlekriterijumko Kompromisno Rangiranje, *ARAS* Additive Ratio ASessment, *PROMETHEE* Preference Ranking Organization Method for Enrichment Evaluation, *EDAS* Evaluation based on Distance Average Solution

4 Results and Discussion

4.1 Analysis of Morphometric Parameters

Using formulas from Table 1, 18 morphometric parameters are computed for each SW and tabulated (Table 4). The Strahler stream order method is used to assess stream networks in the selected river basin and the total streams are determined to be 1977. The stream section consists of 5 orders, 1st order with 46.99%, 2nd order with 24.53%, 3rd order with 15.63%, 4th order with 9.31% and 5th order with 3.54%. Based on Sinha and Eldho (2021), the compound parameter of morphometry is classified into beneficiary (RHO, C, R_f, R_s, R_n) and non-beneficiary ($R_b, R_l, C_c, L_o, D_d, D_t, F_s, R_e, R_c, R_h, R_r, S_a, HI$) parameters used for the analysis of Entropy, SAW method and ARAS method.

4.1.1 Linear Aspects

The length of the basin (L_b) signifies the watershed's longest dimension, aligned with the principal drainage channel (4.62–32.80 km), as given in Table 4. Among the sub-watersheds, SW2 exhibits the highest basin length, while SW7 shows the lowest. The mean length ratio (R_{lm}) ranges from 0.20 to 16.60, with SW13 recording the highest value while SW1 has the lowest. Mean bifurcation ratio (R_{bm}) indicates the stream number ratio between specified and higher orders (0.98–3.59), with SW9 showing the highest value and SW 13 the lowest. The RHO coefficient (RHO) reflects watershed connectivity and retention capacity (0.11–27.96), with SW13 having the maximum value and SW9 the minimum.

4.1.2 Areal Aspects

Low drainage density (D_d) explores dense vegetation, low elevation, and permeable surfaces, as seen in Table 4. For the selected river basin, D_d ranges from 0.75 to 1.00 per km, with SW6 showing the highest density and SW3 the lowest. Drainage texture (D_t), influenced by infiltration rate, varies across SWs, with SW2 exhibiting the highest value and SW7 the lowest. The length of overland flow (L_o) impacts catchment flow (0.5–0.67 km),

Table 4 Computation of Morphometry, LULC and Topography parameters in the SWs

	SWs	1	2	3	4	5	6	7	8	9	10	11	12	13
Morphometric Parameters	Area	111.74	289.21	110.9	198.45	251.6	18.88	9.19	111.35	97.82	279.74	144.09	138.16	42.47
	P	73.93	89.13	66.56	83.81	94.14	22.66	20.06	51.51	54.6	129.43	85.07	64.69	41.61
	L_b	19.11	32.8	19.03	26.48	30.31	6.96	4.62	19.07	17.72	32.19	22.08	21.56	11.03
	RHO	0.14	0.24	0.45	0.31	0.17	0.22	0.23	0.21	0.11	0.32	0.4	0.23	27.96
	Rbm	1.48	1.5	0.99	2.55	2.97	0.98	1.00	3.06	3.59	1.37	1.21	1.58	0.59
	Rlm	0.2	0.36	0.45	0.8	0.52	0.22	0.23	0.64	0.39	0.44	0.48	0.37	16.6
	Cc	1.97	1.48	1.78	1.68	1.67	1.47	1.87	1.38	1.56	2.18	2.00	1.55	1.8
	C	1.17	1.23	1.34	1.2	1.18	1.00	1.23	1.21	1.11	1.18	1.21	1.24	1.22
	L_o	0.58	0.62	0.67	0.6	0.59	0.5	0.61	0.6	0.55	0.59	0.6	0.62	0.61
	D_d	0.86	0.81	0.75	0.84	0.84	1.00	0.81	0.83	0.9	0.85	0.83	0.81	0.82
	D_t	1.11	4.25	1.97	2.47	2.55	0.75	0.4	1.65	2.67	2.33	2.37	2.21	0.84
	F_s	0.73	1.31	1.18	1.04	0.95	0.9	0.87	0.76	1.49	1.08	1.4	1.04	0.82
	R_e	0.62	0.59	0.62	0.6	0.59	0.7	0.74	0.62	0.63	0.59	0.61	0.62	0.67
	R_c	0.26	0.46	0.31	0.35	0.36	0.46	0.29	0.53	0.41	0.21	0.25	0.41	0.31
	R_f	0.31	0.27	0.31	0.28	0.27	0.39	0.43	0.31	0.31	0.27	0.3	0.3	0.35
	R_s	3.27	3.72	3.27	3.53	3.65	2.57	2.33	3.27	3.21	3.7	3.38	3.36	2.87
	R	106	82	239	612	623	51	32	123	76	372	80	96	49
	R_h	1.11	0.35	2.88	3.69	2.93	2.69	4.28	1.33	0.86	1.57	0.67	0.86	1.4
	R_r	1.43	0.92	3.59	7.3	6.62	2.25	1.59	2.39	1.39	2.87	0.94	1.48	1.18
	R_n	0.09	0.07	0.18	0.51	0.53	0.05	0.03	0.1	0.07	0.31	0.07	0.08	0.04
	S_a	0.013	0.015	0.012	0.011	0.011	0.012	0.012	0.012	0.013	0.012	0.013	0.013	0.013
	HI	0.447	0.459	0.263	0.191	0.210	0.445	0.444	0.298	0.51	0.217	0.490	0.523	0.420

Table 4 (continued)

SWs		1	2	3	4	5	6	7	8	9	10	11	12	13
LULC and topography in percentage	A	7.25	27.13	3.40	5.08	12.80	0.76	0.62	4.43	8.16	10.96	12.46	5.28	1.67
	BL	4.37	35.95	1.93	3.55	5.40	0.17	0.10	1.46	11.04	8.17	24.21	3.23	0.42
	F	0.40	0.88	5.15	27.58	51.78	0.23	0.00	1.58	0.72	10.40	0.56	0.37	0.37
	S	4.19	14.00	3.14	8.21	8.55	3.01	1.35	2.60	7.17	12.27	10.47	6.62	18.41
	V	7.68	6.84	9.23	13.80	12.13	1.46	0.69	9.18	3.43	19.77	3.23	10.94	1.62
	SL1	6.34	12.55	3.78	6.56	9.12	1.62	1.29	7.94	8.28	20.20	10.84	9.50	1.96
	SL2	0.76	2.55	5.31	8.67	13.89	0.74	0.24	0.73	1.10	3.47	0.85	0.94	7.87
	SL3	0.07	0.20	1.70	5.46	6.70	0.05	0.00	0.12	0.03	1.33	0.04	0.20	0.46
	SL4	0.02	0.017	0.52	2.76	2.96	0.00	0.00	0.02	0.00	0.384	0.00	0.04	0.02
	SL5	0.00	0.00	0.11	2.23	5.05	0.00	0.00	0.00	0.00	0.19	0.00	0.00	0.00

Where, P Perimeter, L_b Basin Length, RHO RHO coefficient, R_{bm} Mean bifurcation ratio, R_{lm} Mean stream length ratio, Cc Coefficient Compactness, C Constant channel maintenance, L_o Length of overland flow, D_d Drainage Density, D_t Drainage Texture, F_s Stream Frequency, R_e Elongation Ratio, R_c Circulatory Ratio, R_f Form Factor, R_s Shape Factor, R Relief, R_h Relief ratio, R_n Ruggedness number, S_a Basin Slope, HI Hypsometric Integral, A Agriculture, BL Barren Land, F Forest, S Settlement, V Vegetation, $SL1$ Slope(<5°), $SL2$ Slope(5°–10°), $SL3$ Slope(10°–15°), $SL4$ Slope(15°–20°), $SL5$ Slope(> 20°)

with SW3 having the highest value and SW9 the lowest. Stream frequency (F_s) indicates erosion potential (0.73–1.49), with SW9 recording the maximum and SW1 the minimum. Compactness constant (C_c) reflects erosion risk (1.8–2.18), with SW10 having the highest and SW8 the lowest value. Constant channel maintenance (C) inversely correlates with drainage density (1.00–1.34 km), with SW6 having the lowest and SW3 the highest value.

4.1.3 Shape Aspects

The Elongation Ratio (Re) provides insights into the geological makeup of a river basin (0.59–0.74), as shown in Table 4. In the selected basin, SW7 displays the highest Re value, while SW2 and SW5 have the lowest. Circulatory Ratio (Rc) reflects basin shape (0.21–0.59), with SW10 presenting a higher imperviousness and erosion susceptibility compared to SW8, which has a lower Rc value. Form Factor (Rf) indicates the geometry of the watershed (0.27–0.43), with SW7 showing a relatively high value and SW5 a low one. Shape Factor (Rs) impacts water and sediment yield (2.33–3.72), with SW2 having the highest and SW 7 the lowest value.

4.1.4 Relief and Hypsometric Aspects

Relief (R) represents the disparity between the highest and lowest elevations within the watershed (32–629 m), as shown in Table 4. SW 5 exhibits the greatest relief, indicating steep terrain and heightened erosion potential, whereas SW7 has the lowest relief. Relative relief (Rr) reflects the overall steepness of the watershed and its erosion susceptibility due to gradient (0.92–7.3). SW4 records the highest Rr value of 7.3, while SW2 shows the lowest at 0.92. Ruggedness number (Rn) signifies basin topography and its correlation with erosion (0.03–0.1). Higher Rn values indicate increased erosion rates. SW5 and SW4 have the highest Rn values, while SW7 and SW13 record the lowest. Basin Slope (Sa) influences surface runoff and time of concentration (0.011–0.015). SW10 demonstrates the steepest slope, resulting in high runoff, whereas SW2 displays the lowest gradient. Hypsometric Integral (HI) categorizes watershed growth phases (0.191–0.523), with SW3, SW6, and SW10 in the old phase, and others in the mature phase. There are no young phase HI values in the selected river basin.

4.2 Analysis of LULC and Topography Parameters

In this study, RTC techniques are used to classify land cover at SW level in the selected river basin which includes agricultural land (0.62–27.13%), vegetation (0.69–19.77), settlement areas (1.35–14.00%), barren land (0.10–35.95%), forests (0.37–51.78%), and water bodies (1.29–20.20%), as shown in Table 4 and Fig. 3a. Further, the accuracy of the classification is determined to be 0.84 of K and 87% of OA. The topography parameters are classified into 5 groups, namely SL1 (1.29–20.20%), SL2 (0.73–13.89), SL3 (0.03–6.70%), SL4 (0.02–2.96%), SL5 (0.11–5.05%), as depicted in Table 4 and Fig. 3b. Based on Sinha and Eldho (2021), the compound parameter of LULC and topography is classified into beneficiary (F,V) and non-beneficiary (A,BL,S,SL1,SL2,SL3,SL4,SL5) parameters used for the analysis of Entropy, Simple Additive Weightings (SAW) method and Additive Ratio Assessment (ARAS) method.
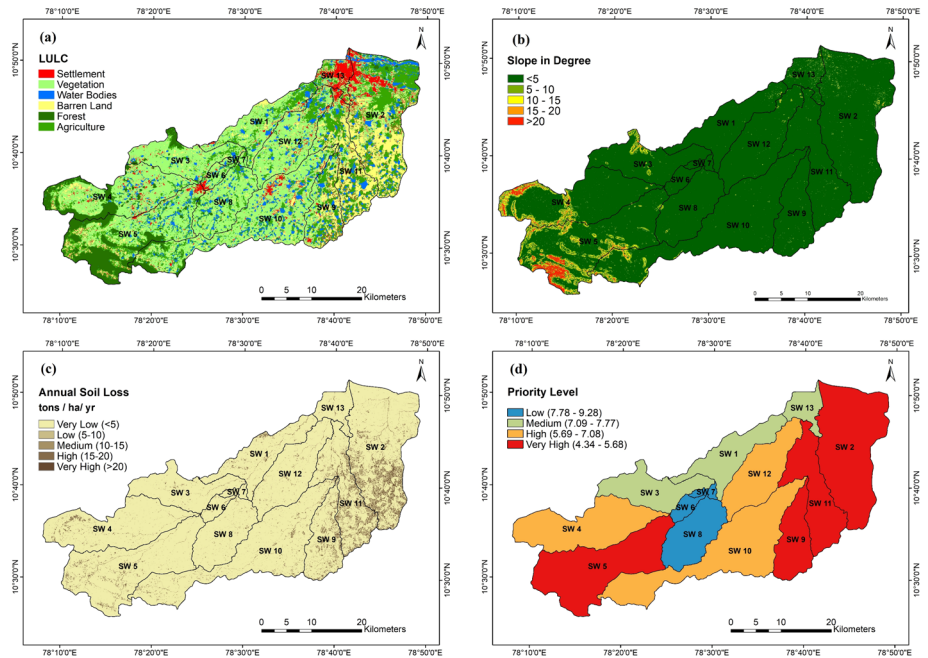
Fig. 3 **a** Land use/land cover Map, **b** Topography Map, **c** Annual Soil Loss Map and **d** Integrated SWs Prioritization Map

4.3 Analysis of Soil Loss and Prioritization of SWs

Based on RUSLE model findings (Fig. 3c), SW11 has very high mean loss at 62.79 tons/hr/yr, followed by SW2, SW9, SW1 with 56.21, 44.22, 16.27 tons/ha/yr, and ranked 1, 2, 3, 4, respectively. SW5, SW10, SW6 experience high respective mean losses of 16.24, 15.60, 11.64 tons/ha/yr and are ranked 5, 6, 7. SW4, SW7, SW13 have respective moderate losses of 11.47, 10.55, 9.63 tons/hr/yr, ranked 8, 9, 10. Conversely, SW12, SW3, SW8 exhibit the lowest respective mean losses with 8.00, 7.79, 5.18 tons/hr/yr, ranked 11, 12, 13.

4.4 Weighting of Morphometric, LULC and Topography Parameters

Based on morphometric parameters, RHO coefficient has higher parametric weights with 0.6735, 0.4166 and 0.401 in SVP, Entropy and SD methods, respectively, while HI has higher weight with 0.181 in CRITIC method (Table 5). The MW method has the same weight of 0.056 for all eighteen morphometric parameters. Based on LULC and topography parameters, it is seen that forest class has higher parametric weights with 0.459 and 0.264 in SVP and SD methods whereas agriculture and SL5 have higher weights with 0.153 and 0.295 in CRITIC and Entropy methods, respectively (Table 5). The MW method has the same weight of 0.10 for ten LULC and topography parameters.

Table 5 Weights of Morphometric parameters, LULC and Topography parameters

	Parameters	SVP	CRITIC	Entropy	SD`	MW
Morphometry	R_{bm}	0.0126	0.061	0.0415	0.055	0.056
	R_{lm}	0.2302	-0.076	0.3051	0.234	0.056
	RHO	0.6735	0.075	0.4166	0.401	0.056
	Cc	0.0007	-0.151	0.0018	0.012	0.056
	C	6.9E-5	0.127	0.0004	0.004	0.056
	L_o	1.75–5	-0.127	0.0004	0.002	0.056
	D_d	4.1E-5	0.130	0.0005	0.003	0.056
	D_t	0.0121	0.149	0.0272	0.054	0.056
	F_s	0.0007	0.257	0.0049	0.013	0.056
	R_e	2.45E-5	0.013	0.0005	0.002	0.056
	R_c	0.0001	0.137	0.0068	0.005	0.056
	R_f	2.65E-5	-0.013	0.0021	0.003	0.056
	R_s	0.0021	0.135	0.0017	0.022	0.056
	R_h	0.0179	-0.086	0.0409	0.065	0.056
	R_r	0.0495	-0.079	0.0497	0.109	0.056
	R_n	0.0004	0.089	0.0887	0.009	0.056
	S_a	9.2E-9	0.178	0.0005	5E-5	0.056
	HI	0.0002	0.181	0.0107	0.006	0.056
LULC and Topography	A	0.100	0.153	0.018	0.123	0.100
	BL	0.225	0.116	0.086	0.185	0.100
	F	0.459	-0.149	0.189	0.264	0.100
	S	0.050	0.136	-0.012	0.087	0.100
	V	0.062	0.056	0.0003	0.097	0.100
	SL1	0.053	0.110	-0.010	0.090	0.100
	SL2	0.034	0.147	0.054	0.072	0.100
	SL3	0.010	0.145	0.160	0.038	0.100
	SL4	0.002	0.142	0.219	0.018	0.100
	SL5	0.004	0.143	0.295	0.025	0.100

4.5 Analysis of Ranks Based on Morphometric Parameters

Based on scores of different hybrid methods with morphometry, the ranks of 13 SWs are assigned which range from 1 to 13 (Table 6). As seen in Table 6, in SVP method based on morphometry, SW13 is ranked highest in SAW, VIKOR and ARAS, while SW6 has the highest priority in WASPAS, PROMETHEE, and EDAS methods. In CRITIC method, SW2 is ranked highest in WASPAS, TOPSIS, SAW, and ARAS, while SW9 and SW13 have priority in VIKOR and PROMETHEE methods. In entropy method, SW6 is given higher priority in SAW, ARAS, PROMETHEE, and EDAS, while SW13 tops in WASPAS and TOPSIS methods. SW13 gains higher priority in SD method using WASPAS, SAW, ARAS, and PROMETHEE methods. In the MW method, SW13 has higher priority in most MCDM techniques, except VIKOR, which accords high priority to SW6.

Table 6 Prioritization based on Morphometric Parameters, LULC and Topography Parameters

Weights	SWs	Morphometric Parameters							LULC and Topography Parameters						
		WASPAS	TOPSIS	SAW	VIKOR	ARAS	PROMETHEE	EDAS	WASPAS	TOPSIS	SAW	VIKOR	ARAS	PROMETHEE	EDAS
SVP	1	2	9	2	4	2	2	2	10	4	5	5	9	9	8
	2	5	5	4	3	4	4	5	4	1	1	1	3	3	4
	3	11	1	9	9	7	10	11	7	10	8	10	7	7	6
	4	12	4	12	13	12	12	12	2	12	11	12	2	2	2
	5	10	10	10	12	11	11	7	1	13	13	13	1	1	1
	6	1	12	13	8	13	1	1	12	8	10	7	12	12	12
	7	4	7	3	6	3	6	4	13	9	12	8	13	13	13
	8	7	8	11	11	10	8	9	9	7	6	9	10	10	10
	9	3	11	7	10	8	3	3	6	3	3	3	6	6	7
	10	9	3	8	7	9	9	10	3	11	9	11	4	4	3
	11	8	2	6	2	5	7	8	5	2	2	2	5	5	5
	12	6	6	5	5	6	5	6	8	5	4	6	8	8	9
	13	13	13	1	1	1	13	13	11	6	7	4	11	11	11
CRITIC	1	8	6	7	6	6	11	10	11	10	11	12	10	7	10
	2	1	1	1	4	1	4	1	1	3	5	2	3	1	3
	3	9	10	9	9	8	7	11	9	8	8	7	7	10	6
	4	11	12	13	12	12	2	8	6	2	2	3	2	9	2
	5	10	11	11	11	11	3	5	4	1	1	1	1	11	1
	6	12	5	5	2	5	13	12	12	12	12	10	12	12	12
	7	13	8	8	8	9	12	13	13	13	13	11	13	13	13
	8	6	7	6	10	7	8	6	10	11	10	13	11	8	11
	9	2	2	2	1	2	5	2	5	7	7	8	8	4	7
	10	7	9	12	7	10	6	7	2	4	3	5	4	3	4
	11	4	3	3	3	3	9	4	3	5	4	6	5	2	5
	12	5	4	4	5	4	10	3	8	9	6	9	9	6	9
	13	3	13	10	13	13	1	9	7	6	9	4	6	5	8

Table 6 (continued)

Weights	SWs	Morphometric Parameters							LULC and Topography Parameters						
		WASPAS	TOPSIS	SAW	VIKOR	ARAS	PROMETHEE	EDAS	WASPAS	TOPSIS	SAW	VIKOR	ARAS	PROMETHEE	EDAS
Entropy	1	12	5	11	12	8	2	3	9	6	13	6	8	8	8
	2	8	3	10	6	11	6	4	3	3	8	3	3	2	5
	3	4	13	5	10	5	10	10	7	7	10	9	6	7	4
	4	2	11	7	1	7	12	12	2	2	3	2	2	3	2
	5	3	10	8	4	9	11	11	1	1	6	1	1	1	1
	6	13	4	1	2	1	1	1	13	11	7	11	12	12	12
	7	11	2	12	5	12	5	2	12	10	11	10	13	13	13
	8	6	9	3	7	3	7	8	8	12	9	12	11	10	10
	9	9	8	2	3	2	8	6	6	5	2	5	7	6	7
	10	5	12	9	11	10	9	9	4	13	5	13	4	5	3
	11	7	7	6	9	6	4	5	5	4	1	4	5	4	6
	12	10	6	4	8	4	3	7	10	8	4	7	9	9	9
	13	1	1	13	13	13	13	13	11	9	12	8	10	11	11
SD	1	12	9	2	11	3	12	2	10	10	5	5	10	9	9
	2	9	11	4	9	4	9	4	4	13	1	1	3	2	4
	3	4	2	9	4	9	4	10	7	3	9	11	7	7	6
	4	2	1	12	1	12	2	12	2	2	10	12	2	3	2
	5	3	3	11	2	11	3	11	1	1	11	13	1	1	1
	6	13	12	13	7	13	13	1	12	5	12	7	12	12	12
	7	10	10	3	6	2	8	3	13	4	13	8	13	13	13

Table 6 (continued)

Weights	SWs	Morphometric Parameters							LULC and Topography Parameters						
		WASPAS	TOPSIS	SAW	VIKOR	ARAS	PROMETHEE	EDAS	WASPAS	TOPSIS	SAW	VIKOR	ARAS	PROMETHEE	EDAS
	8	6	5	10	5	10	6	8	9	6	7	10	11	10	10
	9	11	8	7	3	7	7	5	6	11	3	3	6	6	7
	10	5	4	8	8	8	5	9	3	7	8	9	4	4	3
	11	7	6	5	12	5	10	7	5	12	2	2	5	5	5
	12	8	7	6	10	6	11	6	8	9	4	6	8	8	8
	13	1	13	1	13	1	1	13	11	8	6	4	9	11	11
MW	1	12	13	3	11	4	12	11	11	5	11	8	10	10	9
	2	8	6	5	6	3	8	9	4	12	2	2	4	2	4
	3	4	7	9	12	9	4	4	7	6	9	13	6	8	5
	4	2	2	8	4	8	2	2	2	11	3	11	2	4	2
	5	3	3	6	5	6	3	3	1	13	6	1	1	1	1
	6	13	10	13	1	13	13	13	12	3	12	10	12	12	12
	7	11	9	2	3	2	9	12	13	2	13	9	13	13	13
	8	7	5	11	7	11	7	6	9	1	10	12	11	11	11
	9	6	4	12	2	12	6	7	6	7	4	6	8	6	7
	10	5	12	4	13	5	5	5	3	8	7	4	3	3	3
	11	10	11	7	9	7	11	10	5	10	1	5	5	5	6
	12	9	8	10	8	10	10	8	8	4	5	7	9	7	8
	13	1	1	1	10	1	1	1	10	9	8	3	7	9	10

Table 7 Percentage of change and severity of change

	Parameter	MCDM	SVP	CRITIC	Entropy	SD	MW
Percentage of change	**Morphometry**	WASPAS	56.04	65.93	59.34	65.93	57.14
		TOPSIS	72.53	56.04	75.82	78.02	68.13
		SAW	63.74	59.34	63.74	60.44	65.93
		VIKOR	76.92	63.74	80.22	74.73	79.12
		ARAS	63.74	58.24	68.13	62.64	62.64
		PROMETHEE	59.34	84.62	61.54	65.93	53.85
		EDAS	60.44	69.23	57.14	71.43	59.34
	LULC and Topography	WASPAS	56.04	71.43	61.54	51.65	56.04
		TOPSIS	73.63	48.35	61.54	75.82	81.32
		SAW	75.82	59.34	84.62	72.53	73.63
		VIKOR	71.43	75.82	58.24	79.12	71.43
		ARAS	53.85	49.45	56.04	54.95	57.14
		PROMETHEE	53.85	71.43	61.54	54.95	56.04
		EDAS	61.54	50.55	56.04	54.95	59.34
Severity of change	**Morphometry**	WASPAS	10.93	8.31	8.62	9.98	9.07
		TOPSIS	13.64	8.68	8.86	12.47	8.91
		SAW	10.71	8.49	9.89	11.44	9.66
		VIKOR	9.99	9.52	12.92	12.15	12.19
		ARAS	10.61	8.69	9.50	11.45	9.65
		PROMETHEE	10.81	10.49	8.60	9.82	8.92
		EDAS	10.96	8.53	8.61	13.96	9.19
	LULC and Topography	WASPAS	8.58	8.36	7.86	8.32	8.78
		TOPSIS	11.81	7.58	8.00	11.10	14.96
		SAW	11.53	7.91	10.61	11.91	10.23
		VIKOR	11.87	7.68	8.06	13.01	9.69
		ARAS	8.36	7.60	7.73	8.16	8.91
		PROMETHEE	8.36	11.20	7.74	8.10	8.86
		EDAS	8.62	7.62	7.73	8.33	8.99

4.6 Analysis of Ranks Based on LULC and Topography Parameters

Based on scores of different hybrid methods with LULC and topography, the ranks of 13 SWs are assigned which range from 1 to 13, as shown in Table 6. It is noted that in the SVP method based on LULC and topography, SW5 is ranked highest in WASPAS, ARAS, PRO-METHEE, and EDAS, while SW2 takes priority in TOPSIS, SAW, and VIKOR methods. In CRITIC method, SW5 is ranked highest in TOPSIS, SAW, VIKOR, ARAS and EDAS, whereas SW2 takes priority in WASPAS and PROMETHEE methods. In the entropy method, SW5 leads across all techniques except SAW, which ranked SW11 the highest. In the SD method, SW5 is higher in WASPAS, TOPSIS, ARAS, PROMETHEE and EDAS while SAW and VIKOR give priority to SW2. In MW method, SW5 is prioritized across most techniques, except TOPSIS and SAW, which ranked SW8 and SW11 higher.

4.7 Valuation of Ranking

The validation by percentage of change reveals that the lowest variation is identified in MW-PROMETHEE with 53.85% of morphometric parameters, and CRITIC-TOPSIS with 48.35% of LULC and topography parameters, as shown in Table 7. The validation by severity of changes reveals that the lowest variation is found in CRITIC-WASPAS method with 8.31 of morphometric parameters and CRITIC-TOPSIS method with 7.58 of LULC and topography parameters. The lower variation in percentage of changes and severity of changes indicates the higher efficiency in prioritizing SWs according to morphometric, LULC and topography parameters.

4.8 Integration of Ranks

The final priority maps for the selected river basin are generated based on 71 integrated models (Fig. 3d). The outcomes of grade average method show that SW2, SW11, SW5, SW9 with grade values of 4.34, 5.45, 5.56, 5.68 fall under very high priority level and are ranked 1, 2, 3, 4, respectively. SW4, SW10, SW12 with grade values of 6.06, 6.56, 7.08 fall under high priority with ranks of 5, 6, 7, respectively. SW3, SW13, SW1 with grade values of 7.68, 7.70, 7.77 fall under moderate level with ranks 8, 9, 10, respectively. SW8, SW7, SW6 with grade values of 8.58, 9.25, 9.28, fall under low priority level and are ranked 11, 12, 13, respectively.

5 Conclusions

This research study employs various combinations of objective weighting and MCDM techniques to rank sub-watersheds in the Ponnaniyar river basin, considering soil loss, morphometry, land use/land cover, and topography parameters. A total of 71 models are used, including 35 for morphometry, 35 for LULC and topography, and 1 based on the RUSLE model, to prioritize the SWs with different weighting and MCDM combinations. From the study, it is found that using multiple MCDM techniques is a logical and efficient approach for decision-making. Hybrid methods like CRITIC-TOPSIS, MW-PROMETHEE, and CRITIC-WASPAS are identified as effective for prioritizing SWs prone to soil erosion. The results indicate that PROMETHEE and WASPAS methods show better agreement with morphometric parameters, while the TOPSIS approach is more aligned with LULC parameters. The CRITIC weighting technique performs consistently across all three parameter sets, while the MW method is consistent only for morphometry. Using the grade average technique, the final priority of SWs in the selected basin is obtained by averaging the rankings from the 71 models. SW2, SW11, and SW5 are identified to be severely affected by soil erosion. This study recommends the installation of water harvesting structures in these severely affected sub-watersheds. The findings of this study are valuable for land degradation prevention and watershed management.

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Data Availability Depending on valid requests, research data and information will be provided.

Declarations

Competing Interest The authors would like to state that there is no potential conflict of interest relevant to this research study.

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