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A Hybrid WSA and AHP-TOPSIS Modeling for Soil Erosion Assessment and Prioritization of the Sub-watershed of Karmanasa River Basin

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Research Article

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Posted Date: July 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10342326/v1

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Additional Declarations:
No competing interests reported.

Tables 1 to 8 are available in the Supplementary Files section.

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Abstract

Climate change and human-induced changes are severely affecting soil degradation and erosion; these changes pose a serious threat to the sustainability of the river basin and to the loss of agricultural land and livelihoods. In the last few decades, the availability of high-resolution satellite images, field observations, and modeling tools has provided insightful information for the assessment, monitoring, and management of natural resources, and for predicting and protecting the restoration of river ecology. The Karmanasa River is an important perennial river of the Middle Ganga Plain, supporting extensive agricultural land and comprising a diverse geological and geomorphological landscape, and is currently facing severe soil erosion and land degradation. In this study, an integrated approach is used to identify and delineate watersheds and to analyse parameters to understand the river mics. Thereafter, hybrid multi-criteria decision-making (MCDM) techniques such as Weighted Sum Analysis (WSA), Sediment Production Rate (SPR), and the Analytical Hierarchy Process Technique for Order Preference by Similarity to Ideal Solution (AHP–TOPSIS) are used to prioritize watersheds based on their susceptibility to soil erosion. The results indicate that the WSA and SPR models identified that nearly 38–40% and 42.6% of the watersheds were vulnerable to erosion, respectively. The AHP–TOPSIS approach, with a consistency ratio (CR) of 0.016 and a ranking of 39.8%, falls under the high-priority erosion susceptibility category. To validate the AHP–TOPSIS results, the Spearman Rank Correlation Coefficient and Kendall Tau Correlation Coefficient were used; both yielded a positive correlation coefficient of 0.37. The present study explores significant data to identify priority watersheds, restoration measures, and strategies to mitigate soil erosion, thereby enhancing sustainable land and basin management and supporting the Sustainable Development Goals (SDGs). Furthermore, findings can be applied to other river basins and provide a practical framework for river basin management.

Keywords: AHP-TOPSIS modeling, Soil Erosion Susceptibility, Karmanasa River, and Middle Ganga Plain.

- **Soil Erosion Modelling**
- **Watershed Prioritization**
- **AHP-TOPSIS and statistical techniques**

1. Introduction

Land and water resources are essential components of natural ecosystems and support human development. In recent decades, rapid population growth, urban expansion, and climate change have raised serious concerns and placed significant pressure on the environment, human health, and natural resources. Land degradation and soil erosion pose major threats to land productivity, long-term agricultural sustainability, and water security, especially in semi-arid regions (Kumar et al. 2026). Furthermore, unplanned urbanization, unscientific agricultural practices, and excessive sand mining from rivers have significantly increased river erosion, degraded river ecosystems, and caused recurrent flooding. Soil erosion is considered one of the most common forms of land degradation globally, which leads to severe economic loss, water quality issues, loss of agricultural productivity, and long-term threats to the ecosystem and environmental sustainability (S & Paul, 2025; Keesstra et al., 2016; Borrelli et al., 2017).In India, nearly 175 million hectares of land, almost 53% of the land, is impacted by soil erosion and land degradation every year, as per the data available, around 5,334 million tonnes of soil is lost, and nearly 29% is transported to the oceans and about 10% is deposited in reservoirs, (Mandal & Sharda, 2011; Singh & Singh, 2018).It is very important to understand the causes of soil erosion and land degradation through detailed watershed studies and proper characterization, considering key watershed parameters and their assessment. Watershed characterization provides highly informative data on topography, land use, and hydrology to understand the terrain and its relationship to soil erosion and runoff estimates.(Singh et al., 2014; Pande and Moharir, 2017; Panfe et al., 2020).In recent times, a large number of case studies have been published on watershed morphometric analysis to understand the drainage morphology and dynamics, considering the physical behavior and pattern of the watershed to understand the soil erosion of the river basins using satellite data and other hydrometeorological information to map the response of the watershed for soil erosion. (Horton, 1945; Schumm, 1956; Strahler, 1957).Watershed morphometric parameters, such as linear, areal, and relief features derived from digital elevation models (DEMs) along with multispectral satellite images, provide a very important input data to understand and delineate the watershed and its prioritization for soil and water conservation, and restoration plans (Sarkar et al. 2022 and Mohaparta & Singh 2026).The information derived through the watershed analysis is extensively utilized for the development of groundwater recharge structures, soil texture, and conservation measures, and

for developing the relationship of each variable with recharge, conservation, and prospect mapping (Arabameri et al., 2020; Kumar et al., 2021; Saha & Singh, 2017).In the recent past, a considerable number of research papers have been published on watershed prioritization and soil erosion modeling using integrated approaches. Researchers have employed various statistical and multi-criteria decision-making techniques to develop these integrated models, and the results have been validated using appropriate statistical tools.The integrated approach is also applicable to data-scarce regions, where field-based soil erosion data is limited and temporal constraints are present, making integrated geospatial techniques a powerful and efficient tool for watershed assessment, management prioritization, and decision-making. Multi-Criteria Decision-Making (MCDM) techniques are powerful tools for sub-watershed prioritization because they can manage large, complex, multi-dimensional datasets and effectively incorporate expert judgment to support structured, reliable decision-making (Ameri et al., 2017; Abassi et al., 2024).Soil Erosion Assessment and Prioritization for the watershed have been attempted through the Weighted Sum Analysis (WSA) approach, in which all contributing factors were assigned normalized weights to the morphometric parameters based on correlation coefficients, generating a composite index for ranking soil erosion susceptibility (Kadam et al., 2019). In recent years, the integration of geospatial technologies and machine learning has enabled the extraction of crucial information on soil erosion, its restoration, and planning for it. The findings of the present models are highly useful for optimizing soil, water, and vegetation conservation measures within selected watersheds, thereby contributing to sustainable land management and effective erosion control (Srinivasan et al., 2021; Singh et al., 2021). Many statistical methods were used in the recent past for watershed characterization and management. The AHP–TOPSIS hybrid model integrates the Analytical Hierarchy Process (AHP), which derives weights from pairwise comparison matrices, with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which ranks alternatives based on their distances from the ideal and anti-ideal solutions. This approach has been used in several studies and yields better results than individual MCDM (Meshram & Sharma, 2015; Arabameri et al., 2020; A. Kumar et al., 2022). Despite the hydrological and ecological importance of the Karmanasa River basin, systematic sub-watershed prioritization using advanced MCDM techniques integrated with morphometric analysis has not yet been carried out. Previous work in the Vindhyan basins and the Gangetic plain has reported significant erosion problems (Chowdhury & Saha, 2025). Moreover, the Karmanasa river basin remains underexplored for soil erosion risk assessment and the use of integrated models. This highlights the need for integrated geospatial and

morphometric approaches to address this research gap. The present study aims to bridge this gap by: (1) delineating six sub-watersheds using SRTM DEM data and GIS techniques and computing 28 morphometric parameters; (2) prioritizing sub-watersheds using WSA, SPR, and AHP–TOPSIS models; (3) evaluating and comparing model performance using non-parametric statistical tests (SCCT and KTCCT); and (4) identifying priority zones for soil conservation planning.

2. Geographic Characteristics

The Karmanasa River is an important left-bank tributary of the Ganga River, flowing through the complex geological and geomorphological setting of the Kaimur Plateau, which extends eastward from the Vindhyan Range and lies along the boundary between Uttar Pradesh and Bihar. The river originates from the Kaimur Range of the Vindhyan Supergroup near the village of Sarodag in Kaimur district, Bihar. It drains an area of approximately 8,019.86 km² before meeting the Ganga near Chausa in the Buxar district of Bihar. The basin is characterized by lithological formations such as sandstone, shale, and limestone-derived soils, which are highly susceptible to erosion.

The Karmanasa River Basin (KRB) spans parts of Bihar and Uttar Pradesh. It lies between the latitudes 24°33’19.73" N and 25°30’05.84" N and the longitudes 82°56’20.73" E and 84°23’23.95" E, with a semi-arid climate characterized by hotter summers and colder winters. The region receives most of the rainfall between July and September. The elevation of the basin varies from a high altitude of 642.16 m (MSL) at the peak of the basin to 52.5 m (MSL) at the convergence of the river with the River Ganga (Figure 1).

Figure 1: Location map of the Karmanasa River Basin

3. Geology and Geomorphology

The Vindhyan is a fragmented range of hills, non-tectonic mountains formed by the down faulting of the Narmada Rift Valley. An ancient Proterozoic sequence underlies the Karmanasa basin. The Vindhyan sequences comprise clastic, argillaceous, carbonate, and volcanogenic sedimentation of the Proterozoic era, divided into two: Lower Vindhyan (Semri Group) and Upper Vindhyan (Kaimur Group), which are composed mainly of sandstone, limestone, quartzite, and schist. The Rohtas Plateau comprises a series of descending fluvial plateaux that run along the Kaimur Range.

The Karmanasa River basin is characterized by highly erodible alluvial and colluvial soils composed primarily of sand, silt, and clay. These soils are particularly vulnerable to erosion and sediment transport during the Indian Summer Monsoon (June to September). The Geomorphic units formed within and adjacent to the active river channel function as key indicators of erosional and depositional processes, offering valuable insights into the basin's hydrogeomorphic regime.

Point bars are low-relief, arcuate depositional landforms that accumulate along the inner (convex) banks of meander bends as a result of helical secondary flow (Dietrich & Smith, 1983). These features display a downstream fining sediment sequence, ranging from coarse to medium sand at the bar head to fine sand and silt at the bar tail. The growth of point bars, coupled with erosion of opposing cutbanks, indicates active lateral channel migration. Abandoned point bars, preserved as scroll bars, document previous channel shifts (Figure 2) (Ghinassi et al., 2013).

Sandbars and mid-channel bars are ephemeral to semi-permanent depositional features that form where decreased flow velocity leads to the deposition of bedload sediments (Figure 2) (Hoey & Sutherland, 1991). These bars may develop as lateral or medial features, are frequently reworked during monsoon floods, and often become partially stabilized by riparian vegetation in the dry season. Their presence and evolution reflect the basin's sediment transport and channel adjustment processes.

Figure 2: Field photographs of different locations of the basin representing different Geomorphic features.

4. Materials and Methods

The methodological framework adopted in this study, illustrated in Figure 3, follows a nine-stage sequential workflow beginning with the acquisition of multi-source geospatial data, including the SRTM DEM at 30 m resolution, which was downloaded from the USGS Earth Explorer portal (https://earthexplorer.usgs.gov/) for terrain analysis, sub-watershed delineation, and extraction of other morphometric parameters (2). Survey of India (SOI) Toposheets at a 1:50,000 scale were used to cross-check and validate the DEM-derived products. (3) Geological data were obtained from the Geological Survey of India (GSI) on a 1:250,000 scale (https://bhukosh.gsi.gov.in). (4) Soil Data taken from the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) at a 1:150,000 scale. The Spatial data were processed and analyzed using ArcGIS 10.8 (ESRI). Hydrological processing of the

DEM. The pre-processing of the satellite data was carried out to maintain hydrological continuity. The DEM was processed under the Spatial Analyst Extension of ArcGIS. Standard image-processing and GIS approaches are used to delineate the basin's watersheds and perform morphometric calculations. (Arabameri et al., 2020).

Figure 3 : Flowchart of the methodology followed

Twenty-two morphometric parameters spanning linear, shape, and landscape/relief aspects were extracted and systematically classified as direct or inverse with respect to erosion susceptibility prior to application of three MCDM models: The Weighted Sum Analysis (WSA), the Sediment Production Rate (SPR) model, and the AHP-TOPSIS ensemble model. Model outputs were statistically compared using the Spearman Correlation Coefficient Test (SCCT) and Kendall Tau Correlation Coefficient Test (KTCCT) (Szmidt and Kacprzyk, 2011) to identify the most reliable prioritization approach.

5. Prioritization of Soil Erosion Using WSA, SPR, and AHP-TOPSIS

In this study, three statistical methods were used to prioritize basins across different soil-erosion vulnerability zones.

1. Weighted Sum Analysis (WSA)

The WSA method has been extensively used for watershed analysis, following a Multi-Criteria Decision-Making (MCDM) approach to prioritize watersheds and sub-watersheds for assessing soil erosion and flood risk. In this approach, each parameter was assigned a weight based on its contribution to soil erosion and flood risk. Afterward, the overall score was calculated by multiplying each parameter's weight by its value and summing the results. The alternative with the highest aggregated score is considered the most suitable (O'Shea et al., 2025). After normalization of criteria to a single dimensionless scale, the optimal alternative is selected based on the maximum aggregated score, as expressed in equation (1).

$$A_{iWSM} = \sum_{j=1}^{n} wja_{ij}$$

Where Ai indicates the overall WSM score of the alternative i, wj is the weight of criterion j, and aij indicates the performance value of the alternative i under criterion j.

Compared with other Multi-Criteria Decision-Making (MCDM) methods, the Weighted Sum Method (WSM) is preferred for its simplicity, clear structure, and ease of interpreting results (Taherdoost & Madanchian, 2023). Unlike AHP and PROMETHEE, which involve complex pairwise comparisons and advanced preference modeling, WSM uses a simpler weighted-aggregation approach to rank alternatives (Cinelli et al., 2020). In this study, morphometric parameters related to the drainage network, relief, and basin geometry were analyzed for each sub-watershed, as they influence soil erosion. Weights (Wi) for each parameter were assigned based on their importance and then normalized to eliminate scale differences.

Total Erodibility Index (EI) is defined for each sub-watershed by the following equation:

$$EI = \sum_{j=1}^{n} w_j y_{ij}$$

Where EI

$$W = \frac{Correlation\ coefficient\ sum}{Correlation\ total}$$

2. Sediment Production Rate (SPR) model

SPR was first developed and used by Jose and Das (1982), who developed a sediment production rate model based on geomorphological parameters, linking sediment yield with morphometric characteristics. In contrast, Reid and Dunne (1984) emphasized the influence of hillslope processes and channel dynamics on sediment generation. Collectively, these approaches provided a comprehensive geomorphological framework for assessing sediment yield and identifying priority areas for soil conservation measures.

The SPR values were further used to rank the sub-watersheds of the Karmanasa River Basin by their susceptibility to soil erosion.

SPR Model can be defined as:

$$\log(SPR) = 4919.80 + 48.64\log(100 + Rf) - 1337.77\log(100 + Rc) - 1165.65\log(100 + Cc)$$

Where the SPR, *Rf* defines form factor, *Rc* indicates the circulatory ratio, and *Cc* defines the compactness coefficient.

3. AHP-TOPSIS model

The Analytic Hierarchy Process (AHP), introduced by Thomas L. Saaty in 1980, was employed to determine the relative weights of morphometric parameters. These parameters were selected and weighted based on expert opinion and an extensive review of highly cited scientific studies. A panel of 15 subject specialists assessed the significance of spatial geomorphometric variables contributing to land degradation and increased erosion susceptibility in rugged terrain.

For prioritizing the sub-watersheds, a systematic AHP approach was used. The principal steps involved in the procedure are presented below:

1. A pairwise comparison matrix was prepared to evaluate the relative significance of each criterion within the decision-making framework using equation (1). The matrix was arranged in an n × n format, where n represents the total number of parameters considered in the analysis.

$$D = \begin{bmatrix} a_{11} & a_{12} & a_{1n} \\ a_{21} & a_{22} & a_{2n} \\ . & . & . \\ a_{m1} & a_{m2} & a_{mn} \end{bmatrix}$$

2. The criterion weights were obtained from the pairwise comparison matrix. Normalization was carried out by dividing each element by its corresponding column sum, and the final weights were then computed from the normalized matrix Thomas L. Saaty, 1978).
3. The consistency of assigned weights was calculated using the consistency ratio (CR). The CR was calculated as:

$$CR = \frac{CI}{RI}$$

Where Consistency Index (CI) is $CI = \frac{\lambda_{max} - n}{n-1}$

Here, λmax represents the maximum eigenvalue of the comparison matrix, while n indicates the number of criteria considered. A consistency ratio (CR) value below 0.10 is regarded as acceptable and signifies satisfactory consistency in the assigned weights, Thomas L. Saaty (1978).

The TOPSIS model (Hwang and Yoon, 1981) evaluates the parameter alternatives based on their Euclidean distances from the positive ideal solution (PIS) and the negative ideal solution (NIS). The initial step is to determine the geometric distances from both the PIS and the NIS.

To enhance clarity, the proposed method is explained systematically below:

a. Construction of the normalization decision matrix:

$$A_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

Where Aij, an element of the normalized decision matrix, and xij is the numerical value of the ith alternative for the jth criterion.

b. Construction of the weighted normalized decision matrix:

Vij = wj * Aij

Where

Vij indicates the weighted normalized matrix,

Aij denotes the normalization decision matrix, and wj represents the weight of criterion j.

c. Determine positive-ideal and negative-ideal solutions: two alternatives, A+ and A-, can be defined as:

$$A^+ = \left\{\left(\begin{matrix}max\\ i\end{matrix} V_{ij} | j \in J\right), \left(\begin{matrix}min\\ i\end{matrix} V_{ij} | j \in J'\right) | i = 1,2,3, \dots, m\right\}$$

$$= V_1^+, V_2^+, V_3^+, \dots \dots .. V_j^+ \dots \dots V_n^+$$

$$A^- = \left\{\left(\begin{matrix}min\\ i\end{matrix} V_{ij} | j \in J\right), \left(\begin{matrix}max\\ i\end{matrix} V_{ij} | j \in J'\right) | i = 1,2,3, \dots, m\right\}$$

$$= V_1^-, V_2^-, V_3^-, \dots \dots .. V_j^- \dots \dots V_n^-$$

Where J= {j=1,2, 3, …., n|j it is benefit criteria}

J'= {j=1,2, 3, …., n|j it is cost criteria}

d. Calculation of the separation measure:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_i^+\right)^2}, i = 1,2,3, \dots ., m$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_i^-\right)^2}, i = 1,2,3, \ldots., m$$

e. Calculation of the relative closeness to the ideal solution:

$$C_i^+ = 1 - \frac{S_i^+}{S_i^+ + S_i^-};\ 0 < C_i^+ < 1$$

i = 1, 2, 3, …., m

When $C_i^+ = 1$ if $S_i^+ = 0$, indicating alternative exhibits zero separation from the PIS,

$C_i^+ = 0$ if $S_i^- = 0$, indicating zero separation from the NIS.

6. Integrated Statistical Validation of Erosion Prioritization Models

To identify the most effective model for soil erosion prioritization among the multi-criteria decision-making approaches (AHP–TOPSIS, WSA, and SPR), nonparametric correlation analyses were performed on the final rankings. The Spearman Correlation Coefficient (SCCT) and Kendall's Tau Correlation Coefficient tests (KTCCT) were employed for this purpose (Sadhasivam et al., 2020; Pomerol & Barba-Romero, 2000).

In general, watershed characterization and erosion studies adopt rankings rather than absolute numerical values, and

Kendall's tau test provides a reliable statistical measure for comparing models by examining the relative ordering of all possible rank pairs. Since it is entirely rank-based, the method does not require assumptions about the data distribution, unlike parametric correlation techniques.

Kendall's tau is expressed as:

$$\tau = \frac{C - D}{\frac{n(n-1)}{2}}$$

Where c is the number of concordant pairs, and D is the number of discordant pairs, n is the total number of sub-watersheds.

Spearman's Rank Correlation (rs) is a nonparametric statistical method used to determine the degree of association between two independent ranking systems by measuring the strength and direction of their monotonic relationship.

The coefficient is expressed:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

Here, n represents the total number of ranked sub-watersheds, while di denotes the difference between the ranks assigned by the models for the sub-watershed.

7. Methodology

Demarcation of the drainage network and Morphometric Analysis

The drainage network and watershed boundaries were delineated in ArcMap 10.8 using Shuttle Radar Topography Mission (SRTM) DEM data with a 30 m spatial resolution. Several hydrological processing steps, including sink filling, flow direction, flow accumulation, stream ordering, watershed delineation, and drainage basin extraction, were performed to derive the drainage system and sub-watershed boundaries. The Karmanasa River Basin was divided into six sub-watersheds (SW1–SW6). Among them, SW-3 is the largest, covering 2142.21 km², whereas SW-6 is the smallest, at 804.510 km² (Figure 4).

Figure 4 Drainage map with the stream orders

After delineating the sub-watershed boundaries and drainage network of the basin, morphometric analysis becomes essential for assessing the susceptibility of individual sub-watersheds to soil erosion and for prioritizing the basin. The morphometric characteristics are grouped into three categories: linear, areal, and relief aspects (Table 1).

The watershed parameters like stream order, stream number, stream length, stream frequency, drainage density, drainage texture, drainage intensity, bifurcation ratio, mean bifurcation ratio, length of overland flow, mean stream length ratio, constant of channel maintenance, infiltration number, and Rho coefficient collectively describe the structural and drainage behavior of the channel network.

Areal parameters such as basin length, basin area, perimeter, circulatory ratio, elongation ratio, form factor, compactness coefficient, lemniscate ratio, and shape index are used to quantify the spatial form and geometry of the drainage basin.

Figure 5: a) Slope and b) Drainage density map of the basin

Relief parameters, including basin relief, relief ratio, and ruggedness number, represent the vertical characteristics of the terrain and indicate slope steepness and elevation variability across the watershed (Tables 2 &3).

8. Result

Morphometric Analysis

Linear Parameters

Stream order refers to the hierarchical ranking of streams within a drainage basin, as proposed by Strahler (1964). In this classification system, first-order streams represent the smallest channels with no tributaries. When two streams of the same order merge, they form a stream of the next higher order, and this process continues throughout the drainage network. In the KRB, six sub-watersheds were identified, with first-order streams ranging from 52 to 136, second-order streams from 12 to 30, third-order streams from 2 to 7, and fourth-order streams from 1 to 3. Fifth-order streams were represented by two channels, while only a single sixth-order stream occurred within the sub-watersheds (Table 3).

Horton (1945) found that the number of streams declines exponentially with increasing stream order, and this parameter is influenced by many physical and biophysical variables, such as basin relief, slope characteristics, and lithology, which collectively control runoff generation and drainage development (Table 3). Among the sub-watersheds, SW3 recorded the highest total stream count (177), whereas SW6 exhibited the lowest number of streams (72).

Watershed stream length (Lu) provides basic information about the basin's hydrological behavior. It is important to calculate surface runoff, groundwater infiltration, and the basin's response under different hydrological conditions. Stream length is completely influenced by the topography, geology, structure, land-use patterns, and climate within the river basin (Horton, 1945). Generally, longer stream segments are associated with gentler slopes, greater surface runoff, and lower infiltration rates. In contrast, steeper terrains promote rapid runoff, enhanced erosional activity, finer drainage texture, and relatively shorter stream channels (Strahler, 1964) (Table 3).

The stream length ratio (RL) provides insights into the geomorphic development and various stages of the drainage basin. It is calculated as the ratio of the mean length of streams of a given order to that of the next higher order (Horton, 1945). Variations in this parameter reflect differences in basin morphology and play a substantial role in controlling erosion and discharge characteristics (Thomas et al., 2010; Kanhaiya et al., 2018; Singh et al., 2018) (Table S1).

The bifurcation ratio (Rb) represents stream segments of a particular order to the number of stream segments in the immediately succeeding higher order (Schumm, 1956). The bifurcation ratios across all stream orders in the watershed range from 2.90 to 4.86 (Table 4). A higher value of Rb indicates strong structural influences on drainage development and is often associated with hydrograph peaks, increased flood discharge, and enhanced susceptibility to soil erosion (Strahler, 1964).

Areal Aspects

It is observed that in basins with higher drainage density, there is more runoff, less infiltration, and fine-grained soil formations, which promote greater soil erosion. The Karmanasa river basin and sub-watersheds no. SW5 had the highest drainage density (0.535) (Figure 5b), whereas SW2 had the lowest (0.393) (Table 4). Stream frequency (Fs) is expressed as the number of stream segments per unit area of a watershed (Horton, 1945). The basin's geological characteristics largely influence this parameter, indicating drainage texture and runoff potential. In the present study, stream frequency values ranged from 3.91 to 9.99 across the sub-watersheds (Table 4).

Drainage texture (Dt) is defined as the ratio of the total number of stream segments to the basin perimeter (Horton, 1945). It is an important morphometric parameter that reflects the combined effects of lithology, slope characteristics, vegetation cover, infiltration capacity, and the degree of drainage development within a watershed. In the present study, drainage texture values range from 0.21 to 0.60, indicating that all sub-watersheds have very coarse drainage texture (Table 4).

The form factor (Ff) is defined as the ratio of the basin area to the square of the basin length (Horton, 1945). It is a useful indicator of basin shape, describing whether a watershed is elongated or circular. Form factor values approach 1.0 for circular basins and decrease toward 0 for elongated basins (Table 4). Lower form factor values generally indicate

elongated watersheds, which tend to exhibit lower peak flows and greater susceptibility to soil erosion due to prolonged runoff concentration times.

Rc Values close to 1.0 indicate a nearly circular, more mature basin, whereas values below 0.4 indicate an elongated drainage basin. Rc values controlled by several factors, including stream length, drainage frequency, basin relief, land use, and climatic conditions, influence the circularity ratio. In the present study, Rc values range from 0.09 to 0.33, indicating that the sub-watersheds are predominantly elongated (Table 4). The elongation ratio of the basin ranges from 0.51 to 0.54, indicating elongated basins characteristic of a youthful stage of landscape evolution (Table 4). The basins are commonly associated with steeper slopes and a greater potential for soil erosion. The length of overland flow (Lg) plays an important role in understanding watershed hydrology and erosion processes. Higher Lg values indicate longer flow paths, which can increase runoff accumulation, channel discharge, and erosive power. In the Karmanasa River Basin, the length of overland flow ranges from 0.68 to 0.79 across the sub-watersheds (Table 4). The compactness coefficient (Cc) reflects the watershed's overall compactness and geometric configuration and influences its hydrological response and erosion characteristics. Lower values indicate more compact basins, while higher values indicate elongated basins. In the study area, the compactness coefficient values vary from 1.7 to 3.2, indicating considerable variation in basin shape among the sub-watersheds.

Relief characteristics provide important information about elevation variation and the topographic complexity of a drainage basin. In the Karmanasa River Basin, the elevation of the six sub-watersheds ranges from 52.50 m to 642.16 m, indicating considerable topographic variability and a generally rugged landscape (Table 2). The basin relief values for the six sub-watersheds vary from 176.93 m to 575.16 m, while the relative relief ranges between 0.71 and 1.97, reflecting variations in terrain steepness and erosional potential.

The relief ratio (Rh), proposed by Schumm (1956), is a measure of the slope of a surface. Higher relief ratio values are generally associated with steep slopes, rapid surface runoff, and increased soil erosion. In the study area, Rh values range from 2.32 to 6.78, suggesting moderate to high relief conditions across the sub-watersheds. The ruggedness number (Rn), introduced by Schumm (1956), ranges from 0.09 to 0.28, indicating relatively low terrain ruggedness and predominantly gentle-to-moderately undulating topography.

In the present study, HI values range from 0.083 to 0.454. Sub-watersheds with HI values between 0.35 and 0.50 are interpreted as being in the mature stage of geomorphic

development. In contrast, values below 0.35 indicate an old or highly eroded stage of landscape evolution. The hypsometric curves exhibit a transition from convex to concave forms, suggesting that the basin has undergone substantial erosion and has reached a relatively stable geomorphic condition (Strahler, 1952) (Figure 6).

Sub-Watershed prioritization for Soil Erosion Using WSA and SPR model

The WSA model was applied using the correlation matrix of 22 morphometric parameters (Table S2), and compound factor (CF) rankings derived from the WSA approach are presented in Table 5. The computed WSA scores range from 1.682 to 3.198, with WS4 recording the lowest score and therefore receiving the highest priority for soil erosion management, whereas WS1, with the highest score, was assigned the lowest priority (Table S3) (Figure 7a).

The sediment production rate (SPR) values were calculated for each sub-watershed using the logarithmic SPR equation (Equation 2), incorporating key morphometric parameters, including form factor (Rf), circularity ratio (Rc), and compactness coefficient (Cc). The calculated SPR values among the six sub-watersheds varied considerably, ranging from 0.000013 in SW6 to 0.50 in SW5 (Table 6) (Figure 7b).

AHP–TOPSIS Approach for Soil Erosion-Based Watershed Prioritization

The AHP–TOPSIS approach was implemented using 14 selected morphometric parameters as decision criteria. A pairwise comparison matrix was developed and evaluated by 15 domain experts. Weights and rankings were assigned based on each parameter's relative influence on soil erosion (Table S4 & S5). The consistency of the judgments was confirmed by the consistency ratio (CR = 0.016237), which is below the acceptable threshold of 0.10, indicating reliable, consistent results. The TOPSIS analysis produced closeness coefficient (Cl^+) values for the six sub-watersheds ranging from 0.22 to 0.75 (Figure 8).

9. Discussion

Identifying erosion-prone zones is essential to support effective planning and sustainable watershed management. However, the limited availability and uncertainty of field-based data affect the calculation and estimation of soil erosion. In such cases, an innovative, integrated approach that combines modeling tools and satellite data provides valuable information to prioritize sub-watersheds and control erosion. In the Karmanasa River Basin, relatively low drainage density values (0.34–0.53 km/km²) indicate higher permeability and porosity in

Kaimur Group sandstones than in Himalayan catchments. Stream frequency is higher in areas underlain by impermeable Bijaigarh Shale, which are characterized by steep slopes and sparse vegetation, collectively promoting greater surface runoff and increased channel development. Few sub-watersheds correspond to zones of active gully erosion and easily erodible shale formations, confirming its effectiveness in identifying erosion-sensitive areas. A positive relationship between relief ratio and sediment yield was established by Schumm (1963) and later supported in Indian basins by. Basin slope also plays a crucial role in controlling erosion rates by influencing splash detachment and overland flow velocity. Steeper slopes, combined with reduced vegetation cover due to deforestation and agricultural expansion, constitute the most erosion-prone conditions in the basin (Yadav et al., 2016).

The downstream transition from Kaimur sandstone to Quaternary alluvium introduces fine-textured floodplain deposits that are highly vulnerable to lateral bank erosion and monsoon-induced flooding, contributing substantial sediment loads to the Ganga River system. Three multi-criteria decision-making (MCDM) approaches, WSA, SPR, and AHP–TOPSIS, were applied for sub-watershed prioritization. Among these, the AHP method is widely adopted because it provides a structured framework for assigning weights and ranking criteria according to their relative importance.

The results of the study indicate that AHP–TOPSIS yields the most consistent prioritization outcomes, with the highest correlation values in both KTCCT and SCCT compared with the WSA and SPR models. The spatial pattern of erosion susceptibility derived from WSA reflects clear lithological and topographical controls within the basin. Linear morphometric parameters show a strong positive correlation, whereas shape parameters generally exhibit a negative relationship with linear attributes. Very high-priority sub-watersheds, particularly WS4, are located on the Kaimur plateau and in the transitional zones between the plateau and the alluvial plain, where steep slopes, high drainage density, and erodible Rewa Shale formations collectively create highly favourable conditions for intense soil erosion.

The (SPR) varies significantly across the six sub-watersheds, ranging from 0.000013 in SW6 to 0.50 in SW5, indicating considerable spatial variability in sediment generation. Based on SPR classification, SW5 is identified as the most erosion-prone sub-watershed, falling under the very high priority category (SPR = 0.50). The zones were approximately 25% high-risk for erosion, with SW3 and SW1 grouped in the high-priority category (SPR > 0.3), while SW2 is classified as low priority (SPR ≈ 0.004). The very-low-priority class (SPR < 0.004)

includes SW2 and SW6. The AHP results indicate that linear morphometric parameters, particularly drainage density (Dd: 0.168) and stream frequency (Fs: 0.061), play a major role in erosion susceptibility. In contrast, shape-related parameters (Re, Rf, Rc, K, and Cc), which indirectly influence erosion, were assigned lower weights. The AHP–TOPSIS results indicate that WS-3, WS-2, and WS-1 fall into the very high erosion-priority category. At the same time, WS-3 represents the high-priority group, and WS-6 exhibits the lowest susceptibility. Overall, the very high-priority sub-watersheds identified through the AHP–TOPSIS model account for approximately 46% of the total basin area.

SCCT and KTCCT-Based Model Comparison

The performance of the MCDM models was evaluated using non-parametric correlation statistics derived from all pairwise model comparisons. The results of SCCT and KTCCT analyses are presented in Table 7. The AHP–TOPSIS model shows a positive correlation with the SPR approach in the SCCT test (SCCT = 0.37), whereas the WSA model exhibits only weak relationships with the outputs of both SPR and AHP–TOPSIS. Overall, AHP–TOPSIS exhibits the highest mean correlation across both statistical tests, indicating its superior reliability for prioritizing sub-watershed erosion in the Karmanasa River Basin. AHP–TOPSIS and SPR (0.37) show a significant level of agreement between the two models, and both are the same sub-watersheds (WS3, WS4, and WS5) susceptible to erosion.

Soil Conservation Measures and Management Recommendations

The soil conservation measures required to manage an entire river basin are often challenging; therefore, this study prioritizes sub-watersheds by identifying those highly susceptible to soil erosion. This approach provides a cost-effective and sustainable alternative to conventional watershed prioritization methods. Based on the final ranking from the most reliable model, sub-watersheds classified as very high- to high-priority require immediate and comprehensive management interventions to reduce the risk of soil erosion and land degradation in the Karmanasa River Basin (Table 8).

Conclusion

This study presents a morphometric investigation and MCDM-based prioritization of sub-watersheds in the Karmanasa River Basin, a geomorphologically dynamic catchment located along the Uttar Pradesh–Bihar border. Using SRTM DEM data and GIS techniques, 22 morphometric parameters were derived for delineating six sub-watersheds. In addition, three

multi-criteria decision-making approaches—WSA, SPR, and AHP–TOPSIS—were employed to evaluate erosion susceptibility across the basin.

The major observations of the study show that the basin has a 6th-order drainage network with relatively high drainage density (mean Dd = 0.535), notable ruggedness (Rn up to 0.28), and a youthful-to-mature stage of geomorphic evolution, collectively indicating moderate-to-high erosion susceptibility at the basin scale. The WSA approach indicates that SW4 is a very high-priority erosion zone covering nearly 40% of the basin area. The SPR analysis revealed that about 42.67% of the basin experiences high sediment production, with WS5 and WS3 emerging as the most critical sub-watersheds.

The AHP–TOPSIS model, incorporating expert-derived weights to improve decision reliability, classified WS3, WS1, and WS2 as high-priority zones, with closeness coefficients ranging from 0.227 to 0.755. (5) Non-parametric correlation tests (SCCT and KTCCT) confirm that AHP–TOPSIS yields the most stable and consistent prioritization results, consistent with findings from previous comparative studies. (6) Spatial analysis shows that the highest erosion susceptibility is concentrated in the Kaimur Plateau and plateau–plain transition zones, primarily due to erodible Vindhyan sandstone, steep slopes, high drainage density, and limited vegetation cover.

Overall, the integrated morphometric–MCDM framework provides a transferable and cost-effective approach for erosion risk assessment in data-limited Vindhyan and Gangetic tributary basins. The results offer a strong scientific basis for targeted soil and water conservation planning by the governments of Uttar Pradesh and Bihar, and also contribute to India's commitments under the UNCCD and the Sustainable Development Goals (SDGs).

Funding Declaration: The authors declare that the proposed work did not receive any financial support or funding from any agency.

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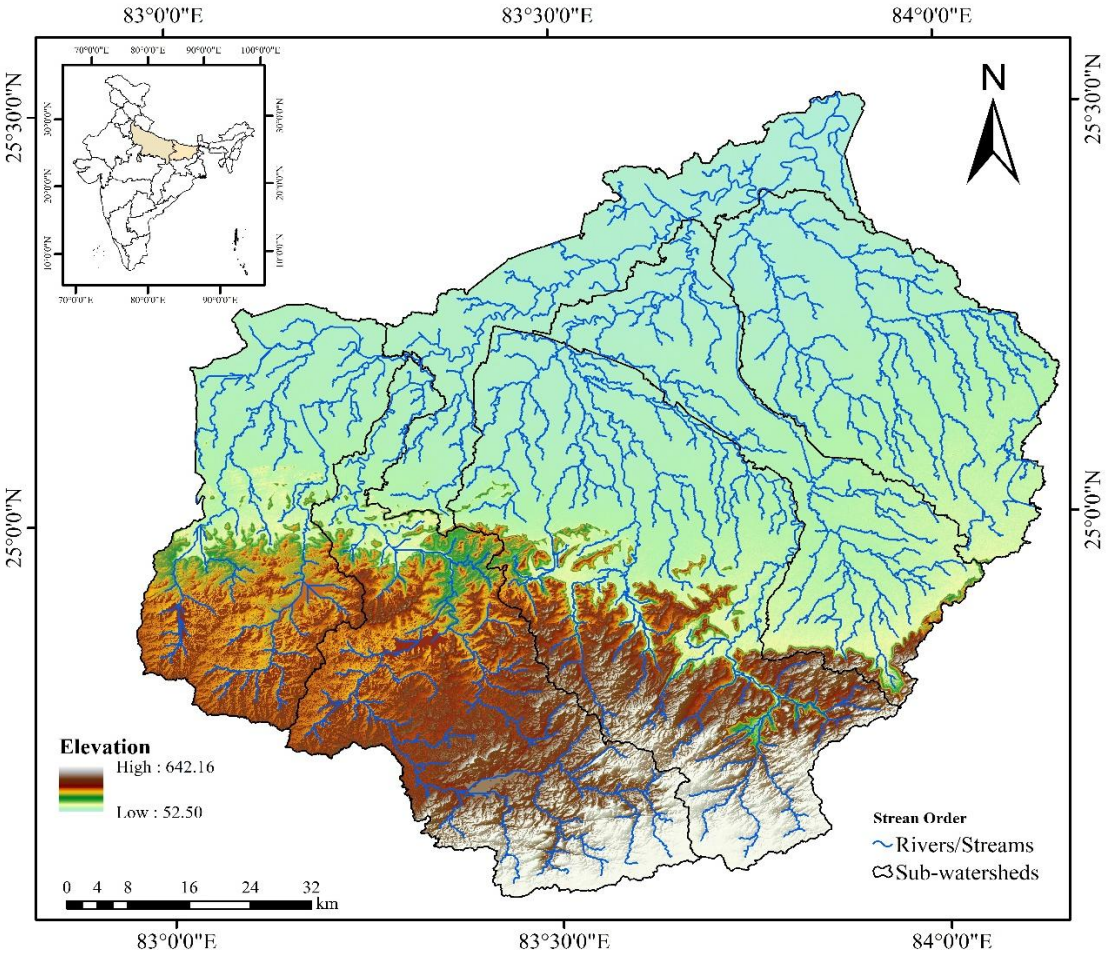


Figure 1 Location map of the Karmanasa River Basin



Figure 2: Field photos of different locations of the basin representing different Geomorphic features.

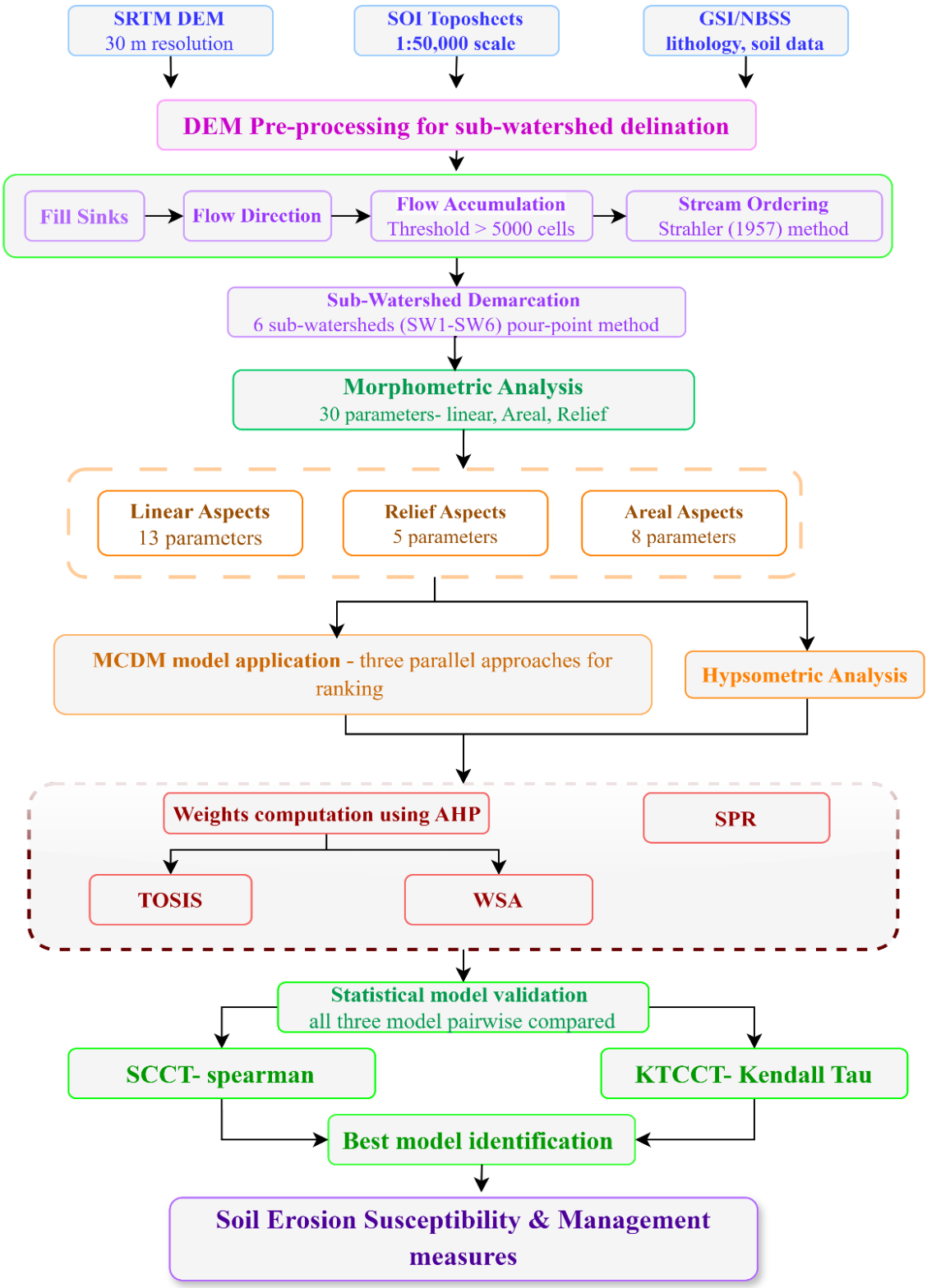


Figure 3 : Flowchart of the methodology followed

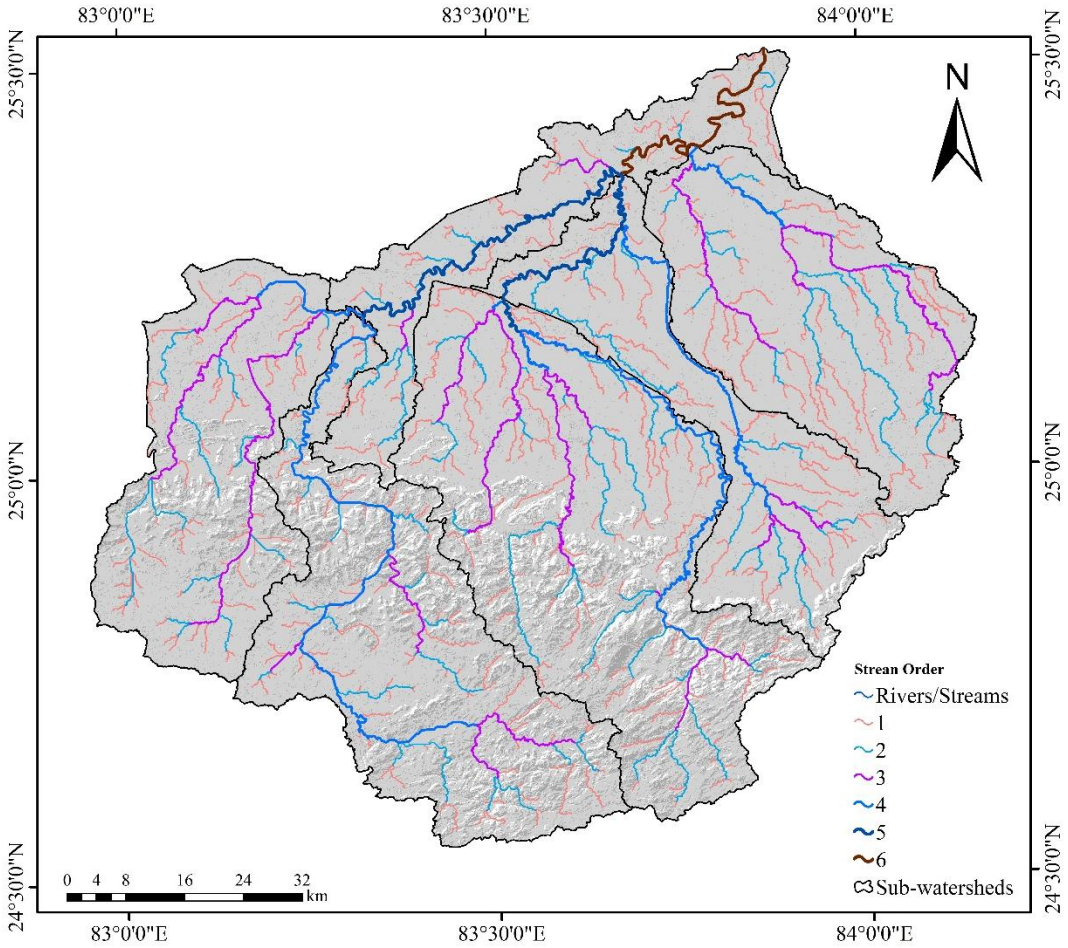


Figure 4 Drainage map with the stream orders

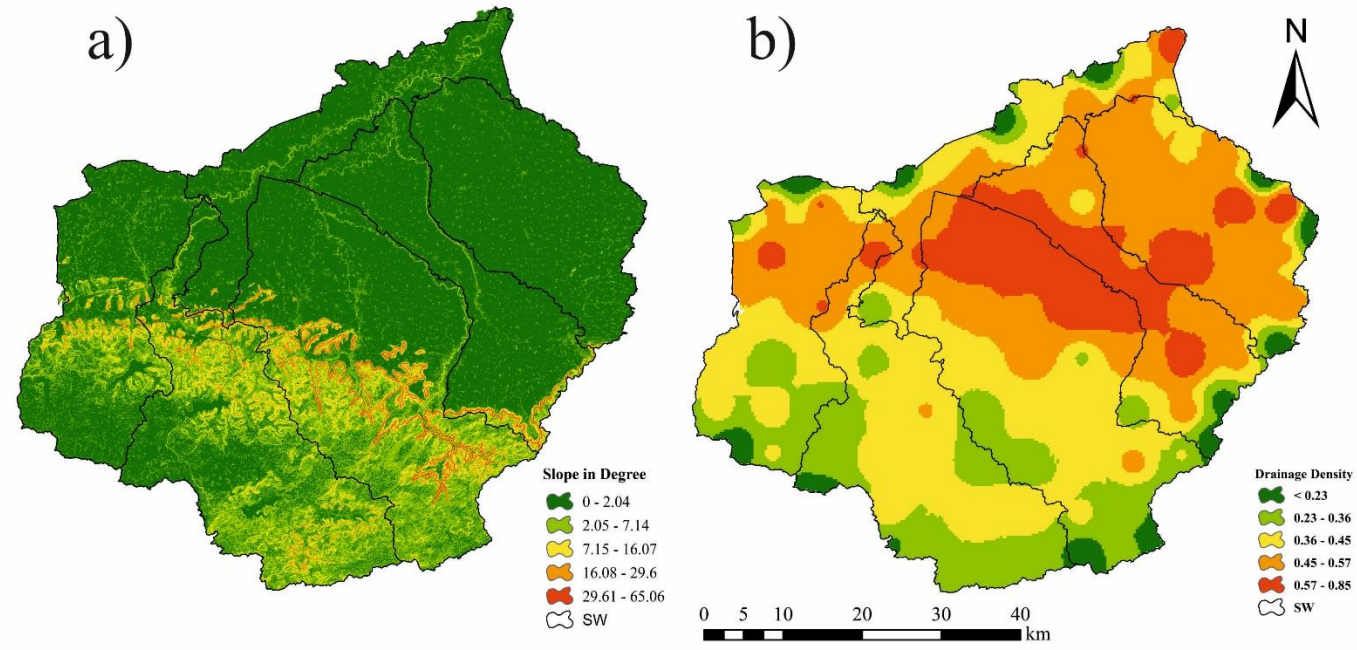


Figure 5: a) Slope and b) Drainage density map of the basin

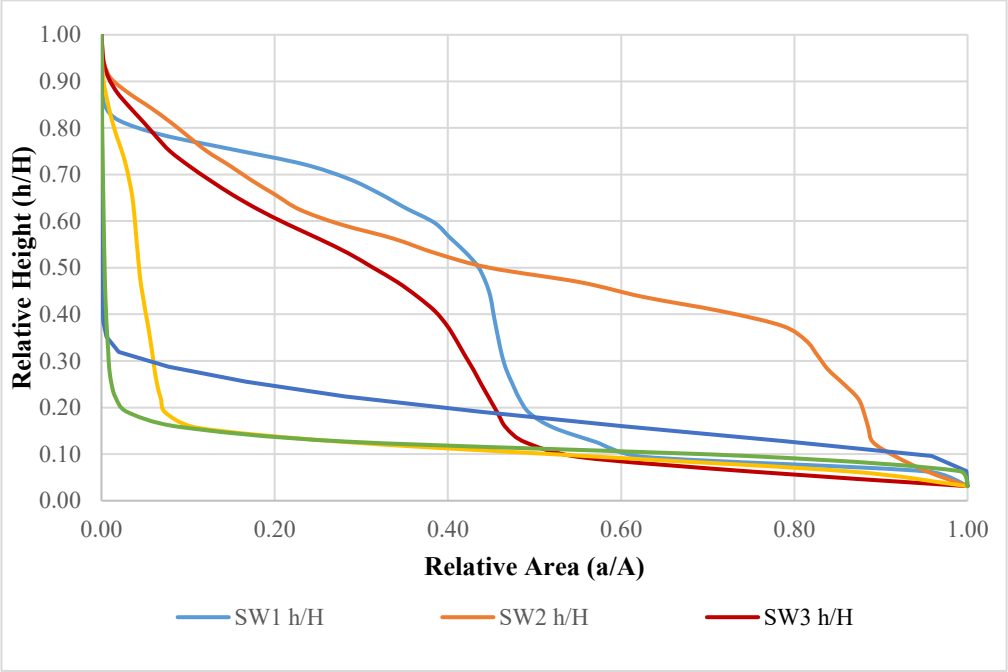


Figure 6: Hypsometric curves of sub-watersheds showing the stages of development.

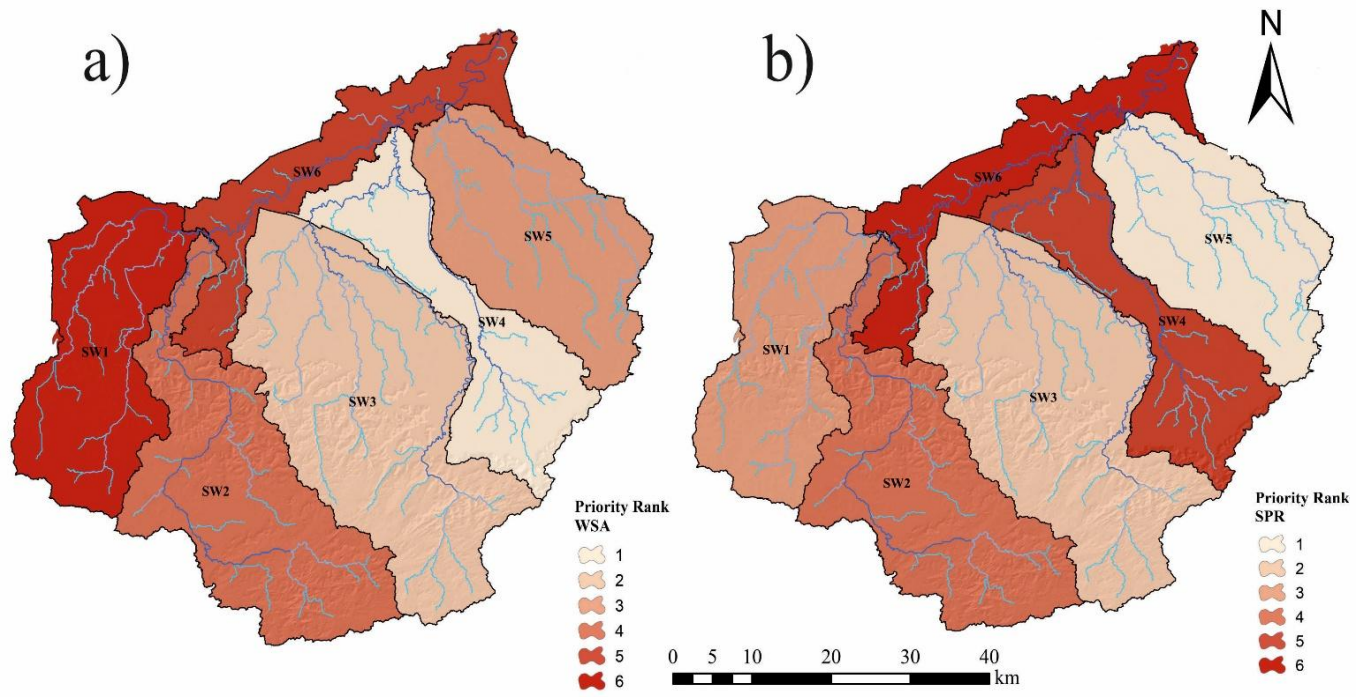


Figure 7: Soil Erosion Priority based on WSA and SPR model

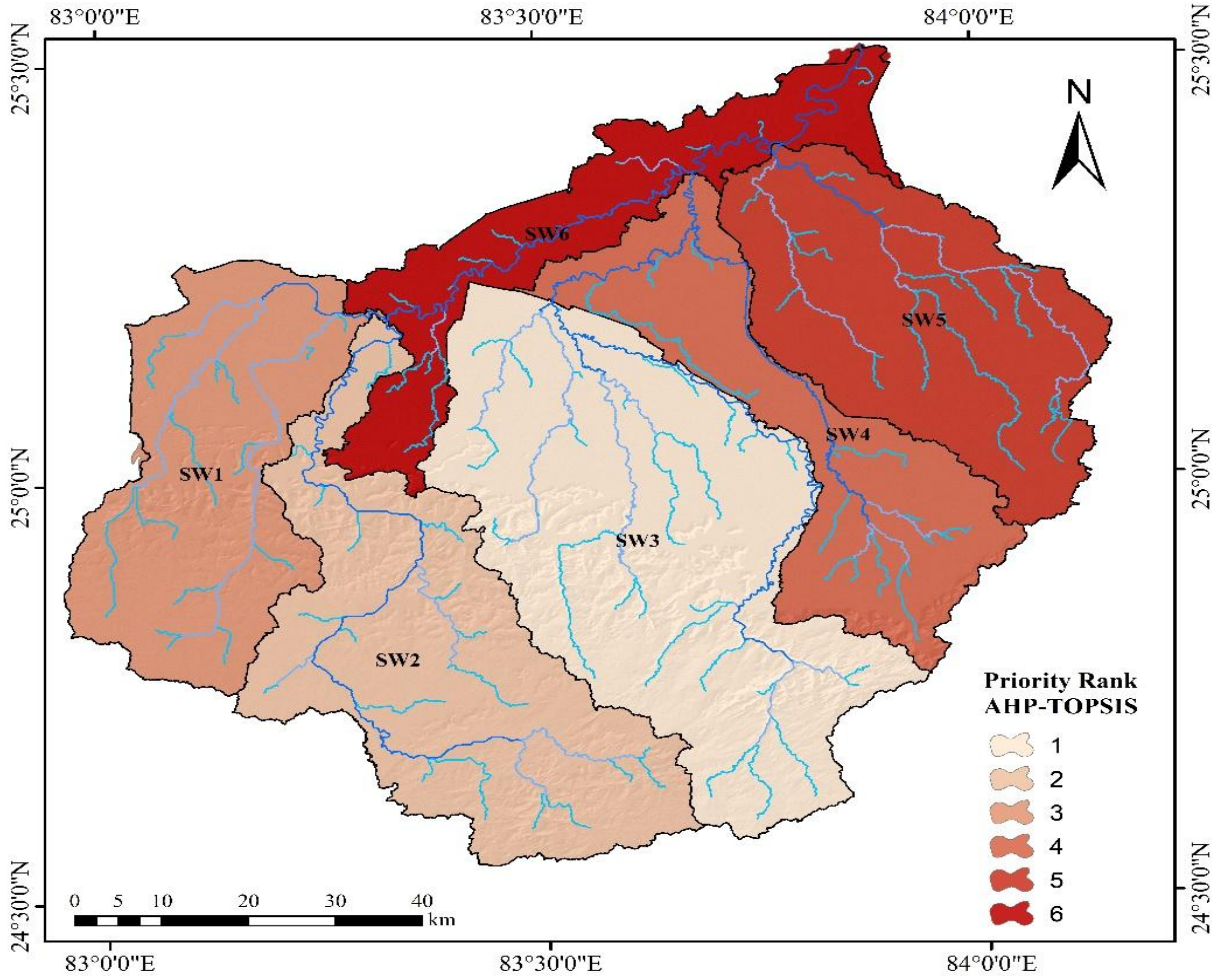


Figure 8: Soil Erosion Priority based on AHP-TOPSIS model

Supplementary Files

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