



Original Paper

# Nagmati River Sub-watershed Prioritization Using PCA, Integrated PCWS, and AHP: A Case Study

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Prioritization of potential regions that are severely threatened by soil erosion is a prerequisite for formulating and implementing conservation measures and management practices, particularly in fragile semiarid regions. The present study prioritized eight delineated Nagmati sub-watersheds located in the Kutch District of Gujarat State, India, based on three approaches, namely principal component analysis (PCA), integrated PCA with weighted sum (I-PCWS), and analytical hierarchy process (AHP), and on 10 morphometric erosion risk parameters (ERPs). Sub-watersheds were categorized into three priority classes, namely high, medium, and low. PCA retrieved the three most significant ERPs (i.e., length of overland flow, *Lo*; drainage texture, *Dt*; and compactness coefficient, *Cc*) explaining 86.876% of the variance and exhibiting the highest correlation, i.e.,  $r = 0.961$ ,  $0.986$ , and  $0.934$  for the first three principal components. Sub-watersheds SW2 and SW7 were rated high priority, SW1 was rated low priority, and the rest were rated medium priority. The I-PCWS approach revealed that sub-watersheds SW2, SW6, and SW7 were in high-priority zone, followed by SW3, SW4, and SW8 in medium-priority zone and SW1 and SW5 in the low-priority zone. The AHP assigned the highest and lowest ranks to “*Lo*” and “*Cc*,” respectively, with consistency ratio of 8.1% and principal eigenvalue of 11.075. Results from AHP revealed sub-watershed SW2 to be the highest priority and sub-watersheds SW1 and SW5 to be the lowest priority. Out of eight prioritized sub-watersheds from three approaches, five were found to be the common priority classes, with SW2, SW6, and SW7 demanding urgent implementation of efficient soil conservation measures to prevent further degradation of the identified regions. Results from I-PCWS approach closely complied with the existing land-forms within the study area, and this approach was considered more reliable and robust than the other two approaches. The methodology adopted in this study can be applied to different vulnerable, data-scarce regions to sustainably manage and conserve soil erosion through efficiently framed strategies.

**KEY WORDS:** Nagmati watershed, GIS and remote sensing, Morphometric analysis, Prioritization, PCA, AHP.

## INTRODUCTION

A watershed is any portion of the earth's surface defined by topographic slopes that converts precipitation into runoff and diverts it to a single drainage outlet, preferably at a lower elevation, that ultimately meets another water body. In other

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words, a watershed carries water that has been “shed” from any geographical region after rainfall and snow melts. Watersheds play a prominent role in the evolution of landforms; hence, they are important in geomorphic studies.

Morphometry deals with the statistical and mathematical analysis of the earth's surface configuration, landforms, and proportions (Clarke 1996). Watershed analysis can be achieved through measurement of linear, aerial, and relief aspects by employing remote sensing (RS) and geographic information system (GIS) techniques. Morphometric characteristics, including stream order, drainage density, aerial extent, watershed length and width, channel length, channel slope, and relief, are crucial in interpreting the hydrological response of a watershed. The morphometric characteristics of any region directly influence the hydrological behavior, leading to variation in flood frequencies, soil erosion, and sedimentation, which, in turn, indirectly affect the weather conditions and ecology of an area. Therefore, there is a need for a precise analysis of the hydrology at the drainage outlet (Fazelniya et al. 2012). At the national level, many studies have focused on morphometric analysis over varied watershed conditions using RS and GIS (Nautiyal 1994; Srivastava 1997; Nag 1998; Nag and Chakraborty 2003; Srinavasa et al. 2004; Chopra et al. 2005; Joshi et al. 2005; Tiwari et al. 2008; Rekha et al. 2011; Meshram and Sharma 2017; Chandniha and Kansal 2017; Said et al. 2018; Sahu et al. 2018).

Prioritization of watersheds includes assigning ranks to sub-watersheds as per the degree of vulnerability-based upon several factors, such as average annual soil loss, water resource depletion, and ecological degradation. Sub-watershed prioritization facilitates the development of effective strategies for controlling sediment yield and consequently managing soil erosion within an area. Owing to the complexity of variables involved in soil erosion, it is difficult to precisely evaluate or forecast the level of erosion taking place. In earlier studies, watershed prioritization was achieved by utilizing different approaches to account for soil erosion modeling or sediment yield indexing (SYI), morphological characterization, and socioeconomic perspectives, whereas other studies focused on classification of the erosion-prone priority areas (Nookaratnam et al. 2005; Pandey et al. 2009; Niraula et al. 2011; Pai et al. 2011).

Morphometric analysis and prioritization of sub-watersheds involve RS, GIS, mathematical and

statistical procedures, and multiple criteria decision making (MCDM) (Singh 1994; Grohmann 2004; Sreedevi et al. 2009; Aher et al. 2010; Rao et al. 2011). Nookaratnam et al. (2005) analyzed check dam positioning through prioritization of micro-watersheds employing SYI model and morphometric analysis, based on RS and GIS, in the Midnapur District of West Bengal. Arun et al. (2005) employed a rule-based physiographic characterization of a drought-prone watershed through RS and GIS techniques in the Gandeshwari watershed in the Bankura District of West Bengal. Aher et al. (2013) utilized the fuzzy analytical hierarchy process (F-AHP)-based approach to prioritize the Pim Palagon watershed in India based on nine morphometric parameters. Results revealed that around 61% of the total region was classified as moderate-to-extreme priority, indicating the need for urgent intervention. Mishra et al. (2007) prioritized the sub-watersheds of a semi-humid tropical ecosystems in India based on morphometric parameters through the soil and water assessment tool (SWAT). The fuzzy MCDM method was employed by Vivien et al. (2011) for prioritizing the sub-watersheds to identify the most effective environmental management strategies. Arami et al. (2017) prioritized watersheds using F-AHP to assist in the implementation of government-based conservation measures. Hence, the integrated use of RS, GIS, and AHP/F-AHP is regarded as a reliable technique for morphometric analysis and the precise prioritization of sub-watersheds (Sreedevi et al. 2009; Aher et al. 2010).

Other multivariate statistical approaches, namely cluster analysis (CA), principal component analysis (PCA), and factor analysis (FA), are helpful in determining principal components (PCs) that account for maximum variance of the morphometric parameters (Ouyang et al. 2006; Shrestha and Kazama 2007; Sharma et al. 2010). These techniques are designed to minimize the variable count while preserving the relationships in the actual data. Numerous studies have been carried out using PCA for sub-watershed prioritization as well as potential water quality index identification (Gajbhiye et al. 2010, 2015) and geo-morphometric characterization (Sharma et al. 2009). Mangan et al. (2019) applied the PCA technique to eight sub-watersheds of the Kanhiya Nala watershed in Madhya Pradesh, India, to categorize the selected parameters under various components using correlation analysis. The results revealed that some parameters bear a strong correlation with the components; however, the hypso-

metric integral did not exhibit any correlation with the PCs.

The rapid and extensive deterioration of farmlands in arid and semiarid regions necessitates the accurate evaluation of watershed runoff and sediment yield, which allows for improvements in government sustainable conservation programs and policies (Gajbhiye et al. 2014; Singh and Singh 2018; Kadam et al. 2019). Farhan et al. (2017) prioritized 43 sub-watersheds of the Zerqa watershed in northern Jordan via morphometric analysis and PCA approach, which revealed morphometric analysis to be more consistent than the PCA approach. Zhou et al. (2018) proposed the combination AHP-PCA method to evaluate the significance of parameters toward sustainability assessments of water resources in the Jinsha River Basin, China, while reducing the existing dispersions involved in the traditional AHP approach. The PCA and AHP have been widely utilized in diverse engineering and bio-engineering applications, such as in vitro diagnostic research, constituting a critical aspect of the modern drug creation process (Ting et al. 2019). The PCA and AHP have been used to elucidate the role and inter-dependence of governing factors in the effective management of the international manufacturing network (IMN) (Mishra et al. 2019), in the suitability analysis of geomagnetic aided navigation systems (Zhang et al. 2019), and in the analysis of human errors involved in railway accidents, using the human factors analysis and classification system (HFACS) (Zhou and Lei 2018). Furthermore, recent studies have demonstrated more effective methodologies for sub-watershed prioritization, which involve hybridization of PCA and the weighted sum approach (WSA). Malik et al. (2019) successfully employed this hybridized PCWS approach to prioritize nine sub-watersheds of the Bino watershed in India and revealed that the proposed hybrid approach was more dynamic and efficient compared to the traditional watershed prioritization methods.

The present study investigates the performance of AHP, PCA, and I-PCWS toward sub-watershed prioritization of the semiarid, data-scarce Nagmati River watershed, located in the Kutch District of Gujarat in India, utilizing RS data and a GIS framework. The Nagmati watershed was delineated into eight sub-watersheds (i.e., SW1 to SW8) for morphometric analysis and prioritization of the most vulnerable regions where the immediate implementation of soil conservation measures is needed.

## STUDY AREA AND DATA USED

The Nagmati River watershed is located in the Bhuj City of the Kutch District in Gujarat and covers an area of 129.41 km<sup>2</sup> between longitudes 69° 31' E to 69° 41' E and latitudes 23° 4' N to 23° 12' N (Fig. 1).

The elevation of the watershed ranges from a maximum of 259 m above the mean sea level (mamsl) to a minimum of 58 mamsl. The climate of the district is semiarid, with an average annual rainfall of approximately 358 mm. The average annual temperature is 26.3 °C, with maximum temperatures exceeding 48 °C during the summer season and the minimum temperatures ranging from 10 °C to 12 °C during winters (Kachchh 2016). The western state is characterized by four distinct seasons: pre-monsoon (March to May), post-monsoon (October and November), winter (December to February), and monsoon (June to September). Ninety-seven small rivers flow through the district on which 20 major dams, and numerous smaller dams are constructed to capture the runoff generated from precipitation. Farming is the primary source of sustenance for the agrarian population that constitutes mostly a tribal community. Recurring drought together with enhanced groundwater exploitation has resulted in lowering of the groundwater table at an alarming rate in the region.

The present study utilizes linear and aerial morphometric parameters for the prioritization of the Nagmati sub-watersheds, namely drainage density (*Dd*), stream frequency (*Fs*), length of overland flow (*Lo*), bifurcation ratio (*Rb*), drainage texture (*Dt*), circularity ratio (*Rc*), elongation ratio (*Re*), form factor (*Rf*), basin shape (*Bs*), and compactness coefficient (*Cc*), by employing AHP, PCA, and I-PCWS techniques. The 1:50,000 topographic map (No. F42-D12) and CartoDEM with 2.5-m resolution (Fig. 2) were acquired for generating the drainage map of the study area and used as a base map for the study. Attributes were assigned to generate a digital database of the drainage network layer of the Nagmati watershed. The CartoDEM is an Indian National DEM generated from Cartosat-1 stereo data that fulfills the specifications of height and horizontal accuracies at a 90% confidence level as compared with ASTERDEM and SRTM data. Moreover, CartoDEM exhibits fairly high-quality drainage demarcation capabilities (Muralikrishnan 2012). The ArcGIS (version 10.2) software was uti-

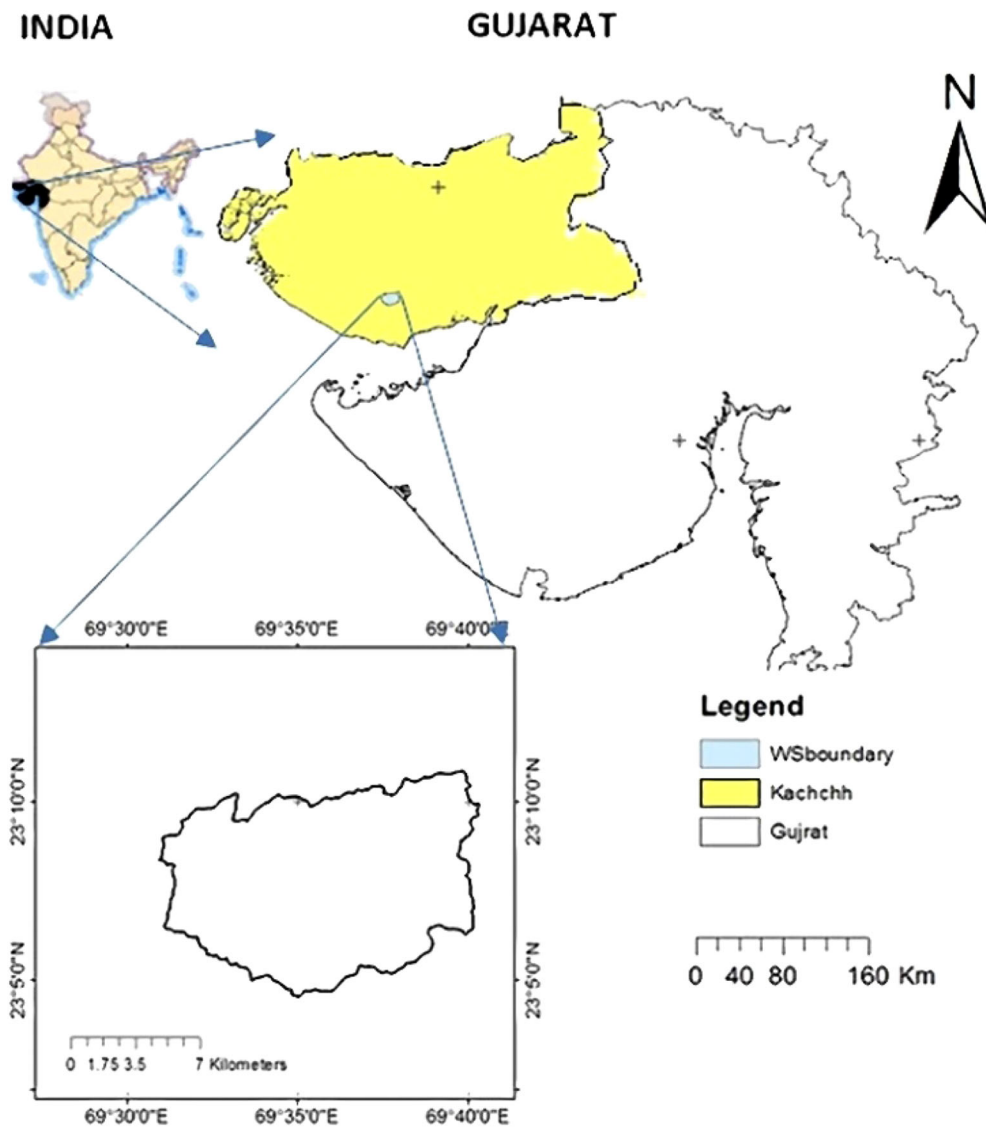


Figure 1. Location map of the study area (Nagmati watershed).

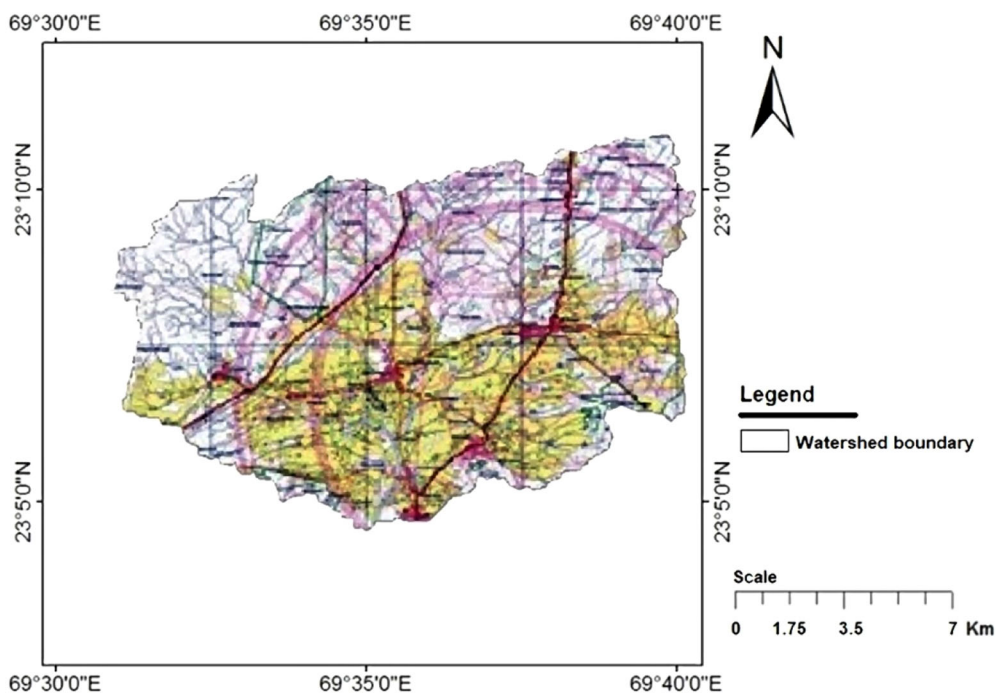
lized for generating thematic maps along with other relevant data.

## RESEARCH METHODOLOGY

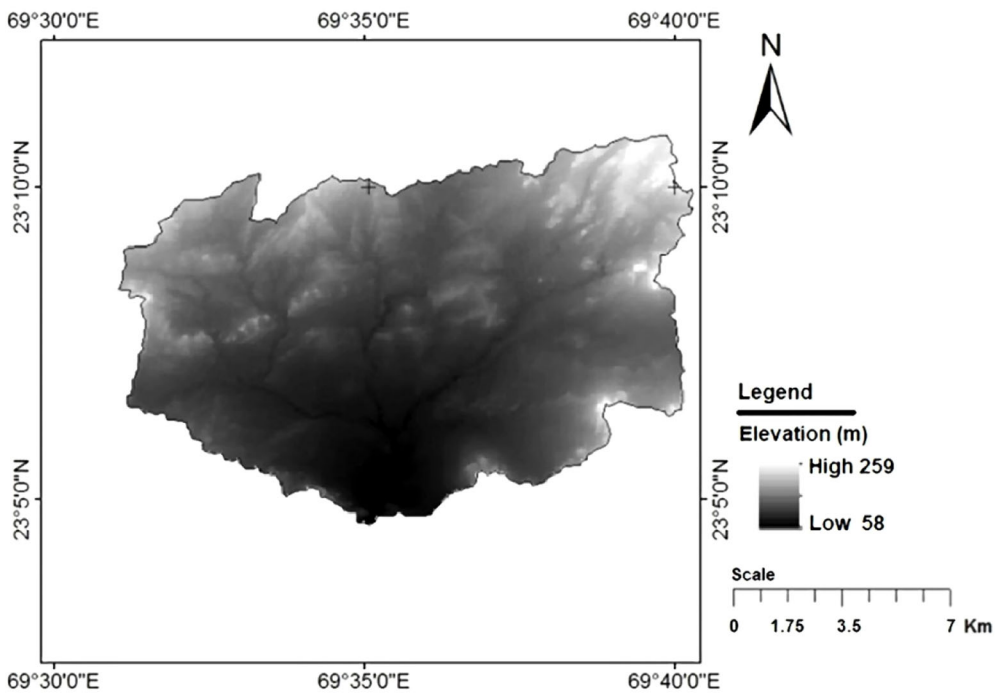
### Drainage Network Analysis and Delineation of Sub-watersheds

The CartoDEM of the study area was downloaded from the Indian space research organization (ISRO) geo-portal, Bhuvan ([www.bhuvan.nrsc.gov.in/](http://www.bhuvan.nrsc.gov.in/)),

in tagged information file format (TIFF) format. CartoDEM along with the topographic map was utilized to delineate the watershed boundary and generate the drainage network map (Fig. 3a) comprising a pattern of stream coverage each assigned with a unique identifier in accordance with the order, following Horton's law of stream order (Horton 1945). The number of streams of each order was recorded and the fundamental morphometric parameters, namely stream numbers ( $N_s$ ), stream length ( $L_w$ ), watershed area ( $A$ ), perimeter ( $P$ ), and

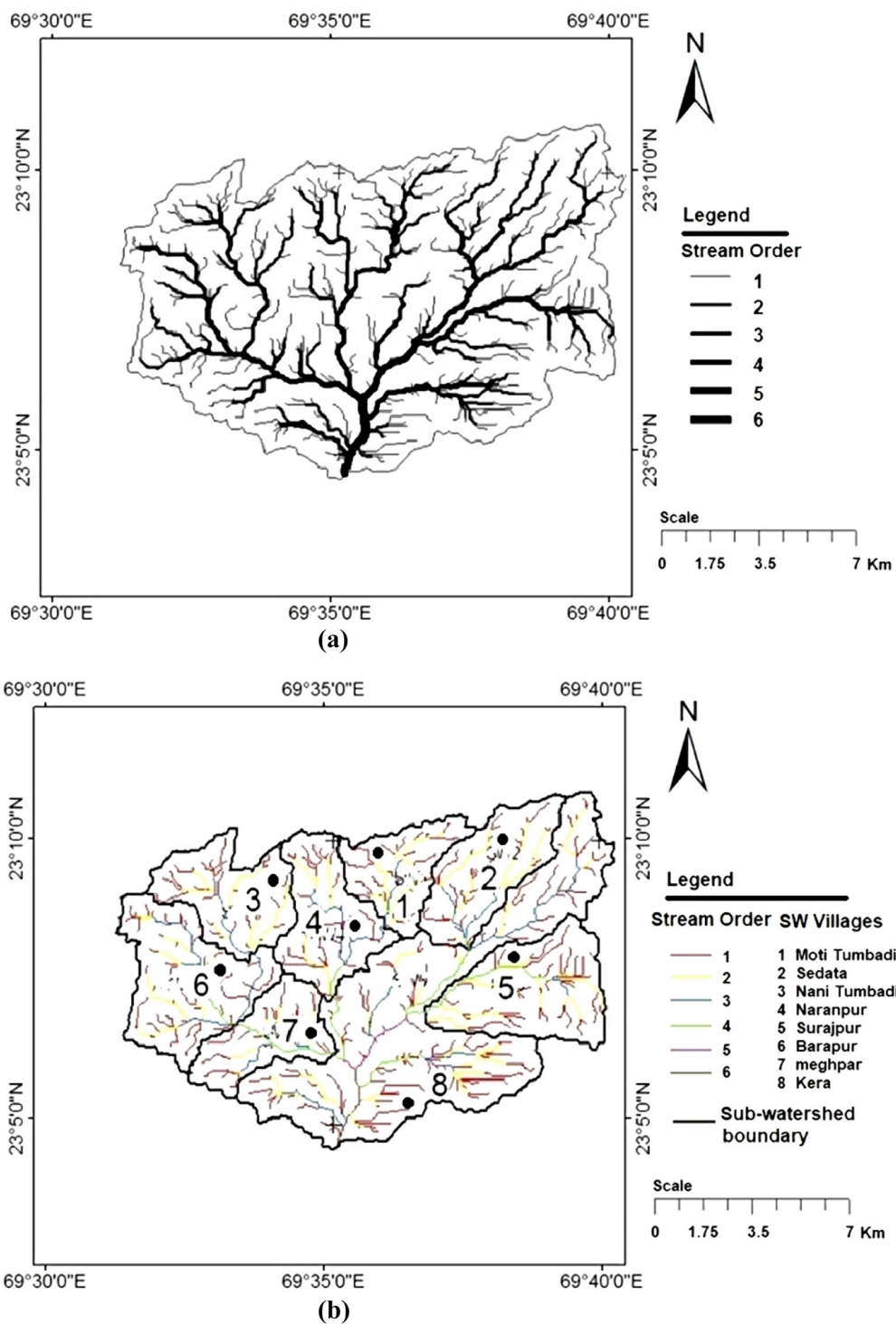


(a)



(b)

Figure 2. (a) Survey of India Topo-sheet No F42-D12. (b) CartoDEM of Nagmati watershed.



**Figure 3.** (a) Drainage network map of the study area with stream order. (b) Delineated sub-watersheds of the Nagmati River Basin (black dots represent the existing villages within each sub-watershed).

basin length ( $L$ ), were obtained from the stream network map.

The medium-sized Nagmati watershed was subdivided into eight sub-watersheds based on ridgelines, water divide, contours, and other hydro-morphological features in conjunction with the CartoDEM. The sub-watershed boundaries were delineated by considering existing villages within each sub-watershed (Fig. 3b). Sub-watersheds were assigned labels SW1 to SW8 in sequence from the smallest (SW1), 8.576 km<sup>2</sup>, to the largest (SW8), 43.671 km<sup>2</sup>.

### Morphometric Analysis

Morphometric analysis was used to examine the characteristics and geometry of the entire watershed as well as at the sub-watershed level. The linear and areal morphometric parameters of the watershed were evaluated using standard formulae proposed by Horton (1932, 1945), Strahler (1964), Miller (1953), Melton (1957), and Faniran (1968), which are presented in Table 1.

Ten ERPs were utilized for sub-watershed prioritization:  $Dd$ ,  $Fs$ ,  $Lo$ ,  $Rb$ ,  $Dt$ ,  $Rc$ ,  $Re$ ,  $Rf$ ,  $Bs$ , and  $Cc$ . The drainage pattern of any geographical area reveals significant information at the surface as well as subsurface level. The  $Dd$  is evaluated in terms of km/km<sup>2</sup>, and it reflects the closeness of channel spacing. The higher the  $Dd$ , the greater the run-off. Therefore,  $Dd$  accounts for the run-off generated in the area or the volume of rainwater that would percolate. The  $Fs$  defines the total number of stream segments of all orders per unit area (Horton 1932). Low  $Fs$  values indicate an area with low relief with permeable subsurface strata. The  $Rf$  signifies the shape of the watershed, which determines the stream discharge characteristics. The  $Rf$  can be defined as the ratio of the watershed to the square of watershed length (Horton 1932). Smaller values of  $Rf$  indicate an elongated watershed shape. The  $Rc$  defines the shape measured with respect to the stream flow in the sub-watershed (Miller 1953). The  $Rc$  is mainly governed by the length and frequency of stream, geological structures, land use/land cover, relief, and slope of the watershed. The  $Re$  is the ratio of watershed circumference to the watershed length. A circular watershed is more effective in run-off generation than an elongated one (Singh 1967). The value of  $Re$  generally varies from 0.6 to 1.0; values close to 1.0 signify low relief, and values ranging

from 0.6 to 0.8 represent high relief and steep slope (Strahler 1964). The  $Rb$  is an indicator of relief and dissection of streams, as per Horton (1945). Strahler (1957) established that  $Rb$  is highly influenced by geological factors with lower values implying a structurally less disturbed watershed. The length of overland flow ( $Lo$ ) denotes the flow of precipitated water leading to the formation of stream channels. The  $Lo$  is more significant in smaller watersheds. The  $Dt$  expresses the relative channel spacing, which depends on the underlying lithology, infiltration capacity, and relief aspect, and it is considered as an important factor in the morphometric analysis. The  $Cc$  is the measure of watershed shape measured as the ratio of watershed perimeter to the circumference of the watershed area. As the  $Cc$  value reaches 1.0, the watershed shape corresponds to a perfect circle. If the  $Cc$  value is 1.3, the catchment is more square-shaped, whereas when the  $Cc$  value is  $> 3.0$ , the catchment is considered elongated (Zavoianu 1985). The  $Bs$  refers to the ratio of the square of the basin length to the corresponding area and indicates the circular nature of the watershed.

### Prioritization of Sub-watersheds Using PCA

PCA is a multivariate statistical technique for reducing the dimensionality of a data set by maintaining the reliability of the original data. Trimming is achieved by converting the original data into two or more principal components, which are uncorrelated and orthogonal to each other and arranged according to their relative significance. An essential feature of the new orthogonal components accounts for upholding of total maximum variance of the variables. The first PC comprises a single parameter or few parameters that account for the maximum variance in the data set, while successive components represent low or negligible variance inferring that none of the components is correlated with each other. The method is most suited when all variables are measured at the same scale. PCA can be employed for almost all geo-morphometric parameters to obtain the PCs and to ascertain the most significant parameters. PCA was carried out following the four broad steps discussed below.

In the first step, the data set was standardized to enhance the performance of PCA. Standardization was carried out by subtracting each data value from the overall mean and dividing it by the standard deviation of the data set. This process transforms the

**Table 1.** Standard formulae for computation of morphometric parameters

S. No.	Morphometric parameters	Formula/definition	References
1	Bifurcation ratio ( <i>Rb</i> )	$Rb = Nu/Nu + 1$ , where <i>Rb</i> = bifurcation ratio, <i>Nu</i> = total number of stream segments of order <i>u</i> , and <i>Nu + 1</i> = number of stream segment of next higher order	Schumm (1956)
2	Drainage density, km/km <sup>2</sup>	$D_d = L/A$ , where <i>L</i> = total length of stream and <i>A</i> = area of basin.	Horton (1945)
3	Stream frequency ( <i>F<sub>s</sub></i> )	$F_s = \Sigma Nu/A$ , where <i>Nu</i> = total number of stream segments of all orders	Horton (1945)
4	Length of overland flow	$Lo = 1/2 D_d$ , where <i>D<sub>d</sub></i> is drainage density	Horton (1945)
5	Basin shape	$Bs = (L_b)^2/A$ , where <i>A</i> = area of basin and <i>L<sub>b</sub></i> = basin length	Horton (1945)
6	Form factor	$R_f = A/(L_b)^2$ , where <i>A</i> = area of basin and <i>L<sub>b</sub></i> = basin length	Horton (1932)
7	Elongation ratio	$Re = (2/L_b) \times \sqrt{(A/\pi)}$ , where <i>A</i> = area of basin, $\pi = 3.14$ , and <i>L<sub>b</sub></i> = basin length	Schumm (1956)
8	Circularity ratio	$Rc = 2\pi (A/P^2)$ , where <i>A</i> = area of basin, $\pi = 3.14$ , and <i>P</i> = perimeter of basin	Miller (1953)
9	Compactness coefficient ( <i>C<sub>c</sub></i> )	$C_c = 0.2821 \times P/A^{0.5}$ , where <i>A</i> = area of the basin, km <sup>2</sup> , and <i>P</i> = basin perimeter, km	Horton (1945)
10	Drainage texture ( <i>D<sub>t</sub></i> )	$D_t = Nu/P$	Horton (1945)

entire data to have zero mean and unit standard deviation. The process was achieved as follows:

$$Z = (c_{ij} - c_j)/S_j \tag{1}$$

where *Z* denotes the standardized matrix of parameters, *c<sub>ij</sub>* stands for *i*th observation on the *j*th parameter, *i* ranges from 1, 2...*n* (number of observation), *j* ranges from 1, 2...*p* (number of parameters), *c<sub>j</sub>* mean of the *j*th parameters, and *S<sub>j</sub>* standard deviation of the *j*th parameter.

The second step involved the computation of the covariance matrix in order to identify any possible correlation between the variables of the data set. Let us assume *Z* matrix of *n* observations, and *p* number of PCs may be represented in the matrix notation as:

$$Z = X \times P \tag{2}$$

where *Z* and *X* are the *n* × *p* matrices and *P* indicates coefficient matrix with *p* × *p* dimension, *j*th PC *Z<sub>j</sub>* is generally expressed as:

$$Z_j = Xa_j \text{ for } j = 1, 2, \dots, p \tag{3}$$

where *Z<sub>j</sub>* is *n* × 1 (column) vector and *a<sub>j</sub>* is *p* × 1 (column) vector of coefficients. In general, the covariance matrix is represented as:

$$C = \frac{X'X}{(n-1)} = \begin{bmatrix} c_{11} & \dots & c_{1p} \\ \vdots & \ddots & \vdots \\ c_{p1} & \dots & c_{pp} \end{bmatrix} \tag{4}$$

where *X'* denotes the transpose of the standardized matrix of *X* predictor variables. Every covariance matrix element is evaluated as:

$$c_{ij} = \frac{1}{(n-1)} \sum_{k=1}^n X_{kj}X_{ki} \tag{5}$$

In step three, the eigenvalues and eigenvectors for the covariance matrix were calculated to determine the PCs of the data. If  $\lambda'$  is an eigenvalue for covariance matrix *C*, the solution can be explained through the characteristic equation as:

$$|(C - \lambda'I)| = 0 \tag{6}$$

where *I* is the identity matrix of the same dimension (i.e., *p* × *p*) as *C* and is regarded as a necessary condition for matrix subtraction. For every eigenvalue  $\lambda'$ , the corresponding eigenvector, *v*, can be solved as:

$$|(C - \lambda'I)| \times v = 0 \tag{7}$$

If the eigenvalues are ranked in decreasing order, we get  $\lambda'1 > \lambda'2$ , suggesting that the eigenvector



corresponding to the first PC (PC1) is  $v_1$  and the one that corresponds to the second PC (PC2) is  $v_2$ .

The fourth and final step dealt with the formation of the feature vector and PCs. The feature vector is a matrix of eigenvectors, corresponding to the largest eigenvalue (i.e., PC1) or simply both PC1 and PC2 if there are two PCs. The final PC loading matrix was formed by taking the transpose of the feature vector and left-multiplying it with the transpose of a scaled version of the original data set and represents a degree of correlation between the  $X$  variables and the different  $F$  factors that is equivalent to the correlation between the  $X$  variables and the  $Z$  PCs. As a result, the PC loading matrix was obtained by pre-multiplying the square roots of the eigenvalues of the  $C$  matrix with the characteristics values of the correlation matrix ( $P$ ). The PC loading matrix ( $R$ ) can be written as:

$$R = PD^{1/2} \tag{8}$$

where  $D^{1/2}$  represents the diagonal matrix featuring nonzero elements as reciprocals of the square roots of the eigenvalues of the  $C$  matrix expressed by Eq. 4. In this study, the eigenvalues and eigenvectors were calculated using Eqs. 6 and 7, and a rotated loading matrix of the available variables was obtained for identifying the most significant morphometric parameters for prioritization of the Nagmati sub-watersheds.

### Prioritization of Sub-watersheds Using I-PCWS

The I-PCWS approach was employed to the significant morphometric parameters identified through PCA to calculate the compound parameter ( $C_p$ ) value for assigning the final priority ranking of each morphometric parameter. The mathematical expression for  $C_p$  computation can be written as (Aher et al. 2014; Kadam et al. 2017; Singh and Singh 2018):

$$C_p = PR_{MP} \times W_{MP} \tag{9}$$

where  $C_p$  is the compound parameter,  $PR_{MP}$  is preliminary priority rank of the significant morphometric parameter identified through PCA, and  $W_{MP}$  is the weight of the significant morphometric parameter obtained using cross-correlation analysis and it is expressed as:

$$W_{MP} = \frac{\text{Sum of correlation coefficient}}{\text{Grand total of correlation}}. \tag{10}$$

The final ranking was carried out with respect to  $C_p$  values such that the highest  $C_p$  was assigned the priority rank 1, next higher  $C_p$  was assigned the rank of 2, and so on for all eight sub-watersheds of the Nagmati watershed.

### Prioritization of Sub-watersheds Using AHP

The AHP is a powerful MCDM approach that enables the organization and analysis of complicated problems and ascertains the assessment consistency (Saaty 1980; Mishra et al. 2013). The AHP generates a matrix of pairwise comparisons among the erosion risk morphometric parameters. The parameters are scaled from 1 to 9, where 1 suggests that two parameters are equally important and 9 indicates that one parameter is extremely important than the other. The reciprocal of 1 to 9 (i.e., 1/1 to 1/9) expresses less importance of one parameter to the other. Table 2 illustrates Saaty’s rating scale relating the preferences on a one-to-one basis for each criterion.

Assigning of ranks to the parameters under consideration relates to the relative importance of parameter, which was determined by expert opinions and using Pearson’s inter-correlation among the considered ERPs. To complete the comparison matrix, each parameter was compared with other parameters, with a total number of  ${}^n C_2$  comparisons. If the judgement criteria lie to the left side of the diagonals in the comparison matrix (constituting the upper portion from the diagonals), then the lower portion of the matrix is loaded by the reciprocal values of the upper triangular matrix and, hence, the comparison matrix is obtained, which is followed by

**Table 2.** Saaty’s rating scale of relative importance (Saaty 2005)

Scale	Numerical rating	Reciprocal
Extremely Preferred	9	1/9
Very strong to extremely	8	1/8
Very strongly preferred	7	1/7
Strongly to very strongly	6	1/6
Strongly preferred	5	1/5
Moderately to strongly	4	1/4
Moderately preferred	3	1/3
Equally to moderately	2	1/2
Equally preferred	1	1

the standardized matrix. Standardization of the pairwise comparison matrix was carried out by dividing each criterion of the column cell by the column sum. Each standardized criterion in a matrix cell (priority vector) represents the total column sum. The pairwise comparison matrix after standardization enables the calculation of relative weights for assessing the influence of each criterion (i.e., ERPs) on surface erosion (Zolekar and Bhagat 2015). The average of the sum of the criteria in a row of the standardized matrix defines the weight of each criterion (Zolekar and Bhagat 2015; Maddahi et al. 2017). The stepwise procedure adopted for AHP is explained as follows.

A standardized comparison matrix  $Z_{std}$  ( $m \times m$ ) is obtained by making the sum of all the values of each column-wise criterion equal to 1, and the standardized value of each matrix cell, i.e.,  $\bar{a}_{ij}$  is obtained as follows:

$$\bar{a}_{ij} = \frac{a_{ij}}{\sum_{l=1}^m a_{il}} \quad (11)$$

where  $a_{ij}$  is the non-standardized criteria value with respect to the  $i$ th criterion relative to the  $j$ th criterion. The next step is to calculate the criteria weight  $w_i$  ( $m$ -dimensional column vector), which is obtained by averaging the sum of all the standardized criterion values in each row of  $Z_{std}$ :

$$w_i = \frac{\sum_{l=1}^m \bar{a}_{il}}{m} \quad (12)$$

The consistency check is performed to ascertain the appropriateness of the relative importance of the parameters with respect to each other by obtaining the consistency ratio (CR) defined as the ratio of consistency index (CI) to the random consistency index (RCI). The CR can be computed as:

$$CR = \frac{CI}{RI} \quad (13)$$

The consistency index represents the measure of consistency, and it is computed as:

$$CI = \frac{\lambda_{MAX} - m}{m - 1} \quad (14)$$

where  $\lambda_{MAX}$  is the principal eigenvalue obtained from the priority matrix and  $m$  is the size of the comparison matrix, also referred to as the number of criteria.  $\lambda_{MAX}$  is determined by summing up the products between each element of eigenvector and the sum of columns of the reciprocal matrix. Saaty

(2005) evaluated  $RI$  values for the number of criteria, which are presented in Table 3.

Using  $RI$  and  $\lambda_{MAX}$ ,  $CI$  is evaluated whose value if less than 0.1 establishes the consistent decision for the weights to be accepted. In the present study, 10 different ERPs were utilized for prioritization of Nagmati sub-watersheds through AHP.

## RESULTS

### Morphometric Analysis

The morphometric analysis reveals the Nagmati watershed as sixth order, suggesting significant surface runoff generation and sediment yield into the stream channels. The stream network is dominated by dendritic drainage patterns, which further exemplify homogeneity in texture and lack of structural control. The mean  $Rb$  for the watershed was 3.438, signifying less interference of geologic structures to the drainage pattern. The value of  $Dd$  for the watershed was evaluated as 2.686 km/km<sup>2</sup>, indicating that the study area is composed of highly permeable strata with relatively flat relief. The  $Fs$  was 3.801, indicating that the watershed generates greater runoff. The  $Dt$  value of 8.38 indicates that the area is comprised of very fine texture soft rocks unprotected by vegetation. The  $Rf$  value of 0.722 corresponds to an almost circular shape of the watershed, and the  $Rc$  value of 0.471 indicates that the watershed shape is partially elongated with a moderate runoff discharge. The  $Re$  value for the watershed of 0.956 indicates that the watershed is circular. The  $Lo$  value of the study area of 0.186 km suggests low relief and consequently low to moderate surface runoff. The above discussed morphometric parameters (ERPs) evaluated for Nagmati River watershed and its sub-watersheds are summarized in Table 4.

Table 4 further depicts the highest value of  $Dd$  (i.e., 2.913) for SW5 and the lowest for SW3 (i.e., 2.522) because SW5 is characterized by agricultural fields and barren farmlands, whereas most of the region comprises sparse agricultural fields, low relief with permeable subsoil material, and lies in the moderate category of  $Dd$ . Furthermore, the  $Fs$  values for the sub-watersheds ranges from 3.401 (for SW3) to 5.07 (for SW7), revealing relatively flat relief and permeable subsurface strata for lower values and resistant to low conducting subsurface strata with high relief for higher  $Fs$  values. The  $Rf$  values

Table 3. RI values among number of criteria

<i>m</i>	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
<i>RI</i>	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Table 4. Evaluated ERPs of Nagmati river watershed and its sub-watersheds

S. No.	Morphometric parameters	Entire WS*	SW1	SW2	SW3	SW4	SW5	SW6	SW7	SW8
1	Rb	3.438	5.510	3.262	5.875	5.911	3.737	3.694	3.21	3.507
2	Dd	2.686	2.856	2.573	2.522	2.815	2.913	2.564	2.572	2.707
3	Fs	3.801	4.198	3.395	3.401	3.377	4.152	3.906	5.07	3.64
4	Lo	0.186	0.175	0.194	0.198	0.178	0.171	0.195	0.194	0.184
5	Bs	1.384	1.34	1.27	1.406	2.4	2.161	1.834	1.554	4.117
6	Rf	0.722	0.746	0.787	0.711	0.417	0.462	0.545	0.643	0.242
7	Re	0.956	0.974	0.784	0.951	0.728	0.767	0.833	0.904	0.555
8	Rc	0.471	0.427	0.524	0.418	0.449	0.592	0.455	0.466	0.201
9	Cc	1.455	1.529	1.382	1.546	1.493	1.299	1.483	1.464	2.23
10	Dt	8.38	2.267	2.378	2.102	2.196	3.566	3.032	2.973	3.043

\*Watershed, SW sub-watershed

obtained for the sub-watersheds vary from 0.242 (for SW8) to 0.787 (for SW2), indicating elongated to circular shapes. The higher *Re* values for sub-watersheds SW1, SW3, and SW7 (i.e., > 0.9) indicate circular shape, whereas sub-watersheds SW2, SW4, SW5, and SW6 with moderate *Re* are categorized as oval to less elongated and SW8 with lower *Re* value (i.e., 0.555) has an elongated shape.

**Inter-correlations Among the ERPs**

The inter-correlation matrix was generated using SPSS statistical software for analyzing the degree of association among the 10 selected ERPs (Table 5). The inter-correlation matrix reveals strong correlations (i.e.,  $r \geq 0.9$ ) between *Dd* and *Lo*, *Rf* and *Bs*, and *Rc* and *Cc*. Likewise, there are fairly good correlations (i.e.,  $0.75 \leq r \leq 0.9$ ) between *Re* and *Rf*, *Re* and *Bs*, and *Bs* and *Cc*. Table 5 presents a few more moderately correlated parameters (i.e.,  $r \geq 0.6$ ), namely *Dd* and *Fs*, *Rb* and *Dt*, *Dt* and *Cc*, *Rc* and *Bs*, *Re* and *Cc*, *Rf* and *Cc*, and *Bs* and *Rc*.

The inter-correlation matrix, however, induces difficulty in grouping the parameters into components based on their importance in the region’s vulnerability. Hence, the inter-correlation matrix was subjected to PCA for categorizing the ERPs

into PCs. Table 6 illustrates the total variance explained by the ERPs wherein the first three components (i.e., PC1, PC2, and PC3) account for 86.876% of the total variance. The inter-correlation matrix was also utilized for assigning the relative importance among ERPs for performing the AHP analysis.

**PCA**

PCA indicates the priority ERPs for soil and water conservation by expressing the relationships between the parameters. The analysis generates a PC loading matrix, which depicts the strength of association or correlation between the morphometric parameters and the corresponding component. Through PCA, three significant components were evaluated, and the 10 ERPs were reduced to three PCs. The PCA, therefore, generates the first factor loading matrix and thereafter the rotated loading matrix using orthogonal transformation. The first un-rotated factor loading matrix generated from the inter-correlation matrix is shown in Table 7, which reveals the PC1 to be strongly correlated (i.e.,  $r \geq 0.9$ ) with *Re*, *Rf*, and *Bs* and a good correlation (i.e.,  $0.75 \leq r \leq 0.9$ ) with *Cc*. The PC2 reveals good correlation with *Lo*, whereas the PC3 exhibits good correlation with *Rb* and moderate correlation

**Table 5.** Inter-correlation matrix of ERPs of Nagmati watershed

	<i>Dd</i>	<i>Fs</i>	<i>Lo</i>	<i>Rb</i>	<i>Dt</i>	<i>Rc</i>	<i>Re</i>	<i>Rf</i>	<i>Bs</i>	<i>Cc</i>
<i>Dd</i>	1.000									
<i>Fs</i>	.064	1.000								
<i>Lo</i>	-.999	-.069	1.000							
<i>Rb</i>	.224	-.380	-.197	1.000						
<i>Dt</i>	.226	.486	-.244	-.716	1.000					
<i>Rc</i>	.146	.198	-.119	-.067	.118	1.000				
<i>Re</i>	-.215	.361	.245	.424	-.390	.455	1.000			
<i>Rf</i>	-.368	.125	.389	.189	-.501	.506	.838	1.000		
<i>Bs</i>	.268	-.202	-.299	-.224	.391	-.715	-.887	-.937	1.000	
<i>Cc</i>	-.053	-.199	.019	-.084	.061	-.970	-.614	-.621	.832	1.000

**Table 6.** Total variance explained for Nagmati watershed

Comp.	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings*		
	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %	Total	% Variance	Cumulative %
1	4.305	43.047	43.047	4.305	43.047	43.047	4.149	41.493	41.493
2	2.363	23.632	66.679	2.363	23.632	66.679	2.448	24.480	65.973
3	2.020	20.196	86.876	2.020	20.196	86.876	2.265	22.650	86.876
4	.895	8.955	95.830						
5	.282	2.824	98.654						
6	.126	1.255	99.909						
7	.009	.091	100.000						
8	2.738E-16	2.738E-15	100.000						
9	0.000E+00	-6.632E-16	100.000						
10	0.000E+00	-1.651E-15	100.000						

\*For correlated components, total variance cannot be obtained by the sums of squared loadings; Comp. components

**Table 7.** Un-rotated matrix

ERP	Component		
	1	2	3
<i>Dd</i>	-0.311	0.712	-0.613
<i>Fs</i>	0.175	0.524	0.493
<i>Lo</i>	0.343	-0.758	0.595
<i>Rb</i>	0.276	-0.271	-0.851
<i>Dt</i>	-0.436	0.637	0.562
<i>Rc</i>	0.684	0.599	0.040
<i>Re</i>	0.900	0.000	-0.071
<i>Rf</i>	0.931	-0.138	0.039
<i>Bs</i>	-0.995	-0.062	-0.0156
<i>Cc</i>	-0.812	-0.470	0.019

**Table 8.** Rotated matrix

ERP	Component		
	1	2	3
<i>Dd</i>	-0.014	0.954	-0.072
<i>Fs</i>	0.341	0.014	0.669
<i>Lo</i>	0.046	<b>-0.986</b>	0.055
<i>Rb</i>	0.183	0.313	-0.900
<i>Dt</i>	-0.191	0.182	<b>0.934</b>
<i>Rc</i>	0.857	0.261	0.251
<i>Re</i>	0.843	-0.147	-0.202
<i>Rf</i>	0.819	-0.327	-0.191
<i>Bs</i>	-0.953	0.1803	0.111
<i>Cc</i>	<b>-0.961</b>	-0.179	-0.112

The bold values represent the most significant ERPs

(i.e.,  $r \geq 0.6$ ) with *Dd*. The results of the un-rotated first-factor loading matrix reveal that some parameters are strongly correlated with the PCs, while some are moderately correlated. Therefore, to overcome the difficulty in identifying a significant component, the first-factor loading matrix was ro-

tated for better interpretation. Table 8 shows the rotated factor loading matrix depicting a highest strong correlation of the PC1 with *Cc*, highest correlation of PC2 with *Lo*, and highest correlation of PC3 with *Dt* and these three parameters were thus

**Table 9.** PCA-based final priorities of Nagmati sub-watersheds

Sub-watershed	Area (km)	Morphometric parameters			<i>Cp</i> value	Final priority
		<i>Lo</i>	<i>Dt</i>	<i>Cc</i>		
SW1	8.576	0.175	2.267	1.529	6.33	1
Rank		7	6	6		
SW2	11.782	0.194	2.378	1.382	3.33	8
Rank		3	5	2		
SW3	11.467	0.198	2.102	1.546	5.33	3
Rank		1	8	7		
SW4	11.844	0.178	2.196	1.493	6	2
Rank		6	7	5		
SW5	15.652	0.171	3.566	1.299	5	4
Rank		8	1	1		
SW6	16.642	0.195	3.032	1.483	4.5	6
Rank		2	3	4		
SW7	9.269	0.194	2.973	1.464	3.66	7
Rank		4	4	3		
SW8	43.671	0.184	3.043	2.23	5	5
Rank		5	2	8		

**Table 10.** Cross-correlation matrix of significant morphometric parameters of Nagmati sub-watersheds

Morphometric parameters	<i>Lo</i>	<i>Dt</i>	<i>Cc</i>
<i>Lo</i>	1	- 0.244	0.019
<i>Dt</i>	- 0.244	1	0.061
<i>Cc</i>	0.019	0.061	1
Sum of correlation	0.775	0.817	1.08
Grand total	2.672	2.672	2.672
Weight	0.290	0.305	0.404

considered in prioritizing the Nagmati sub-watersheds.

Table 9 depicts the *Cp* values for eight sub-watersheds and the final priority computed based on three most significant ERPs (i.e., *Lo*, *Dt*, and *Cc*) obtained from the rotated matrix (Table 8). Priorities of the sub-watersheds in accordance with *Cp* values were grouped into high, medium, and low priorities. As seen in Table 9, SW1 attains the maximum *Cp* value of 6.33 and hence the lowest priority, whereas SW2 achieves the minimum *Cp* value of 3.33 indicating the highest priority.

**I-PCWS**

Prioritization of the eight sub-watersheds was performed using the I-PCWS approach by considering the three identified significant ERPs (i.e., *Lo*, *Dt*, *Cc*) from the PCA. The cross-correlations be-

**Table 11.** Nagmati sub-watersheds final priorities based on I-PCWS

Sub- watershed	<i>Cp</i> value	Final priority
SW1	6.23	1
SW2	3.22	7
SW3	5.57	4
SW4	5.91	3
SW5	6.03	2
SW6	3.11	8
SW7	3.6	6
SW8	5.27	5

tween the significant ERPs were determined (Table 10), and *Cp* values were used for evaluating the final priorities of the eight sub-watersheds by utilizing Eq. 9, and the computations are shown in Table 11. The values of *W<sub>MP</sub>* were obtained via the grand total of correlations divided by the sum of correlation coefficient of each significant parameter (Table 11). The *Cp* for sub-watersheds prioritization was computed as:

$$Cp = (0.29 \times PR \text{ of } Lo) + (0.305 \times PR \text{ of } Dt) + (0.404 \times PR \text{ of } Cc). \tag{15}$$

The final priorities of sub-watersheds based on *Cp* values (Table 11) exhibit that SW1 attains the lowest priority with the highest *Cp* value of 6.23 followed by SW5 with the next highest *Cp* value. In addition, SW6 achieves the highest priority with the lowest *Cp* value of 3.11 followed by SW2 and SW7.

**Table 12.** Pairwise comparison matrix between ERPs

Criteria	<i>Dd</i>	<i>Fs</i>	<i>Lo</i>	<i>Rb</i>	<i>Dt</i>	<i>Rc</i>	<i>Re</i>	<i>Rf</i>	<i>Bs</i>	<i>Cc</i>
<i>Dd</i>	1	1	1	3	2	7	9	5	5	7
<i>Fs</i>	1	1	1	3	4	5	5	9	7	6
<i>Lo</i>	1	1	1	9	7	5	5	5	4	7
<i>Rb</i>	0.33	0.33	0.11	1	1	3	3	3	5	7
<i>Dt</i>	0.5	0.25	0.14	1	1	2	7	5	5	3
<i>Rc</i>	0.14	0.2	0.2	0.33	0.5	1	3	3	4	2
<i>Re</i>	0.11	0.2	0.2	0.33	0.14	0.33	1	3	2	2
<i>Rf</i>	0.2	0.11	0.2	0.33	0.2	0.33	0.33	1	2	1
<i>Bs</i>	0.2	0.14	0.25	0.2	0.2	0.25	0.5	0.5	1	1
<i>Cc</i>	0.14	0.17	0.14	0.14	0.33	0.5	0.5	1	1	1

**Table 13.** Weights and rank assigned to ERPs based on pairwise comparisons matrix

S. No.	Category	Weights	Rank
1	Dd	0.197	3
2	Fs	0.204	2
3	Lo	0.262	1
4	Rb	0.086	5
5	Dt	0.093	4
6	Rc	0.051	6
7	Re	0.034	7
8	Rf	0.026	8
9	Bs	0.023	9
10	Cc	0.023	10

### Saaty's AHP

A pairwise comparison matrix was prepared (Table 12) to compute the weights and determining the influence of selected ERPs on surface erosion. The matrix assists in identifying the relative significance of the ERPs in the implementation of soil conservation techniques in the vulnerable regions. The criterion values in the pairwise comparison matrix are divided by the sum of the columns to obtain the standardized pairwise comparison matrix. Based on the weight scale obtained from the standardized pairwise matrix, the CR was evaluated as 8.1% and the  $\lambda_{MAX}$  as 11.075 in 11 iterations.

Finally, ranks were assigned to the ERPs in accordance with the weights given in Table 13, for prioritization of the sub-watersheds in a GIS framework. The highest rank was assigned to the parameter *Lo*, the second highest rank to *Fs*, and the lowest rank to *Cc*.

After assigning the ranks to each ERP, corresponding weights were computed that were added

**Table 14.** Nagmati sub-watershed final priorities based on AHP

Sub-watershed	Cp value	Final priority
SW1	2.28	1
SW2	1.88	8
SW3	2.08	7
SW4	2.11	4
SW5	2.26	2
SW6	2.09	6
SW7	2.2	3
SW8	2.09	5

and averaged out to render a compound value (i.e., *Cp*) against each ERP and a final priority was obtained with respect to every *Cp* value for the eight delineated sub-watersheds (Table 14). The sub-watersheds were categorized into three broad priority classes as per the PCA-based prioritization (i.e., high, medium, and low). The sub-watershed that achieved the maximum *Cp* value was assigned the highest priority. It is observed from Table 14 that SW1 attained the highest *Cp* value of 2.59 and the highest priority, whereas SW2 achieved the lowest priority.

### DISCUSSION

The ERPs that were employed to assign final priorities to the Nagmati River sub-watersheds using three approaches, AHP, PCA, and I-PCWS were grouped in accordance with *Cp* values as high, medium, and low priorities (Table 15). Five sub-watersheds were identified under common priority classes evaluated from the three approaches (i.e., SW1, SW2, SW3, SW4, and SW8) that account for 63% similarity in the results. Sub-watershed SW2

**Table 15.** Comparison of PCA, I-PCWS, and AHP derived priority ranking of Nagmati sub-watersheds

Method implemented	Priority type and level		
PCA	High < 4.0 <b>SW2, SW7</b>	Medium 4.0–6.0 <b>SW3, SW4, SW5, SW6, SW8</b>	Low > 6.0 <b>SW1</b>
PCWS	High < 4 <b>SW2, SW6, SW7</b>	Medium 4.0–6.0 <b>SW3, SW4, SW8</b>	Low > 6.0 <b>SW1, SW5</b>
AHP	High < 2.2 <b>SW2</b>	Medium 2.2–2.5 <b>SW3, SW4, SW6, SW7, SW8</b>	Low > 2.5 <b>SW1, SW5</b>
Common sub-watershed	1	3	1

The bold text represent the common sub-watersheds

was observed as a common region under the high-priority zone (Table 15) associated with a greater degree of soil erosion; therefore, necessitating immediate soil conservation interventions to safeguard the region from further deterioration. Sub-watershed SW2, which includes Sedata village, features vast overgrazed rangelands and barren fields triggering uncontrolled erosion of topsoil. Sub-watersheds falling within medium and low priorities have the possibility of deterioration into high priority. Furthermore, results from the three approaches depict three common sub-watersheds (i.e., SW3, SW4, and SW8) falling within medium priority and a single common sub-watershed, i.e., SW1 falling within the low-priority zone. Strategic management policies are required to address land degradation in the identified priority regions. The final prioritization maps featuring priority vulnerable sub-watersheds from the three approaches were generated in a GIS framework, and these are shown in Figures 4, 5, and 6. Results indicate similar outcomes in terms of identifying the most vulnerable regions within the study area with the exception of a few sub-watersheds. Sub-watershed SW7, which identified as a high-priority region through PCA and I-PCWS, falls under medium priority based on the AHP. Likewise, sub-watershed SW5 is observed to fall within medium priority through PCA but under low priority through I-PCWS and AHP. The PCA and I-PCWS can be considered similar in reducing the number of significant ERPs by establishing a correlation with PCs. The AHP calculates weights based on the relative importance of parameters with respect to each other depending upon the expert’s opinion as well as inter-correlation among the selected morphological parameters.

The results from the three approaches were validated with GeoEye-2 image of the study area on March 12, 2019, with a spatial resolution of 1.34 m in multispectral mode (Fig. 7). Sub-watersheds SW2, SW6, and SW7, which constitute vast overgrazed rangelands and barren lands, are more susceptible to soil erosion. Sub-watersheds SW1 and SW5, classified as low priority, constitute agricultural lands with sparse tree cover covering almost 80% of the region. Sub-watersheds SW3, SW4, and SW8 comprise barren lands and sparse agricultural lands (refer to Fig. 7). The I-PCWS indicated priorities of the eight sub-watersheds that are more consistent with the actual land cover pattern of the entire Nagmati watershed as evidenced from the GeoEye-2 image of the study area compared to the other two approaches. Therefore, it can be inferred that sub-watersheds SW2, SW6, and SW7 require immediate implementation of effective soil conservation measures to prevent further degradation of the region. Recommended structural mitigation measures for high-priority sub-watersheds include afforestation and gully control structures, viz. check dams, boulder bunds, gully plugs, and grass waterways, to prevent topsoil erosion. Furthermore, protection of the present vegetal cover and its rejuvenation in the high-priority areas by means of seeding with appropriate grasses and planning for efficient rangeland management through tree planting is recommended. Sub-watersheds falling under medium priority are susceptible to moderate erosion requiring agronomical measures, such as contouring, strip cropping, and tillage practices, to prevent sheet and rill erosion. The I-PCWS, which integrates morphometric parameters with PCA and WSA in a single frame, offers more dynamic, effective, and viable results as compared to the traditional water-

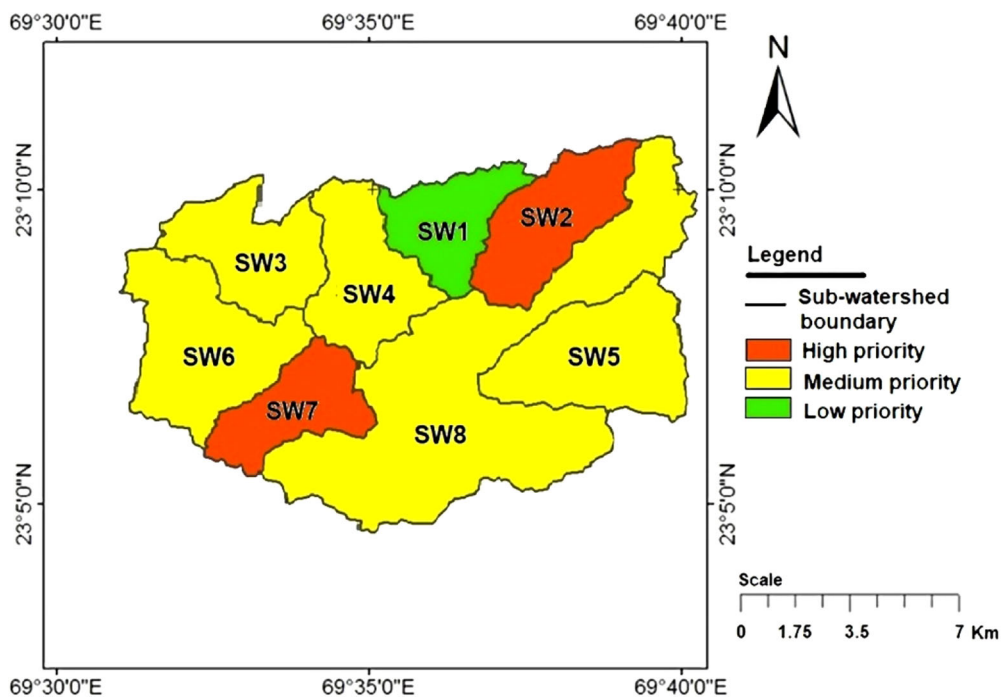


Figure 4. Prioritization of the Nagmati sub-watershed by PCA approach.

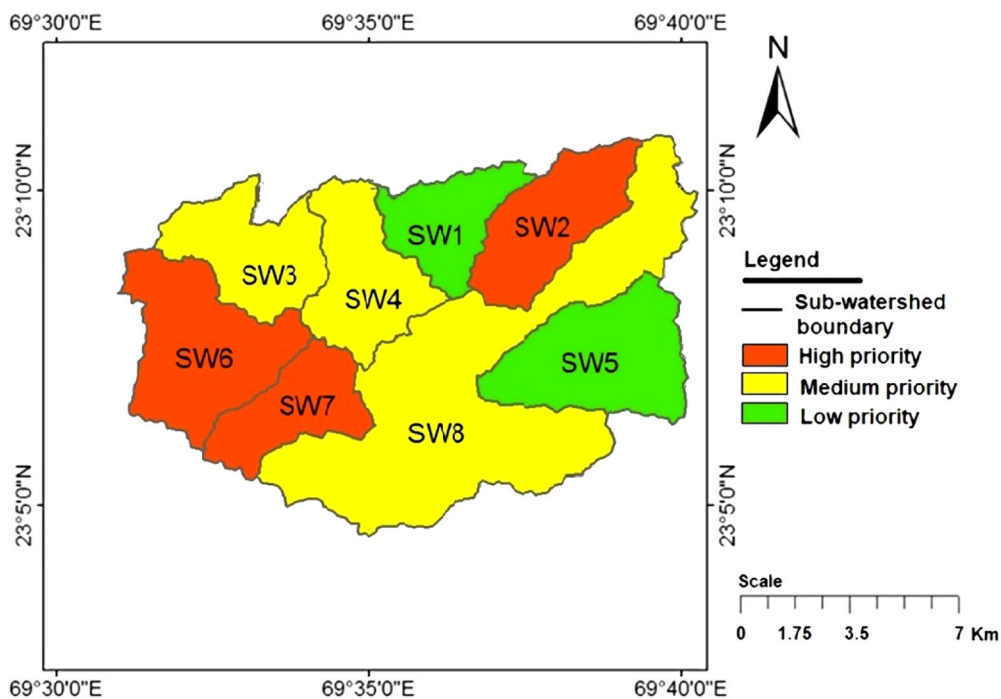


Figure 5. Prioritization of the Nagmati sub-watershed by I-PCWS approach.



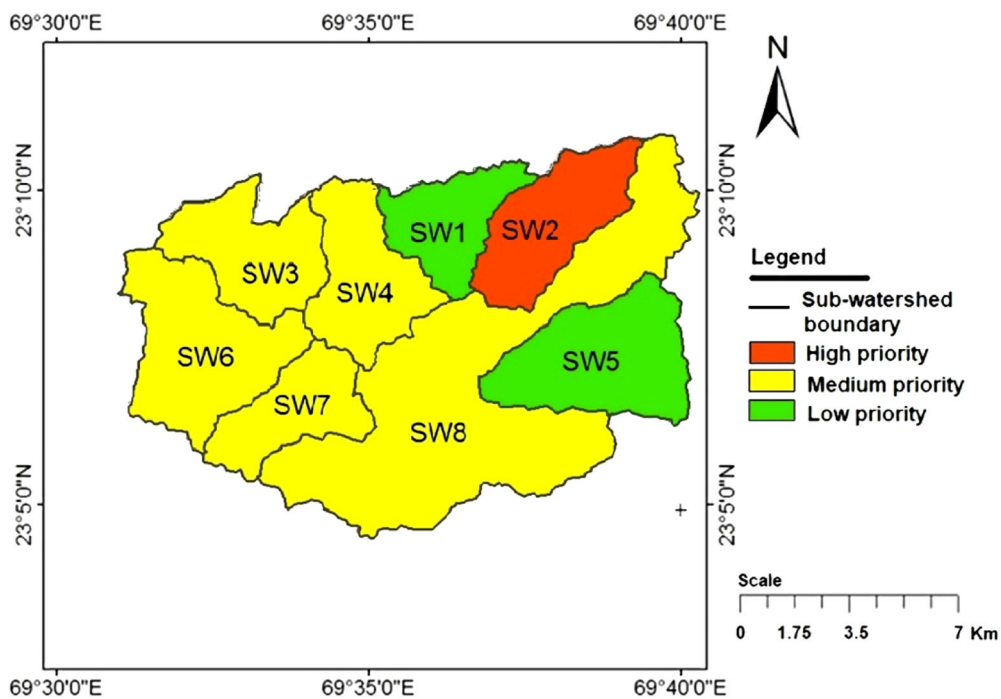


Figure 6. Prioritization of the Nagmati sub-watershed by AHP approach.

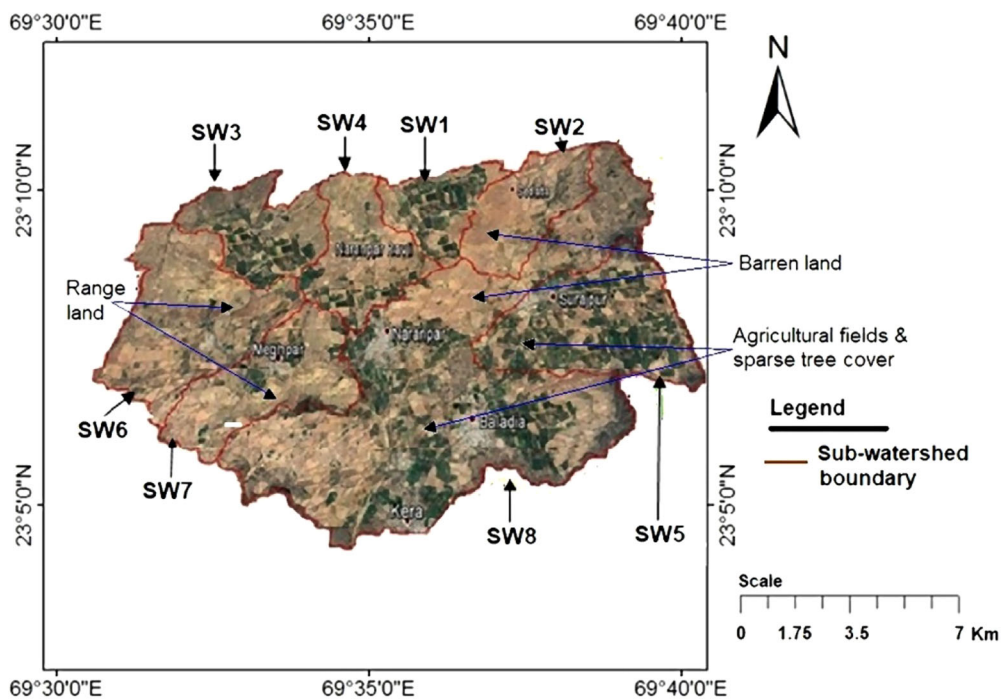


Figure 7. GeoEye-2 image of the Nagmati watershed depicting land cover pattern.

shed prioritization methods. However, there is still a need for future research involving other ecological and socioeconomic perspectives and more reliable modeling techniques that would yield greater insight into watershed prioritization.

## CONCLUSIONS

Soil erosion has severely threatened the vast overgrazed rangelands over most of the sub-watersheds of the Nagmati River; hence, prioritization at sub-unit level could assist in formulating efficient strategies for managing the soil erosion problems within a specific area. The morphometric analysis reveals Nagmati watershed as sixth-order watershed comprising dendritic drainage network that is composed of highly permeable material with low relief that corresponds to almost circular shape capable of generating greater runoff. The Nagmati watershed was delineated into eight sub-watersheds, and the most vulnerable regions were identified using three prioritization methods—namely PCA, AHP, and PCWS. Ten ERPs were used for prioritization of the Nagmati sub-watersheds. The PCA method determined three significant ERPs (i.e., *Lo*, *Dt*, and *Cc*) exhibiting the highest correlation (i.e.,  $r = 0.961$ ,  $0.986$ , and  $0.934$ , respectively) with the three PCs: PC1, PC2, and PC3. Sub-watersheds SW2 and SW7 were identified as high-priority zones, SW1 as low priority, and the rest were categorized as medium priority. In contrast, the AHP is an MCDM tool, which generates a standardized pairwise comparison matrix by assigning ranks based on the relative significance of morphometric parameters. The highest and lowest ranks were assigned to *Lo* and *Cc*, respectively, and the CR and  $\lambda_{MAX}$  were 8.1% and 11.075, respectively. Results from the AHP revealed that sub-watershed SW2 attained the highest priority, whereas sub-watersheds SW1 and SW5 attained the lowest priority. The I-PCWS approach revealed sub-watersheds SW2, SW6, and SW7 as high-priority zones, followed by SW3, SW4, and SW8 as medium-priority zones and SW1 and SW5 as the low-priority zones. Results of the I-PCWS approach were found to be more consistent with the existing land cover pattern of the region, and this approach was considered more effective and sustainable compared to the other two approaches. Relevant soil conservation measures have been proposed in accordance with the priority ascribed to manage the adverse effect on land and the environment. The study

highlights the priority-based analysis of data-scarce regions undergoing noticeable land degradation where dynamic soil conservation and management policies are required. The I-PCWS approach is more robust and effective than the widely used traditional watershed prioritization methods. The methodology adopted herein would assist decision-makers and conservationists in prioritizing regions suffering from severe soil erosion because of the deterioration of natural vegetation.

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