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The Implementation of a Hybrid Model for Hilly Sub-Watershed Prioritization Using Morphometric Variables: Case Study in India

Anurag Malik ^{1,*} , Anil Kumar ¹, Daniel Prakash Kushwaha ¹, Ozgur Kisi ² , Sinan Q. Salih ³, Nadhir Al-Ansari ⁴ and Zaher Mundher Yaseen ^{5,*}

¹ Department of Soil and Water Conservation Engineering, College of Technology, G.B. Pant University of Agriculture & Technology, Pantnagar 263145, Uttarakhand, India; anilkumar_swce61@rediffmail.com (A.K.); danielprakash45499@gmail.com (D.P.K.)

² School of Business, Technology and Education, Ilia State University, 0162 Tbilisi, Georgia; ozgur.kisi@iliauni.edu.ge

³ Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam; sinanq.salih@duytan.edu.vn

⁴ Civil, Environmental and Natural Resources Engineering, Lulea University of Technology, 97187 Lulea, Sweden; nadhir.alansari@ltu.se

⁵ Sustainable Developments in Civil Engineering Research Group, Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam

* Correspondence: anuragmalik_swce2014@rediffmail.com (A.M.); yaseen@tdtu.edu.vn (Z.M.Y.)

Received: 4 May 2019; Accepted: 28 May 2019; Published: 30 May 2019

Abstract: Among several components of watershed prioritization, morphometric parameters are considered to be essential elements for appropriate water resource planning and management. In the current study, nine hilly sub-watersheds are prioritized using novel hybrid model based on morphometric variables analysis at Bino Watershed (BW) located in the upper Ramganga basin, India. The proposed model is based on the hybridization of principal component analysis (PCA) with weighted-sum approach (WSA), presenting a single-frame methodology (PCWSA) for sub-watershed prioritization. The prioritization process was conducted based on several morphometric parameters including linear, areal, and shape. The PCA was performed to identify the significant correlated factor-loading matrix whereas WSA was established to provide the weights for the morphometric parameters and fix their priority ranking (PR) to be categorized based on compound factor value. The findings showed that 37.81% of total area is under highly susceptible zone sub-watersheds (SW-6 and SW-7). This is verifying the necessity for appropriate soil and water conservation measures for the area. The proposed hybrid methodology demonstrated a reliable approach for water resource planning and management, agriculture, and irrigation activities in the study region.

Keywords: prioritization; morphometric variables; PCWSA; Bino watershed; Uttarakhand

1. Introduction

For proper identification and prioritization of areas prone to erosion in any catchment, the morphometric variables of the area are very important [1]. As per Youssef et al. [2], hydrological investigations in a watershed are mainly performed using the morphometric variables of the watershed (linear, areal, and shape); they are also important for studies on the conservation and management of water resources. Furthermore, Bagherzadeh [3] highlighted the importance of soil erosion information when formulating appropriate programs for land and water management to ensure sustainable agricultural development. Thus, policy formulation and decision-making for sustaining an environment

improving land productivity must be based on accurate erosion assessment information. It is, therefore, essential to check soil erosion risk in the regions.

Over recent years various researchers have used morphometric variables (i.e., linear, areal, and shape) to prioritize watersheds using the application of remote sensing (RS) and geographical information system (GIS) by ordinary methods [4–13]. For instance, Shrimali et al. [4] applied the feasibility of RS and GIS techniques to contextually investigate the Sukhana lake catchment in the Shiwalik hills to prioritize the soil erosion zones. Morphometric characteristics are the feasible entity to understand the hydrological behavior of the watershed. Balasubramanian et al. [8] prioritized 29 sub-watersheds (SW) of lower Bhavani basin, located in Tamil Nadu, India, based on morphometric (linear, areal, shape, and relief) parameters. The morphometric were computed in ArcGIS environment using IRS-LISS III, and Cartosat digital elevation model (DEM) data. They found that the 8 SW were highly prone to soil erosion. Sahu et al. [10] prioritized three sub-basins of the Asna river, located in the Marathwada region of Maharashtra, India, based on geomorphometric parameters computed using geospatial tools. They found sub-basin-1 under high category of soil erosion, sub-basin-2 under low category, and sub-basin-3 under moderate category. Mangan et al. [13] studied the morphometry of the Nanganji River Basin, Tamil Nadu, India, using RS and GIS. The inter-relationship between the morphometric parameters was done using a correlation matrix. Pandey et al. [14] studied the Karso watershed in Hazaribagh, Jharkhand for morphological characteristics and recommended the use of GIS for watershed management. The authors suggested different thematic maps integrated with morphometric variables to determine the suitable areas for citing water and soil conservation measures. In India, several studies on watershed prioritization have been performed based on morphometric analysis using the potential of RS and GIS techniques [15–22].

The motivation to explore new reliable methodologies for watershed prioritization has been always the preserve of a hydrologist. A few works have been recently reported on watershed prioritization using principal component analysis (PCA) and weighted-sum approach (WSA) [23–25]. For instance, the use of weighted-sum approach for SWs prioritization was conducted within the Pimpalgaon Ujjaini watershed, India [1]. The authors used a quantitative analysis of morphometric variables based on RS and GIS techniques. PCA was applied based on linear, areal, and shape variables of 8 SW at the Kanhiya Nala watershed, a tributary of Tons River, Madhya Pradesh, India [26], to categorize the used parameters under various components using correlation analysis. The results revealed that some parameters have strong correlation with the components; however, hypsometric integral and texture ratio did not indicate any correlation with the components. PCA-based RS and GIS techniques were used by [23], for morphometric analysis of SW prioritization in the Shakkar River Catchment, India. Meshram and Sharma [27] reduced the dimensionality of data by identifying the significant correlations between the linear, areal, and shape variables based on PCA for SW prioritization in the Mohgaon River catchment, India. Singh and Singh [28] used WSA for prioritization of the Suketi watershed located in the lower Himachal Himalayan region. They reported the WSA to be a more dynamic and effective method in comparison to the traditional methods of watershed prioritization. Malik et al. [22] prioritized 14 hilly SWs of the Naula watershed situated in the upper Ramganga river basin, Uttarakhand State, India, using WSA based on linear, areal, and shape morphometric variables.

Past studies reported that the SW prioritization was carried out based on compound factor values, which are calculated by taking a simple arithmetic average of preliminary priority ranks for final prioritization of SW. In previously used methods, equal importance was given to all the morphometric parameters, which may not be true in reality [1]. In identification of highly susceptible areas for risk assessment and management, the importance of all the input constraints may not be equal as each SW has its own characteristics. In recent years, a few separate studies have been conducted using weighted-sum analysis for watershed prioritization based on morphometric parameters [1,22,28–30], as well as principal component analysis for watershed prioritization [23,25–27]. The recent implementation of the hybridization between the PCA and WSA demonstrated an optimistic strategy for SW prioritization. Therefore, the current study is devoted to prioritize nine hilly SW of the

BW based on morphometric parameters. The modeling procedure is established using morphometric parameters including: (i) linear: mean stream length, basin area and perimeter, stream length, basin length, bifurcation ratio, and stream order; (ii) areal: texture ratio, drainage density, mean length of overland flow, and stream frequency; and (iii) shape: compactness coefficient, form factor, circularity ratio, and elongation ratio. The main objective of doing this research was to provide a reliable methodology for SW prioritization at the BW, contributing to multiple water resource engineering disciplines. This is highly essential for such a region where the reliable watershed management and sustainability is very much needed.

2. Materials and Methods

2.1. Case Study and Data Collection

The study was conducted on the Bino watershed (BW) in the Ramganga river basin, Uttarakhand State, India which was located between 29°47'06" to 30°02'06" N latitudes and 79°6'14.4" to 79°17'16.8" E longitudes (Figure 1). Figure 1 shows six land use and land cover (LULC) classes as dense forest (26.24%), open forest (69.49%), rainfed-agriculture land (27.29%), irrigated agriculture land (2.19%), waste land (19.76%) and water body (1.17%), respectively. The Bino watershed has a total surface area of 295 km² with altitude ranging from 798 m to 2911 m above mean sea level. The area has a mean annual rainfall of 931.3 mm; a significant portion of rainfall in the area comes from the South-West monsoon which commences around mid-June and runs to September. The maximum daily mean temperature is experienced from May to June and the lowest daily mean temperature is experienced from December to January. The geological structure of BW consists of mica, schist, quartzitic sandstone, granitic-gneiss, and some calcareous dolomite rocks. The soil in these watersheds is mainly formed from coarse-textured quartzite although shale and silty-phyllites contribute to the process of pedogenesis in some areas of watershed at middle elevation. The lower surfaces of the watershed are mostly composed of colluvial deposits with fined-grained mica sand; however, the upper surfaces are mainly composed of boulders of metamorphic rocks and well-rounded pebbles. The soil texture varies from gravelly loamy sand to silt loam.

The boundary of BW was marked by using Topo-sheet Nos. 53-N/4, 53-N/8, 53-O/1 and 53-O/5 of Survey of India (SOI) on a scale of 1:50,000 for delineation of watershed. Topo-sheets were scanned (tiff format) and geo-referenced to frame complete image of the region using mosaic operation. The mosaicked image was imported in QGIS and the BW boundary was digitized by monitoring the ridge points from the contours. The outlet position was set at the confluence point of BW with the Ramganga river. The DEM of BW and its SW with drainage network pattern created in ArcGIS 10.2 environment is depicted in Figure 2. The DEM was downloaded from <https://earthexplorer.usgs.gov>; it is Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) resolution is 30 m × 30 m. The BW was divided into nine SW, and codification was done in increasing order from the outlet at BW to the furthest distant sub-watershed as SW-1 to SW-9. The stream order of nine SW of BW is depicted in Figure 3.

Figure 1. Location and LULC map of Bino watershed in Uttarakhand State.

Figure 2. DEM and drainage network pattern of nine sub-watersheds of BW.

Figure 3. Stream order map of the nine sub-watersheds of BW.

2.2. Morphometric Analysis and Assign Preliminary Priority Rank to the SWs

In this study, prioritization of nine SW of BW was done based on linear, areal, and morphometric variables. Linear parameters include basin area (A), basin perimeter (P), stream order (u), stream length (L_u), mean stream length ($\bar{L}_u$), basin length (L_b), and bifurcation ratio (R_b) and their computational formulae are given in Table 1 [31–33]. Areal parameters include drainage density (D_d), stream frequency (F_s), texture ratio (R_t), mean length of overland flow (L_{om}) their computational formulae are given in Table 2 [31,34]. Shape parameters include form factor (F_f), circularity ratio (R_c), compactness coefficient (C_c) and elongation ratio (R_e) their computational formulae are given in Table 3 [32–35]. The more value of R_b , more will be the soil erosion [33]. Rai et al. [36] suggested that the value of $F_f > 0.7854$ indicates that basin is circular, while lower value indicates elongated basin. The smaller value of drainage density indicates that overland flow predominates in the basin, while higher value of D_d indicates that channel flow predominates in the basin. 37. Suresh [37] stated that a lower value of D_d indicates highly permeable sub-surface material and land covered with dense vegetation of low relief, while a higher value of drainage density indicates impermeable sub-surface material with sparse vegetation and high relief. Kumar et al. [38] stated that the drainage density indicates channel development and closeness of the channel spacing in the watershed. The value of R_c generally ranges from 0.2 to 0.8. A high value (>0.5) indicates more circularity and more homogeneity in the geological material, while a low value (<0.5) indicates elongated shape of the watershed. In general, the value of C_c is always ≥ 1 . The value of R_e ranges from 0.4 to 1.0 or ≤ 1.0 for a wide range of climatic and geologic conditions. The value of R_e approximately 1.0 indicates a region of very low relief, while that of 0.4 to 0.8 indicates a region of very high relief and steep ground slope. The R_t , also called drainage texture, is defined as total number of stream segments of all orders to the perimeter of the basin (Horton, 1945). Smith [39] classified the R_t into five different classes of textures: (i) very coarse (<2); (ii) coarse (2 to 4); (iii) moderate (4 to 6); (d) fine (6 to 8); and (e) very fine (>8).

The assignment of the preliminary priority rank (PPR) of 9 SW was performed using a liner (R_b), areal (D_d, F_s, R_t, L_{om}), and shape (F_f, R_c, C_c, R_e) morphometric variables. The linear and areal morphometric parameters have direct relationship to the soil erodibility; higher value of these parameters indicates more erodibility potential. Thus, the largest value of linear and areal parameters was assigned rank 1 (highest priority), the next highest value was assigned rank = 2, and so on for all the SW [5,16]. The shape morphometric parameters have inverse relationship to the soil erodibility; lower value indicates more erodibility potential. Thus, the lowest value of shape parameters was assigned rank 1, and the next-lowest was assigned rank 2, and so on for all the SW [5,16]. When the linear, areal, and shape morphometric parameters of two sub-watersheds have a similar value, an equal rank was assigned to such SW [22,40].

Table 1. Linear morphometric variables computation formulae with references.

Linear Variables	Formula	References
Basin area (A)	Plan area of watershed (km^2)	
Basin perimeter (P)	Perimeter of watershed (km)	
Stream order (u)	Hierarchical rank	[31]
Stream length (L_u)	Length of stream (km)	[31]
Mean stream length ($\bar{L}_u$)	$\bar{L}_u = \frac{L_u}{N_u}$ where $\bar{L}_u$ is the mean stream length (km), L_u is the total length of stream of order u , N_u is the total number of streams of order u	[32]
Basin length (L_b)	$L_b = 1.312 \times A^{0.568}$, (km)	[33]
Bifurcation ratio (R_b)	$R_b = \frac{N_u}{N_{u+1}}$ where N_{u+1} is the number of stream segments of $(u + 1)$ th order	[33]

Table 2. Areal morphometric variables computation formulae with references.

Areal Variables	Formula	References
Drainage density (D_d)	$D_d = \frac{\sum L_u}{A}$, (km/km ²) where $\sum L_u$ is the total length of stream of all orders (km)	[34]
Stream frequency (F_s)	$F_s = \frac{\sum N_u}{A}$, (1/km ²)	[34]
Texture ratio (R_t)	$R_t = \frac{\sum N_u}{P}$, (1/km)	[31]
Mean length of overland flow	$L_{om} = \frac{1}{2D_d}$ where L_{om} is the mean length of overland flow (km)	[31]

Table 3. Shape morphometric variables computation formulae with references.

Shape Variables	Formula	References
Form factor (F_f)	$F_f = \frac{A}{L_b^2}$, ($F_f < 1$)	[34]
Circularity ratio (R_c)	$R_c = \frac{12.57A}{P^2}$, ($R_c \leq 1$)	[35]
Compactness coefficient (C_c)	$C_c = \frac{0.2821P}{A^{0.5}}$, ($C_c \geq 1$)	[32]
Elongation ratio (R_e)	$R_e = \frac{1.128 A^{0.5}}{L_b}$, ($R_e \leq 1$)	[33]

2.3. Principal Component Analysis and Weighted-Sum Approach

A hybrid approach combining the PCA and the WSA is suggested in this study as described below.

2.3.1. Principal Component Analysis

Principal component (PC) is a multivariate method used to reduce the dimensionality in a data set and calculates new orthogonal variables with the descending order of effectiveness [41,42]. In this study, eigenvalues and eigenvectors are estimated using a characteristic equation. Correlation or covariance matrix of the available inputs (variables) was calculated and used for this aim.

Firstly, PC was applied on linear, areal, and shape morphometric variables to compute the correlation matrix and to obtain PCs and to get the most important variables. Here, first factor-loading (FL) and the rotated FL matrices were used [23,27]. Let us assume variables X where each has n observed values, and p number of PCs may be represented in the matrix notation as:

$$Z = XA \quad (1)$$

where Z and X are the $n \times p$ matrices and A indicates coefficient matrix with $p \times p$ dimension, j th PC Z_j is generally expressed as:

$$Z_j = Xa_j, \text{ for } j = 1, 2, \dots, p \quad (2)$$

where Z_j is an $n \times 1$ (column) vector; and a_j is an $p \times 1$ (column) vector of coefficients. The total variance of X is expressed by the sum of the variances of the p individual X variables. The matrix of variance-covariance X can be represented by Σ , a $p \times p$ coefficient matrix σ_{ij} ; $i, j = 1, 2, \dots, p$. In practical applications, the Σ is calculated by the sample covariance matrix C :

$$C = \frac{X^T X}{(n-1)} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1p} \\ c_{21} & c_{12} & \cdots & c_{2p} \\ \vdots & \vdots & \dots & \vdots \\ c_{p1} & c_{p2} & \cdots & c_{pp} \end{bmatrix} \quad (3)$$

where X^T is the transpose of the standardized X variables. The value of each element of covariance matrix C is:

$$c_{ij} = \frac{1}{(n-1)} \sum_{k=1}^n X_{kj} X_{ki} \quad (4)$$

The procedure starts with maximizing the variance of all the PCs (starting with first PC onwards). Extending the results from first PC to all PCs, the λ 's are computed from the roots of;

$$|C - \lambda I| = 0 \quad (5)$$

where λ 's are the eigenvalues (characteristics roots) of the matrix C ; and I is the identity matrix ($p \times p$). The PCA is principally related to the eigenvalues of the sample matrix of covariance or correlation. Finally, the results from principal component analysis can be generalized as;

$$A^T C A = D \quad (6)$$

where D is the diagonal matrix with elements of eigenvalues of covariance matrix C . The correlation between the i th row of X variables and j th PC is provided as

$$r = \text{Cor}(x_i, z_j) = \frac{\text{Cov}(x_i, z_j)}{\sqrt{\text{Var}(z_j)}} = a_{ij} \sqrt{\lambda_j} \quad (7)$$

where r is the correlation coefficient; $\text{Cor}(x_i, z_j)$ is the correlation of X variables in i th row and j th PCs; $\text{Cov}(x_i, z_j)$ is the covariance of X variables in i th row and j th PCs; $\text{Var}(z_j)$ is the variance of j th PCs; a_{ij} is the vector coefficient of i th row and j th PCs; λ_j is the eigenvalues of j th PCs or covariance matrix (C); $i = 1, 2, \dots, n$; and $j = 1, 2, \dots, p$ (number of observations). Value of r greater than 0.90 indicates strong correlation, r between 0.75 and 0.90 indicates good correlation, and r between 0.60 and 0.75 indicates moderate correlation [26]. To reduce the dimensionality of various PCs and identify physically significant variables, factor analysis is proposed as follows.

Factor analysis is used to find out the components (or factors) which are profoundly identified with at least one of the X variables; however, not to the others and thus a set of factors (smaller in number compared to the original variables) are discovered by considering most of the variation in the data array. The basic relationship in factor analysis is:

$$X_i = \sum_{j=1}^m b_{ij} F_j + \varepsilon_i \quad (8)$$

where X_j is the i th variables standardized with zero mean and unity variance; the FLs are b_{ij} , $j = 1, 2, \dots, m$ ($-1 < b_{ij} < 1$); F_j is the mutually uncorrelated common factors with unit variance and zero mean; and ε_i is a component particular to the i th variable, which has zero mean and is uncorrelated with the other components. It pursues that:

$$\text{Var}(X_i) = \sum_{j=1}^m b_{ij}^2 + \text{Var}(\varepsilon_i) \quad (9)$$

The sum of the squares of FLs and the second term on the right-hand side with no relationship with the common factors, are expressed as communality and specificity (uniqueness), individually, of the X_i variables. Additionally, it can be effortlessly checked by:

$$\text{Cov}(X_i, X_j) = \sum_{k=1}^m b_{ik} b_{jk} \quad (10)$$

In this manner, the relationship between the variables is identified by comparing FLs. If the last term in Equation (8) is ignored as it is related to the particular or special factors, and just the common factors are considered, the connection between the factors or components and X variables is written as:

$$F = XH \quad (11)$$

where F is factor score matrix with $n \times p$ dimension; X is an observation matrix with $n \times p$ dimension and it is standardized for every p variable (as in PCA); and H includes the coefficients of factor scores ($p \times p$ matrix). For F to be orthogonal, it can be written as:

$$H = A \times D^{-1/2} \quad (12)$$

where A is characterized by Equation (1); and $D^{-1/2}$ indicates the diagonal matrix in which the non-zero components are the reciprocals of the square roots of the eigenvalues of the C matrix expressed by Equation (3). Hence, from Equations (11) and (12):

$$F^T F = D^{-1/2} A^T X^T X A D^{-1/2} \quad (13)$$

Hence, using Equations (3) and (6), this simplifies to:

$$F^T F = (n - 1)I \quad (14)$$

Consequently, demonstrating the orthogonality of F . The PCs are incorporated using Equations (1) and (11) as follows:

$$F = X A D^{-1/2} = Z D^{-1/2} \quad (15)$$

As a result of this relationship, which essentially includes a set of p constants, the correlations between the X variables and the F factors are the equivalent as those between the X variables and the Z PCs. It pursues Equation (7) and this correlation matrix can be written as:

$$R = A D^{1/2} \quad (16)$$

where $D^{1/2}$ is the diagonal matrix in which the non-zero elements are the square roots of the eigenvalues of the C matrix. The R matrix provides the correlations between the PCs (columns) and the standardized X variables (rows) is occasionally defined by the FL matrix.

Considering the correspondence between the F factors and the Z PCs (Equation (15)), the orthogonal rotation has an impact on the PCs (with changing the relationships with the X variables) and the corresponding factors are the equivalent. We may accordingly explore changes to the PCs. Thus, a comparison is possible with the unrotated components. The rotation ought to be such that getting important physical information from the subsequent components are possible. Thus, using Equations (1) and (12) and expression $H = C^{-1}R$, the original PCs can be composed as:

$$Z = X A = X H D^{1/2} = X C^{-1} R D^{1/2} \quad (17)$$

The orthogonal rotation will change R to RP (where P is orthogonal, i.e., $P^T P = I$). Thus, the rotated components are given as:

$$Z_r = X C^{-1} R P D^{1/2} \quad (18)$$

In the PC FL matrix, eigenvalues indicate how well each of the identified factors fit the data from all the morphometric variables on all the principal components. Eigenvalues greater than one indicates significant PC loading. In this study, principal component analysis was performed using SPSS 22.0 software. More details about the PCA can be found from [43].

2.3.2. Weighted-Sum Approach

The weighted-sum analysis was applied to significant morphometric variables which were identified using PCA, and compound factor (CF) value was calculated for final priority ranking and their related category. The mathematical expression for CF computation is written as [1,22,28–30]:

$$CF = PPR_{SMP} \times W_{SMP} \quad (19)$$

where CF = compound factor; PPR_{MP} = preliminary priority rank of significant morphometric parameter identified using PCA; and W_{SMP} = weight of significant morphometric parameter obtained using cross-correlation analysis, and computed as:

$$W_{SMP} = \frac{\text{Sum of correlation coefficient}}{\text{Grand total of correlations}} \quad (20)$$

In this research, the final priority rank to the nine SW of BW was assigned based on CF value in such a way that the lowest-value CF was assigned priority rank 1, next-lowest value was assigned priority rank 2, and so on for all the SWs. In this study, weighted-sum approach was performed with Microsoft Excel. Figure 4 demonstrates the flowchart of applied methodology used in this study for SW prioritization of the BW.

Figure 4. Working flow chart of nine sub-watershed prioritization of BW.

3. Application Results and Analysis

The morphometric analysis was conducted using RS and GIS for 9 SW of BW to assess the characteristics and properties of the drainage basins. In this study, first linear (A , P , u , L_u , $\overline{L_u}$, L_b and R_b), areal (D_d , F_s , R_t and L_{om}), and shape (F_f , R_c , C_c and R_e) morphometric parameters of nine SW of BW was computed in the ArcGIS environment and their quantitative values are given in Tables 4 and 5, respectively. After morphometric analysis, the PPR were assigned (based on direct

and inverse relationship concept) to nine SW as given in Table 6. After PPR, the PCA was applied for reducing the dimensionality of data (i.e., linear, areal, and shape morphometric variables) by identifying the significant morphometric variables based on correlations and FL matrix for reducing. After PCA, the weighted-sum analysis was performed on significant morphometric variables for CF valve computation, and finally assigned priority rank and category to the nine SWs based on CF value.

Table 5 reveals that the bifurcation ratio varies from 1.619 (SW-5) to 3.476 (SW-1). The value of drainage density of SW (Table 5) varies from 0.695 km/km² (SW-7) to 1.759 km/km² (SW-2). The low value of drainage density for SW-7 indicates highly permeable sub-surface under vegetative cover with low relief, whereas a higher value of drainage density for SW-2 indicates a well-developed efficient drainage network with impermeable sub-surface materials with less vegetative cover and high relief. The value of stream frequency of sub-watersheds varies from 0.421 km⁻² (SW-2) to 0.617 km⁻² (SW-6). A low value of stream frequency indicates low runoff and a higher value indicates more runoff. The value of texture ratio varies from 0.176 km⁻¹ (SW-2) to 0.854 km⁻¹ (SW-7). Accordingly, all SW fall in the very coarse category of drainage texture. The value of mean length of overland flow of 9 SW varies from 0.284 km to 0.719 km in the watershed. Table 5 reveals that the form factor varies from 0.164 to 0.524 indicating elongated shape with lower peak flow for longer duration. The value of circularity ratio for sub-watersheds varies from 0.311 to 0.534 indicating that SW-4, SW-7, and SW-9 have circular shape, while SW-1, SW-2, SW-3, SW-5, SW-6, and SW-8 have elongated shape. The compactness coefficient ranges from 1.358 to 1.778. A high value (>1) of compactness coefficient indicates more compact SWs. The elongation ratio ranges from 0.457 to 0.817, which indicates that all the SWs are of high relief and steep ground slope. Preliminary priority ranking of SWs based on linear, areal and shape parameters of SWs is given in Table 6.

Table 4. Linear morphometric variables of nine sub-watersheds of BW.

Sub-Watershed (SW) Name	Characteristic Variables										
	A (km ²)	P (km)	Streams Order (<i>u</i>)					<i>N_u</i>	<i>L_u</i> (km)	$\overline{L_u}$ (km)	<i>L_b</i> (km)
			1	2	3	4	5				
SW-1	34.849	32.844	14	3	0	0	1	18	31.593	1.755	11.422
SW-2	7.111	16.946	2	0	0	0	1	03	12.527	4.176	6.576
SW-3	22.552	24.341	9	2	1	0	0	12	17.654	1.471	7.601
SW-4	28.089	25.942	13	3	0	0	1	17	23.024	1.354	8.223
SW-5	29.710	31.826	9	2	1	0	1	13	21.156	1.627	11.604
SW-6	51.857	39.913	24	6	1	1	0	32	37.660	1.177	13.809
SW-7	59.623	37.456	23	6	2	1	0	32	41.441	1.295	10.664
SW-8	23.367	28.875	9	2	1	0	0	12	20.980	1.748	11.582
SW-9	37.654	30.361	12	2	1	0	0	15	28.798	1.919	8.944

Table 5. Linear, areal, and shape variables of nine sub-watersheds of BW.

Sub-Watershed	Sub-Watershed Wise Morphometric Variables								
	Linear	Areal				Shape			
	R_b	D_d (km/km ²)	F_s (km ⁻²)	R_t (km ⁻¹)	L_{om} (km)	F_f	R_c	C_c	R_e
SW-1	3.476	0.906	0.516	0.548	0.551	0.267	0.406	1.557	0.583
SW-2	2.000	1.759	0.421	0.176	0.284	0.164	0.311	1.778	0.457
SW-3	2.621	0.782	0.532	0.493	0.638	0.390	0.478	1.435	0.704
SW-4	3.391	0.819	0.605	0.655	0.610	0.415	0.524	1.370	0.727
SW-5	1.619	0.712	0.437	0.408	0.702	0.220	0.368	1.635	0.530
SW-6	2.289	0.726	0.617	0.801	0.688	0.271	0.409	1.551	0.588
SW-7	2.552	0.695	0.536	0.854	0.719	0.524	0.534	1.358	0.817
SW-8	2.621	0.897	0.513	0.4155	0.556	0.174	0.352	1.672	0.470
SW-9	2.884	0.764	0.398	0.494	0.653	0.471	0.513	1.385	0.774

Table 6. PPR of nine sub-watersheds based on linear, areal, and shape variables.

Sub-Watershed	Linear		Areal		Shape				
	R_b	D_d	F_s	R_t	L_{om}	F_f	R_c	C_c	R_e
SW-1	1	2	5	4	8	4	4	6	4
SW-2	8	1	8	9	9	1	1	9	1
SW-3	4.5	5	4	6	5	6	6	6	6
SW-4	2	4	2	3	6	7	8	4	7
SW-5	9	8	7	8	2	3	3	7	3
SW-6	7	7	1	2	3	5	5	5	5
SW-7	6	9	3	1	1	9	9	1	9
SW-8	4.5	3	6	7	7	2	2	8	2
SW-9	3	6	9	5	4	8	7	3	8

3.1. Principal Component Analysis of Morphometric Variables

The PCA was used to get inter-correlation matrix, first FL, and rotated FL matrices through orthogonal transformation. The results of inter-correlation analysis among linear, areal, and shape morphometric variables are given in Table 7. It is observed from the table that a strong correlation ($r > 0.9$) exists between D_d and L_{om} ; between F_f and R_c ; between C_c and R_e ; between R_c and C_c ; between R_c and R_e ; and between C_c and R_e . Though good correlation ($r > 0.75$) does not exist between the variables, a moderate correlation ($r > 0.60$) exists between D_d and R_t ; between R_c and D_c ; between F_s and R_t ; between L_{om} and R_c ; and between L_{om} and C_c . It was observed from Table 8 that the first three components have eigenvalue greater than 1 and together account for about 93.414% of the total variance in the BW. At this stage, it is too difficult to categorize the variables into components and add physical significance. Therefore, the unrotated and rotated first FL matrices of correlation matrix were then obtained using principal component analysis.

The first FL (unrotated) matrix of linear, areal, and shape morphometric variables are given in Table 9, which indicates that the first component (PC-1) was strongly correlated with F_f , R_c , C_c , and R_e , and in good correlation with D_d , R_t , and L_{om} . The second component (PC-2) has no strong, good, and moderate correlation with the morphometric variables. The third component (PC-3) is moderately correlated with R_b and F_s . It was observed from the analysis that some components (PC-1 and PC-3) are strongly, well, and moderately correlated with the morphometric variables, whereas some components (PC-2) do not have any correlation with other morphometric variables. Hence, in this case, it is hard to obtain a physically important component. Therefore, the first FL (unrotated) matrix should be rotated to achieve better correlation.

The rotated FL matrix of first FL (rotated) matrix is given in Table 10, which reveals that the first component (PC-1) is strongly correlated with F_f , R_c , and R_e , and it has a good correlation with C_c which could be named as a stage-form component. The second component (PC-2) is strongly correlated with L_{om} , well correlated with D_d , and moderately correlated with R_t , and it could be named as a relief-density component. The third component (PC-3) has a good correlation with F_s , and it is moderately correlated with R_b , and might be named as organization-process component. It was observed from the rotated FL matrix analysis that the most important morphometric variables are stream frequency (F_s), mean length of overland flow (L_{om}), and form factor (F_f). Finally, these morphometric variables are taken for WSA and prioritization of SW.

Table 7. Correlation matrix between linear, areal, and shape morphometric variables of nine sub-watersheds of BW.

Morphometric Variables	R_b	D_d	F_s	R_t	L_{om}	F_f	R_c	C_c	R_e
R_b	1.000	−0.229	0.377	0.331	0.057	0.421	0.531	−0.546	0.441
D_d	−0.229	1.000	−0.399	−0.710 ***	−0.972 *	−0.527	−0.607 ***	0.675 ***	−0.559
F_s	0.377	−0.399	1.000	0.721 ***	0.350	0.174	0.315	−0.352	0.208
R_t	0.331	−0.710 ***	0.72 ***	1.000	0.738 ***	0.633 ***	0.677 ***	−0.709 ***	0.653 ***
L_{om}	0.057	−0.972 *	0.350	0.738	1.000	0.569	0.615 ***	−0.672 ***	0.597
F_f	0.421	−0.527	0.174	0.633	0.569	1.000	0.975 *	−0.958 *	0.997 *
R_c	0.531	−0.607 ***	0.315	0.677	0.615 ***	0.975 *	1.000	−0.994 *	0.983 *
C_c	−0.546	0.675 ***	−0.352	−0.709	−0.672 ***	−0.958 *	−0.994 *	1.000	−0.972 *
R_e	0.441	−0.559	0.208	0.653	0.597	0.997*	0.983 *	−0.972 *	1.000

* Strong correlation ($r > 0.90$) and *** Moderate correlation ($0.75 \geq r > 0.60$).**Table 8.** Total variance explained for BW.

Morphometric Variables	Initial Eigen Value			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
R_b	5.947	66.079	66.079	5.947	66.079	66.079	4.063	45.140	45.140
D_d	1.347	14.970	81.049	1.347	14.970	81.049	2.696	29.958	75.099
F_s	1.113	12.365	93.414	1.113	12.365	93.414	1.648	18.315	93.414
R_t	0.466	5.182	98.596						
L_{om}	0.118	1.316	99.912						
F_f	0.004	0.049	99.961						
R_c	0.003	0.035	99.997						
C_c	0.000	0.003	100.000						
R_e	0.000	0.000	100.000						

Table 9. Unrotated factor-loading matrix of morphometric variables.

Morphometric Variables	Principal Component		
	1	2	3
R_b	0.507	0.326	0.674 ***
D_d	−0.787 **	0.446	0.247
F_s	0.481	−0.551	0.623 ***
R_t	0.841 **	−0.388	0.155
L_{om}	0.785 **	−0.453	−0.388
F_f	0.903 *	0.372	−0.140
R_c	0.951 *	0.287	−0.018
C_c	−0.972 *	−0.216	0.015
R_e	0.922 *	0.341	−0.123

* Strong correlation ($r > 0.90$); ** Good correlation ($0.90 \geq r > 0.75$); *** Moderate correlation ($0.75 \geq r > 0.60$).

Table 10. Rotated factor-loading matrix of morphometric variables.

Morphometric Variables	Principal component		
	1	2	3
R_b	0.556	−0.251	0.667 ***
D_d	−0.336	−0.858 **	−0.173
F_s	−0.019	0.377	0.883 **
R_t	0.390	0.668 ***	0.532
L_{om}	0.338	0.925 *	0.049
F_f	0.939 *	0.297	0.055
R_c	0.915 *	0.329	0.205
C_c	−0.886 **	−0.389	−0.236
R_e	0.933 *	0.322	0.085

* Strong correlation ($r > 0.90$); ** Good correlation ($0.90 \geq r > 0.75$); *** Moderate correlation ($0.75 \geq r > 0.60$).

3.2. Weighted-Sum Analysis of Significant Morphometric Variables

To prioritize nine SW of BW, 3 significant morphometric variables (F_s , L_{om} and F_f) were considered. The cross-correlation between the 3 variables was performed as shown in Table 11 while CF was used as a factor to determine the priority rank (PR) of the 9 SW using Equation (19) as presented in Table 12. The calculation of the weight values assigned to each morphometric parameter was done by using the grand total of correlations to divide each variables' sum of correlation coefficient (Table 11). A model for the assessment of the final priority ranking was built by assigning weights to different variables. The CF computation for SW prioritization was done thus:

$$CF = (0.561 \times \text{PPR of } F_s) + (0.418 \times \text{PPR of } L_{om}) + (0.020 \times \text{PPR of } F_f) \quad (21)$$

Table 11. Cross-correlation matrix of F_s , L_{om} and F_f variables of nine sub-watersheds of BW.

Morphometric Variables	F_s	L_{om}	F_f
F_s	1.000	0.283	−0.367
L_{om}	0.283	1.000	−0.600
F_f	−0.367	−0.600	1.000
Sum of correlation	0.917	0.683	0.033
Grand total	1.633	1.633	1.633
Weight	0.561	0.418	0.020

Table 12. Final priority rank of nine sub-watersheds based on CF value.

Sub-Watershed	Compound Factor	Priority Rank
SW-1	6.235	6
SW-2	8.276	9
SW-3	4.459	4
SW-4	3.776	3
SW-5	4.827	5
SW-6	1.918	1
SW-7	2.286	2
SW-8	6.337	7
SW-9	6.888	8

3.3. Prioritization of SW Using PCWSA

For the final priority ranking, it was ensured that the lower CF value was assigned rank 1 while the next lower got rank 2, and so on for the rest of the nine SW (Table 12). As Table 12 clearly shows, the SW-6 assigned PR as 1, SW-7 assigned PR as 2, SW-4 assigned PR as 3, SW-3 assigned PR as 4, SW-5 assigned PR as 5, SW-1 assigned PR as 6, SW-8 assigned PR as 7, SW-9 assigned PR as 8, and SW-2 assigned PR as 9. Also, Figure 5 illustrates the final priority rank map of nine SW of BW under observation. Table 13 shows the priority category of nine SW of BW based on CF value. The nine SW have been grouped into the five-priority category [1,22]: (i) very high (1.918 to ≤ 3.161); (ii) high (3.161 to ≤ 4.403); (iii) medium (4.403 to ≤ 5.646); (iv) low (5.646 to ≤ 6.888); and (v) very low > 6.888 (Table 13). Table 13 clearly shows the sub-watersheds SW-6 and SW-7 under very high category, SW-4 under high category, SW-3 and SW-5 under medium, SW-1, SW-8, and SW-9 under low category, and SW-2 under very low category. Figure 6 is the final priority map of nine SW, which demonstrates the percentage area under very high (37.81%), high (9.53%), medium (17.73%), low (32.52%), and very low (2.41%) categories, respectively.

Figure 5. Map of final priority rank of nine sub-watersheds of BW.

Table 13. Priority category of nine sub-watersheds based on CF value [1,22].

Sr. No.	Priority Level	Priority Category	Sub-Watershed	Percentage of Area
1	1.918 to ≤ 3.161	Very high	SW-6, SW-7	37.81
2	3.161 to ≤ 4.403	High	SW-4	9.53
3	4.403 to ≤ 5.646	Medium	SW-3, SW-5	17.73
4	5.646 to ≤ 6.888	Low	SW-1, SW-8, SW-9	32.52
5	> 6.888	Very low	SW-2	2.41

Figure 6. Map of final priority category of nine sub-watersheds of BW.

4. Discussion

Watershed prioritization is a procedure of positioning diverse watersheds in a way in which they will be taken up for treatment through soil and water conservation measures. In organizing watershed parts, the principal goal is to examine the intensity of the issue in each SW on similar principles to the extent. In this research, the feasibility of a hybrid approach i.e., principal component analysis and weighted-sum approach (PCWSA), was evaluated for prioritization of the nine SW of BW located in the Upper Ramganga River catchment, Uttarakhand, India. The PCWSA approach has been formulated by integrating morphometric parameters with PCA and WSA in a single frame. The morphometric parameters (linear, areal, and shape) of nine SW was calculated using RS and GIS, and PPR was assigned. The dimensionality of data was reduced using PCA, and the significant morphometric parameters were identified based on PCA analysis. After the identification of significant morphometric parameters, the WSA was applied for computation of CF value, and a final priority and category was assigned to these nine SW.

Over the past decade, throughout the world, a number of studies have been conducted by researchers on watershed prioritization based on morphometric parameters using a simple average method [5,18], principal component analysis [25–27], and weighted-sum approach [1,22,28–30]. Gajbhiye et al. [5] used simple average method for prioritizing erosion-prone area of 14 SWs of the Manot River catchment, Madhya Pradesh, India, based on morphometric (linear, areal, and shape) parameters. They found SW 13 was more prone to soil erosion and required immediate adaptation of soil

conservation measures. Sharma et al. [26] applied PCA on 13 dimensionless geomorphic parameters of 8 SWs of the Kanhiya Nala watershed, Madhya Pradesh, India, to group the parameters under different components based on significant correlations. They found that the texture ratio and hypsometric integral do not show correlation with any of the components. Kadam [29] used WSA for morphometric analysis of four SWs of the Shivganga watershed, Maharashtra, India, for determining the plant growth potential, and they found that 13.64% to 45.40% of total area fall under good potential growth zone. In general, the morphological parameters-based prioritization of a watershed is in good agreement with the geological field investigations carried out during the field work. Thus, the proposed methodology for watershed prioritization is a feasible approach to identify the susceptibility or risk assessment priority zones for better decision-making in the study area. However, there is still room for future research where other ecology and socio-economic perspectives could be cooperative for producing more reliable modeling strategies that give more insightful visions on watershed prioritization.

5. Conclusions

Prioritization of SW is an essential task for the development and management of watersheds on a sustainable basis. In this research, RS and GIS were used for morphometric (linear, areal, and shape) parameter characterization. The combination of PCWSA was successfully applied for watershed prioritization of nine SW of BW. The study revealed that the sub-watersheds SW-6 and SW-7 fall into very high vulnerability or susceptible zones. Hence, the top priority is assigned to these, followed by SW-4, SW-3, SW-5, SW-1, SW-8, SW-9, and SW-2, respectively. Such studies assist decision-makers in recognizing priority SW which require fast adaptation of appropriate soil and water conservation practices in the study region. Integration of geospatial tools with statistical methods in single topology resulted in PCWSA as one of the viable and significant techniques, particularly over the data hungry prioritization approaches. Also, the proposed hybrid approach offers dynamic, efficacious, and sustainable results over the traditional or ordinary watershed prioritization methods by considering the equal worth of several morphometric parameters in complex way. This information can be used in development, implementation, and adaptation of the best planning and management practices at micro-level to conserve the available natural resources in which to assist the water resource managers and policymakers in better decision-making in the data-scarce area.

Author Contributions: Conceptualization, A.M.; Formal analysis, A.M. and Z.M.Y.; Investigation, O.K. and Z.M.Y.; Software, O.K.; Supervision, A.K.; Validation, Z.M.Y.; Writing—original draft, A.M.; Writing—review & editing, D.P.K., O.K., S.Q.S., N.A.-A. and Z.M.Y.

Conflicts of Interest: The authors declare no conflict of interest.

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