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Prioritizing geographic parcels for improved catchment conservation using morphometry, landuse, and soil characteristics following statistical and MCDM techniques

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Abstract
The study presents a multi-faceted approach to prioritize sub-watersheds for catchment conservation, using morphometry, land use, and soil characteristics in a GIS-assisted framework. By integrating statistical techniques namely Principal Component Analysis for dimension reduction and CRITIC method, the study identifies the most influencing morphometric parameters and weighs them over each other which otherwise largely remains ambiguous. The framework is applied to the sub-basin in the Upper Ganga Basin, Uttar Pradesh where 11 sub-watersheds were analyzed. Morphometric indices namely the drainage density, stream frequency, and slope were prioritized. Additionally, land use and soil data were evaluated to develop a compounded prioritization strategy. The study reveals that around 69% (~21,636 sq. km) of the drainage area falls under high (39.70%) and very high (29.44%) priority classes for conservation interventions. The methodology offers an efficient, data-driven solution for identifying vulnerable areas for soil and water conservation, especially where fiscal and manpower constraints exist. However, it acknowledges limitations related to data granularity and static data inputs, recommending the adoption of semi-distributed hydrologic models to enhance precision in regions of relatively high priority. Withal, the presented work digresses from the contemporary approaches and contributes to the segment of water and soil conservation towards combating land degradation and Climate Change impacts.

Keywords Morphometry · Landuse · Soil · PCA · CRITIC · Relative prioritization

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1 Introduction

Soil and water are often regarded as one of the most imperative elements in administering and persevering life on Earth. These assets not only provide a multitude of services, especially concerning food, settlements, etc., but are also a quintessential component of all ecosystems, either natural or artificial. India, with its fast-growing anthropogenic, loses millions of tons of its soil annually. This coupled with the Climate Change (CC) impacts further worsens the situation. Soil loss often leads to land degradation with some studies suggesting that approx. 55.77 million ha of the country being beset under the same (NRSC, 2019). As such land degradation has become a considerable challenge (Jat et al., 2020), often leading to low agricultural productivity, reduced water availability, and in extreme cases leads to social destitution as well. This mandate towards the identification of geographic parcels that require prompt attention in the context of soil & water conservation followed by the implementation of an apt management strategy for ensuring the future sustainability of water & soil resources. The assessment and inventorization of vulnerable parcels, without a doubt, is key to tuning any policy in the landscape of soil and water conservation (Ahmad Ali & Hagos, 2016). It proves useful in optimizing land acreages in situations where there are manpower and fiscal constraints (Ahmed & Rao, 2015). One pivotal conduct for assessing the relative vulnerability of land acreages prone to soil and water loss is via prioritization of sub-drainage systems (Ahmed et al., 2018; Prakash et al., 2019). Typically, key indices employed under this approach are drainage system morphometry, its land use, and soil characteristics (Bhattacharya et al., 2019; Das et al., 2021; Garde & Kothari, 2016; Gunjan et al., 2019; Mishra et al., 2017; Mundetia et al., 2018; Sukristiyanti et al., 2018).

Prioritization using landuse and soil characteristics is relatively straightforward, as one has to assert the influence of identified classes of land use and soil over processes such as runoff and soil erosion. On the contrary, the selection of morphometric parameters for the same is rather challenging. Watershed morphometry, which actuates the geometry of a drainage area and its associated channel system (Agarwal, 1998), assists in comprehending the hydro-sedimentological responses, its geomorphic & geologic past, diastrophism, and subsequent evolution (Javed et al., 2011). Remote Sensing (RS) and Geographical Information Systems (GIS), following its advent, have continually been used in the discernment of watershed morphometry indices for over 03 decades (Bogale, 2021; Mishra & Nagarajan, 2010; NRSA, 1995). The RS & GIS techniques in this sect being relatively amiable have reduced the overall expenditure on manpower resources, which earlier was relatively large particularly due to the physicalities involved in the data acquisition procedures. Additionally, these techniques have eased out monitoring of remote landscapes as well which otherwise was commensurately strenuous and challenging. A majority of morphometric parameters find their association with the hydro-sedimentological response, therefore, the selection of the most-influencing parameters from the set is relatively ambiguous (Gaikwad & Bhagat, 2018). Even if one manages to select a few morphometric indices, the weighing of the selected parameters over each other largely remains inexplicable. The use of statistical techniques in this context can overcome this dilemma of parameter selection. Many investigations have deliberated the competency of statistical methods like Principal Component Analysis (PCA), correlation analysis, etc., for parameter selection (Kumar et al., 2023; Siddique et al., 2020), and Multi-Criteria Decision Making (MCDM) techniques such as Criteria Importance for Intercriteria Correlation (CRITIC), Analytical Hierarchical Process (AHP), etc., for weighing the parameters with respect to each other (Jaiswal et al., 2015; Meshram et al., 2019; Rahaman et al., 2015; Sangma & Guru, 2020; Sarkar et al., 2022).

Sharma and Mahajan (2020) prioritized the Gaj watershed of Himachal Pradesh, India. Using the GIS and DEM data the study performed morphometric and hypsometric analyses of nine sub-watersheds suggesting the inclusion of morphometric indices such as drainage density, stream frequency, relief ratio, and hypsometric integral to assess erosion susceptibility and landform evolution. Kumar et al. (2021) address soil erosion mapping and watershed prioritization in the Kalsa River watershed, India using PCA and a weighted sum approach to prioritize 10 sub-watersheds. The study found that sub-watersheds with higher drainage density, ruggedness, and stream frequency were most vulnerable to soil erosion. Pathare and Pathare (2021) focused on watershed prioritization in the Darna River basin, Maharashtra (India) utilized PCA for the prioritization of 10 sub-watersheds based on their geomorphometric parameters. Setiawan and Nandini (2021) implemented sub-watershed prioritization in the Sari watershed, Sumbawa Island, Indonesia employed geomorphometric analysis with LULC data to prioritize 07 sub-watersheds based on erosion susceptibility. The study integrated PCA and a weighted sum method to identify significant geomorphometric parameters. Chauhan et al. (2022) examined the Upper Ghaggar watershed in the Lower Shivaliks region, India via integrated geospatial analysis using PCA and Hierarchical Cluster Analysis and demonstrated the significance of magnitude, relief, and drainage composition parameters on the prioritization process. Gururani et al. (2024) implemented watershed prioritization in the Nandhour-Kalish River basin, Uttarakhand, India. The study used PCA to reduce dimensionality, identifying the most influential parameters. These parameters were further analyzed using the CRITIC MCDM technique to assign relative priority scores to the sub-watersheds. The contemplated study is an attempt in this direction with the selection of most-influencing morphometric parameters (criteria parameters) based on via dimension reduction (PCA) and assessment of relative weights of criteria parameters via CRITIC MCDM within a GIS-assisted framework. Additionally, the study coalesces the findings from morphometric prioritization with land use & soil following a compounded-value approach to make the prioritization procedure more holistic., The presented work also resonates with various national and international initiatives such as India's Nationally Determined Contributions (NDCs), namely, the NDC 1 (Mission LiFE) & 6 (Better adapt to CC) and United Nations (UN) Sustainable Development Goals (SDGs), namely, SDG 6 (6.5: Implement integrated water resources management at all levels, and 6.6: Protect and restore water-related ecosystems), SDG 13 (13.2: Integrate climate change measures into national policies, strategies, and planning), and SDG 15 (15.1: Ensure the conservation, restoration, and sustainable use of terrestrial and inland freshwater ecosystems and their services, and 15.3: Combat desertification, restore degraded land, and soil by 2030, and strive to achieve a land degradation-neutral world).

2 Materials and methods

2.1 Study area

The study area is a part of the Upper Ganga Basin. Following the Watershed Atlas of India (CGWB, 2006) the area of interest (AOI) is named as 'Upstream of Gomti Confluence to Muzaffarnagar' (USGCM). It administratively lies in the state of Uttar Pradesh, India, and extends from latitude 24.862°N to 29.478°N and longitude 77.528°E to 83.119°E, enveloping a geographical area of 31,289.76 sq. km with a periphery of 3920 km. The absolute relief of the AOI is from 320 to 11 m above mean sea level (AMSL) with an average elevation of 133.2 m. The sub-basin is an eighth-order drainage system. The headwaters of the sub-basin are in *Muzaffarnagar* district. The *Kali Nadi* is the primary stream flowing through the AOI. Near *Kannauj*, it confluences with the Ganges, which then merges with the *Ramganga* River. The river then flows southeast and merges with the *Yamuna* River at *Prayagraj*. The outlet of the sub-basin is in the *Varanasi* district. The climate of the AOI is typically categorized under the tropical monsoon type, with 03 predominant seasons, namely, winter (November to February), summer (March to June), and southwest monsoon (July to October). Though Retreating Monsoon also exists but has very sparse effects. Likewise, some mild showers can be observed in winter but are primarily due to Western Disturbances. The air temperature typically varies from 0 to 46 °C. The average annual precipitation in the study area is 768.5 mm. A major portion of this is contributed by the southeast monsoon, though western disturbance and northeast monsoon also make some minor beneficence to the annual precipitation (https://nri.up.gov.in/en/page/weather).

The geomorphology of the region is dominated by older alluvial plains followed by older flood plains & moderately dissected structural lower plateau. Other geomorphic units in the AOI are low-dissected structural and moderately dissected denudational lower plateaus, active flood plains, pediment pedi-plain complexes, and waterbodies. The lithology is dominated by oxidized silt–clay with *kankar* and micaceous sand., Five classes of lineaments, namely, break in-slope, drainage parallel, fault, joint/ fracture, and scarp parallel, are also observed within the AOI. Figure 1 illustrates the index map of the study area.

2.2 Sub-watersheds and drainage network

The presented study uses Soil Water Assessment Tool (SWAT) 2012 in ArcGIS version 10.4.1 with 82 geo-referenced Survey of India (SOI) Open Series Maps (no. 53G, 53H, 53L, 54I, 54M, 54N, 63A, 63B, 63C, 63F, 63G, 63K, 63L, and 63O) for the development of catchment boundary, sub-watersheds, and drainage network. ASTER GDEM version 3 (https://search.earthdata.nasa.gov/search), with a spatial resolution of 30 m, was used as an input for catchment delineation under the 'Automatic Watershed Delineation' in the SWAT interface. The developed drainage network was then imported to SWAT for manually defining inlets where water influx was received (from outside of the catchment boundary) and sub-watershed outlets. 11 sub-watersheds (coded from SW1 to SW11) were developed with 05 inlets and 10 sub-outlets. Sub-watershed indices such as area, perimeter, minimum, maximum & average elevation, slope, etc., were computed via the option of 'Calculation of Sub-basin Parameters' in the SWAT interface. These were then retrieved from the attribute table and used for the estimation of 15 morphometric parameters. Figure 2 depicts the sub-watersheds and the drainage network.

2.3 Principal component analysis (PCA)

For the identification of the criteria parameters, a statistical data reduction technique called PCA was used in the IBM SPSS Statistics19. This tool allows the user to conduct the PCA in a semi-automated manner. PCA contrives factors that enable the end user to interpret a large dataset into a small number of components that can be explained

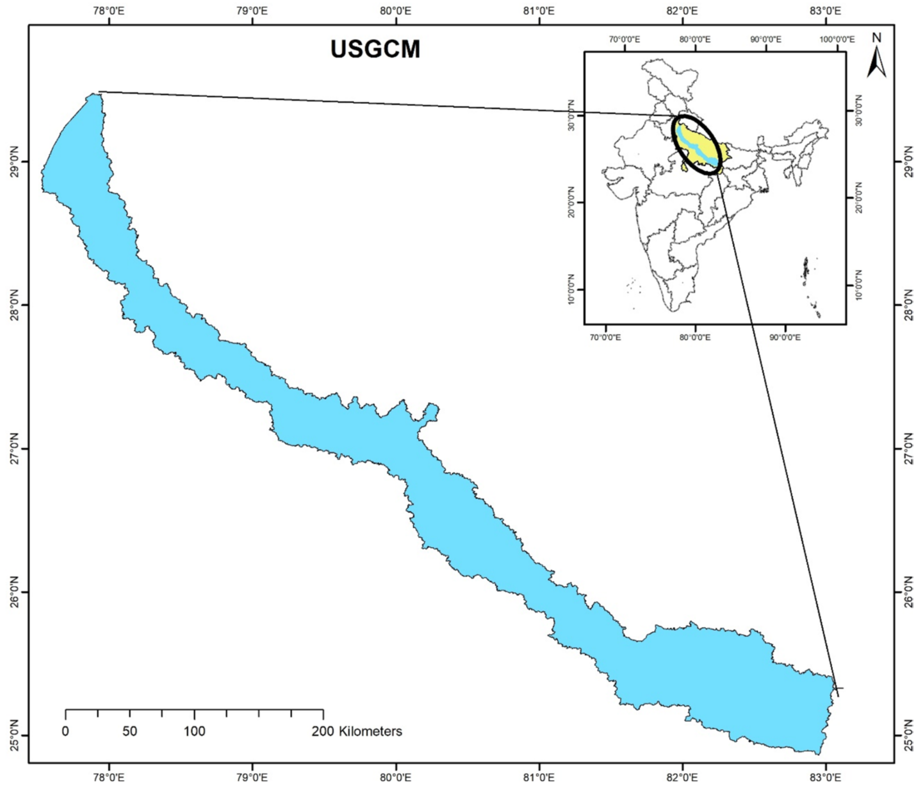

Fig. 1 Index map of the study area

decisively (Kassambara, 2017). Five linear (basin length, avg. stream length, stream number, bifurcation ratio, and stream-length ratio), seven areal (drainage density, stream frequency, texture ratio, elongation ratio, circulatory ratio, length of overland flow, and drainage texture), and three relief aspects (ruggedness number, Hypsometric Integral, and slope) which were computed for all the 11 sub-watersheds were used as input. PCA uses a covariance matrix to quantify the relationship between input variables. The number of developed Principal Components (PCs) equals the input variables, though not all of them are useful in data interpretation and subsequent reduction. To identify how many components should be extracted (legitimate PCs) during the analysis one has to develop a scree plot (a line plot of eigenvalues vs. PCs). A sharp change in the slope of the scree plot marks the PCs that explain most of the variance in the input data. Typically, the PCs that cumulatively account for 70–90% of the variance are retained for further data analysis (Jolliffe, 2002). After the identification of legitimate PCs, the pattern matrix (oblique rotated factor solution) is employed to filter out criteria parameters. Pattern matrix describes how well a given input loads on a developed PC. From each of the legitimate PCs, a few morphometric indices are selected based on their respective loading scores (absolute threshold ≥ 0.8). A total of 10 parameters were selected

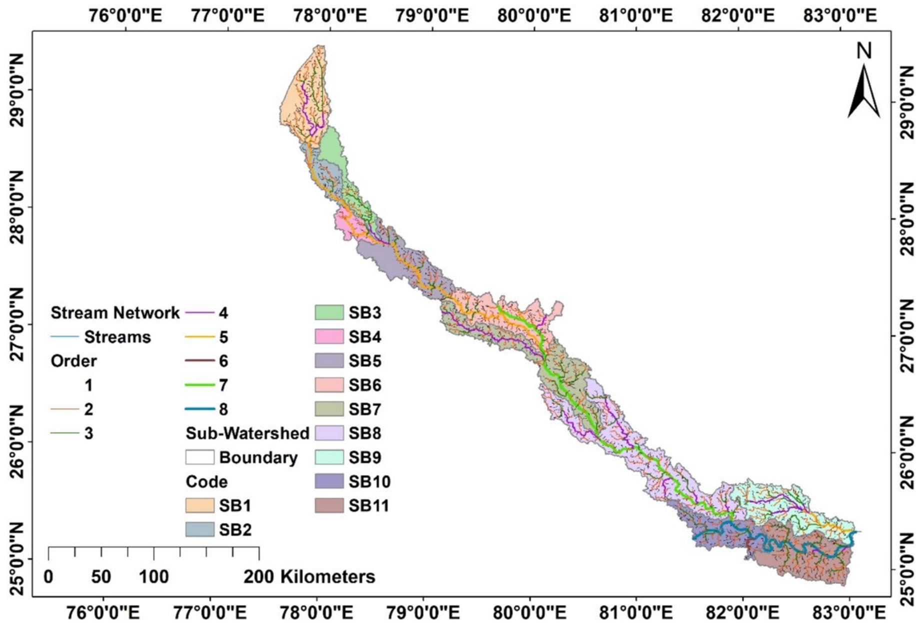

Fig. 2 Sub-watersheds and drainage network for the study area

following the PCA. These were then subjected to CRITIC MCDM for the assessment of their relative weights.

2.4 Criteria importance for intercriteria correlation (CRITIC)

Developed by Diakoulaki et al. (1995) CRITIC MCDM technique was utilized for the assessment of relative weights of 10 criteria parameters. CRITIC measures the score of conflict created (W_{cj}) via appraising information on input parameters through two indices, namely, Contrast Intensity (CI) and Measurement of Conflict (MOC). The CI is equal to the standard deviation (SD) of the normalized decision matrix (NDM) of the criterion values with the higher values suggesting that the criterion has a stronger ability to discriminate among alternatives, hence contributing more to the overall decision-making process (Fan et al., 2021). For MOC Karl Pearson's coefficient of correlation (r_{jk}) is computed between each input parameter and is then subtracted from the maximum value of r_{jk}, i.e., 1. Typically, a higher correlation corresponds to lower MOC and vice-versa. Yilmaz and Harmancioglu (2010) highlighted the application of CRITIC in various domains of water resource management. The procedure commences with the assessment of the most ($X_{j\ most}$) & least ($X_{j\ least}$) effective numeric values for each of the criteria parameters in regard to runoff and sediment generation. If a criteria parameter complements the runoff and sediment generation processes, then its largest value is classified as the most effective and vice-versa. Then NDM for the input data is prepared using Eq. (1) followed by computation of SD for each of the criteria parameters.

$$n_j = \frac{(X_j - X_{j\,least})}{(X_{j_{most}} - X_{j\,least})} \tag{1}$$

where X_j is the individual parameter value from the input matrix.

A Correlation Matrix (CM) was then developed from the NDM and CI for each input parameter is estimated. Afterward, a Symmetric Matrix (SM) and SM Values (SMV) are developed using Eqs. (2) and (3), respectively.

$$\mathrm{SM_i} = (1 - r_{\mathrm{jk}}) \tag{2}$$

$$\mathrm{SMV} = \sum_{\mathrm{i=1}}^{\mathrm{m}} \mathrm{SM_i} \tag{3}$$

The product of SMV and CI is obtained for each of the criteria parameters for the estimation of Criterion Information (C_j). The W_{cj}, in %, is obtained by normalizing the individual C_j values with the summation of C_j for all the input parameters and then multiplying the computed entity by 100. Subsequently, W_{cj} of each criteria parameter was used to estimate the morphometry scores (W_{mk}) of individual sub-watersheds using Eq. (4).

$$\mathrm{W_{mk}} = \sum_{\mathrm{k=1}}^{11} (\mathrm{NCP_k} * \mathrm{W_{cj}}) \tag{4}$$

where NCP_k is the normalized value of the criteria parameter.

2.5 Landuse and soil

Landuse data was adapted from Sentinel-2A of spatial resolution 10 m (https://www.arcgis.com/apps/instant/media/index.html?appid=fc92d38533d440078f17678ebc20e8e2) while the soil data is occupied from the Digital Soil Map of the World database of the Food and Agriculture Organization, UN of scale 1:250 k, respectively. For landuse prioritization score (W_{lk}), sub-watersheds were rated at an integer scale of 1 to 11, based on whether the specific landuse augments or impedes runoff and sediment generation. A rating of 1 equates to the least runoff and sediment generation, while, a rating of 13 corresponds to the maximum. Subsequently, an arithmetic average of the rating of each landuse class is then taken for every sub-watershed to yield W_{lk}. In regards to soil-based prioritization, ratings were given to each soil class based on its texture and USLE K-factor with larger K-values assigned higher ratings (R_{sl}) on an integer scale of 1 to 9. The soil prioritization score (W_{sk}) is then estimated as the product of R_{sl} and Relative area under a specific soil type (A_{rs}) using Eq. (5).

$$\mathrm{W_{sk}} = \sum (\mathrm{R_{sl}} * \mathrm{A_{rs}}) \tag{5}$$

The final priority score (W_{fk}) is then computed as the arithmetic average of W_{mk}, W_{lk}, and W_{sk}, respectively. Subsequently, 04 relative priority classes were developed for the sub-watersheds based on the quartile-based classification of W_{fk}. W_{fk} values less than the first quartile ($<Q_1$) are categorized as low, greater than or equal to Q_1 but less than the second quartile (Q_2) are placed under moderate ($Q_1 \le W_{fk} < Q_2$), greater than or equal to Q_2 but less than third quartile (Q_3) are classified as high ($Q_2 \le W_{fk} < Q_3$), and greater than Q_3 are enumerated under

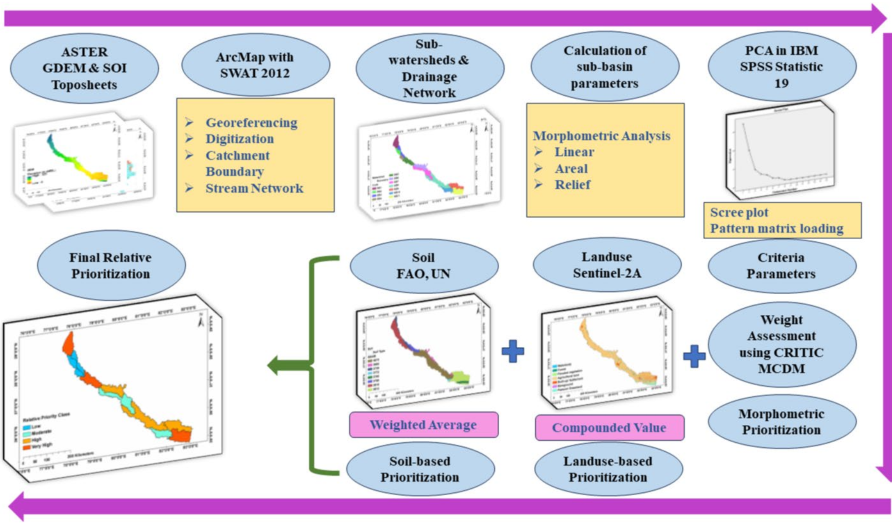

Fig. 3 Adapted methodology

very high class ($W_{fk} > Q_3$) of relative priority. Figure 3 illustrates the adapted methodology for the study.

3 Results and discussion

3.1 Morphometric analysis

The study area is an eighth-order drainage system following the Strahler (1952) classification with 1787 first, 410 s, 84 third, 16 fourth, 03 fifth, 01 sixth, 01 seventh, and 01 eighth-order stream, respectively, with the pattern being sub-dendritic type. The total length stream of all orders is 11,064.98 km with the total length of first, second, third, fourth, fifth, sixth, seventh, and eighth order streams being 5325.65 km, 2694.08 km, 1221.95 km, 634.77 km, 520.70 km, 20.33 km, 392.40 km, and 255.09 km, respectively. The details of the estimated 15 parameters are as mentioned below. Table 1 depicts morphometric parameters for the developed sub-watersheds.

3.1.1 Basin length (L_b), average stream length ($\bar{L}_u$) & stream Number (N_u)

L_b is a crucial index in estimating the time of concentration (NRCS, 1997). For the sub-watersheds, it ranges from 83.25 km (SB4) to 299.66 km (SB8), respectively. The $\bar{L}_u$ ranges from 4.25 km (SW5) to 5.67 km (SB2), while for the entire AOI, it was estimated at 4.80 km. Similarly, the N_u for the sub-watersheds limits from 47 (SW4) to 528 (SW8).

Table 1 Morphometric parameters for the sub-watersheds with least and most effective values

Sub-watershed	L_b (km)	$\bar{L}_u$ (km)	N_u	R_b	R_l	D_d (km/sq.km)	F_s (/sq.km)	R_T (/km)	R_e	R_c	L_g (km)	T (/cu.km)	R_n	HI	S (%)
SB1	131.00	5.57	190	3.578	1.515	0.363	0.065	0.430	0.465	0.188	2.755	0.024	0.042	0.360	2.12
SB2	102.65	5.67	72	2.797	2.287	0.361	0.064	0.202	0.370	0.112	2.772	0.023	0.028	0.576	1.93
SB3	172.60	5.20	57	3.622	2.139	0.199	0.038	0.101	0.252	0.059	5.028	0.008	0.015	0.440	1.77
SB4	83.25	4.83	47	2.460	2.311	0.289	0.060	0.174	0.380	0.135	3.457	0.017	0.019	0.518	1.77
SB5	156.24	4.25	176	3.492	2.192	0.272	0.064	0.296	0.379	0.098	3.682	0.017	0.030	0.589	1.85
SB6	177.62	4.82	219	2.360	1.872	0.363	0.075	0.278	0.343	0.059	2.758	0.027	0.029	0.622	1.84
SB7	264.23	4.66	318	2.543	1.884	0.368	0.079	0.295	0.271	0.044	2.720	0.029	0.033	0.540	1.88
SB8	299.66	4.40	528	2.706	2.057	0.373	0.085	0.374	0.297	0.039	2.680	0.032	0.044	0.567	1.98
SB9	183.57	5.07	258	2.161	1.302	0.399	0.079	0.353	0.352	0.077	2.508	0.031	0.041	0.701	2.10
SB10	169.58	4.86	175	1.981	1.554	0.383	0.079	0.290	0.314	0.077	2.613	0.030	0.055	0.348	2.06
SB11	151.78	4.80	272	2.068	1.638	0.369	0.077	0.454	0.442	0.124	2.709	0.028	0.114	0.317	3.29
$X_{j\ \mathrm{most\ eff}}$	**299.66**	**5.67**	**528.00**	**3.622**	**2.311**	**0.399**	**0.085**	**0.454**	**0.465**	**0.188**	**2.51**	**0.032**	**0.114**	**0.701**	**3.29**
$X_{j\ \mathrm{least\ eff}}$	**83.25**	**4.25**	**47.00**	**1.981**	**1.302**	**0.199**	**0.038**	**0.101**	**0.252**	**0.039**	**5.03**	**0.008**	**0.015**	**0.317**	**1.77**

R_b, R_l, R_e, R_c, R_n, and HI are dimensionless parameters

3.1.2 Bifurcation (R_b) and stream-length ratio (R_l)

The bifurcation ratio finds association in comprehending tectonic attributes of a drainage system ((Gajbhiye et al., 2014) and was estimated using Horton's law of stream numbers. For the USGCM R_b was estimated at 3.191, while for the sub-watersheds the same ranges from 1.981 (SB10) to 3.622 (SB2), respectively. The larger values of R_b assimilate to little control of geologic structures over drainage attributes (Rai et al., 2017) with a dissected morphology with larger potentialities towards flash flooding following excessive rainfall (Bogale, 2021). Concerning R_l, the estimation is made using Horton's law of stream lengths with the value for the AOI being 1.904. For the sub-watersheds, the same lies from 1.302 (SB9) to 2.331 (SB4), respectively.

3.1.3 Drainage density (D_d)

It refers to the relative closeness of streams in the drainage system and directly affects runoff volume at the outlet along with infiltration, with larger D_d values corresponding to lower infiltration and vice-versa (Choudhari et al., 2018). The D_d for the study area was computed to be 0.354 km/sq.km, while for the sub-watersheds the range of 0.199 (SB3) to 0.399 (SB9), respectively. As per Smith (1950), the lower value of D_d corresponds to a very coarse drainage texture.

3.1.4 Stream frequency (F_s) and texture ratio (RT)

The relatively larger values of F_s and R_T connote greater slopes and subsequently low infiltration of the sub-surface matrix (Farhan et al., 2017). At the sub-watershed level, the values of F_s and R_T were 0.038 (SW3) to 0.085 (SW8) per sq. km and 0.101 (SB3) to 0.454 (SB11) per km, respectively.

3.1.5 Elongation ratio (R_e)

This dimensionless index deliberates over the shape of a drainage system. For the sub-watersheds R_e extends from 0.252 (SB3) to 0.465 (SB1), respectively. As per Strahler (1952) classification, all the sub-watersheds were of elongated shape with R_e less than 0.7. This typically conveys a larger time of concentration and lower peaks in runoff.

3.1.6 Circulatory ratio (R_c)

The value of R_c for USGCM was estimated to be 0.026, while for the sub-watersheds the value amplitudes were between 0.039 (SB8) to 0.118 (SB1), respectively. Miller (1953) suggested that the value of R_c changes due to alterations in lithology, slope, and landuse characteristics. Shaikh and Birajdar (2015) proposed that low R_c values, as observed for the AOI, typically correlate to elongated drainage systems with relatively permeable subsurface.

3.1.7 Length of overland flow (L_g)

Das et al. (2021) endorse that low L_g values relate to more channel erosion while larger values accord with sheet erosion. For the study area, L_g was computed to be 1.41 km, while in the case of sub-watersheds the same ranges from 2.51 km (SB9) to 5.03 km (SB3), respectively. L_g is mostly related to the sheet flow with greater values analogous to greater sheet flow and vice-versa.

3.1.8 Drainage texture (T)

Computed as the product of D_d and F_s, drainage texture corresponds to relative channel spacing, especially in a fluvial dissected terrain. The drainage texture for the study area is 0.026 per cu. km, with the values for sub-watersheds ranging between 0.008 per cu. km (SB3) to 0.032 per cu. km (SB8), respectively. Sometimes referred to as infiltration no., T often finds linkage with runoff volume that can be accommodated by a watershed. Smith (1950) suggested that smaller values of T express larger infiltration and vice-versa.

3.1.9 Ruggedness no. (R_n)

This parameter relates to the structural complexity of the terrain and asserts the combined effects of length and slope attributes (Aher et al., 2014). Strahler (1952) recommended that greater values of R_n are linked with larger slopes and basin lengths. R_n for the sub-watersheds extends from 0.015 (SB3) to 0.114 (SB11).

3.1.10 Hypsometric integral (HI)

HI renders the developmental phase of a drainage system and is an indirect measure of activity in geologic structures. For the catchment, the HI was estimated at 0.395 which suggests that the drainage system is in the mature/ equilibrium stage and is shifting towards the old/ monadnock stage of watershed development (Strahler, 1952). In the context of sub-watersheds, the HI value protracts from 0.701 (SB9) to 0.301 (SB11). Furthermore, SB6 & SB9 were in the youthful stage (HI > 0.6), while SB10 and SB11 were under the old/ monadnock stage of watershed development.

3.1.11 Slope (S)

One of the key indices in relation to the hydro-sedimentological response of any drainage system is the slope. Typically, higher flow velocities relate to greater slopes which antecedents to lower time of contact between the water and the soil matrix, and vice-versa. Even drainage density and time of concentration are the function of slope (Wilson et al., 2012). The weighted average slope of the study was 2.10%. For the sub-watersheds, the same varies from 1.77% (SB3) to 3.29% (SB11).

3.2 Results from principal component analysis

The above-computed 15 morphometric indices were subjugated to PCA leading to the development of 18 PCs. An initial scree plot (Fig. 4) indicated that the first three PCs have eigenvalues > 1.5 explaining 81.18% (44.80%, 25.35%, and 11.03%) variance in the input dataset. The break in slope of the scree plot is another indication of the same. One may conclude that these are legitimate PCs that shall be analyzed for the identification of criteria parameters and subsequent data reduction. Successively, the SPSS is re-run by limiting the number of factors to be extracted to 03 using the method of ‘direct oblimin’. This

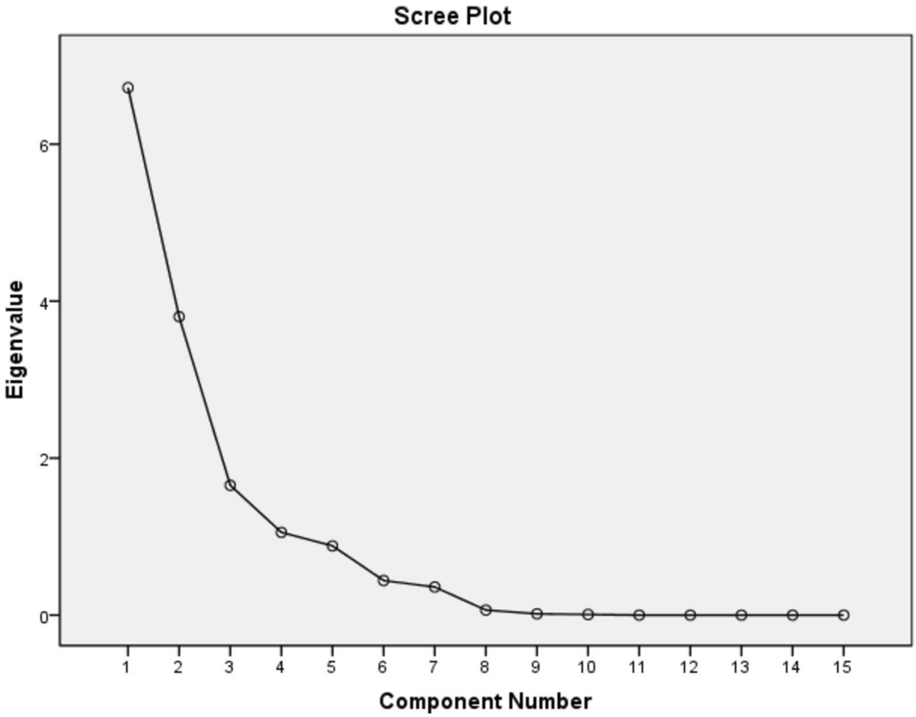

Fig. 4 Initial scree plot following the PCA

Table 2 Pattern matrix of the PCA

Parameter	Communalities	Legitimate PCs		
		PC1	PC2	PC3
D_d	0.978	1.023	0.119	−0.069
L_g	0.962	−1.018	−0.164	0.074
T	0.987	0.953	−0.163	−0.009
F_s	0.962	0.887	−0.277	0.022
R_b	0.495	−0.698	0.061	0.031
R_l	0.515	−0.588	−0.104	−0.281
R_T	0.843	0.574	−0.068	0.567
L_b	0.879	0.172	−0.891	−0.002
R_c	0.871	0.000	0.821	0.342
$\bar{L}_u$	0.595	0.108	0.796	−0.185
N_u	0.847	0.450	−0.693	0.197
R_e	0.800	0.249	0.676	0.441
S	0.863	0.163	−0.001	0.869
R_n	0.919	0.259	−0.112	0.854
HI	0.660	0.334	−0.092	−0.813

Communalities represent the fraction of variance explained method allows to production of an oblique factor rotation in case the factor solutions can be correlated with each other, otherwise, shall produce a near orthogonal factor solution. Following the pattern matrix of the PCA (Table 2) it can be inferred that D_d, T & F_s load quite well in PC1, while, L_g loading is large negative. This means the trio of morphometric indices seems to change together, i.e., if any one is increasing the other seems to follow the same trend, while a strong converse may be deducted in the case of L_g. Similarly, R_c, $\bar{L}_u$ & L_b and S, R_n & HI haul profusely in PC2 and PC3, respectively. This led to the selection of these 10 indices as criteria parameters (33.33% reduction in input parameters) for the application of CRITIC to get the relative importance of these indices over each other. Figure 5 illustrates the loading scores of input indices on legitimate PCs.

3.3 CRITIC results

The 10 criteria parameters were subjected to CRITIC MCDM for assessment of their relative weights. For all the parameters excluding L_g higher values relate to the most effective, whereas lower values were identified as being the least effective parameter in regards to the generation of surface runoff and sediment response. Following the development of NDM using Eq. (1), a CM is developed by using n_j from the NDM. The CM suggests that D_d has a strong positive correlation with T (0.961), F_s (0.892), and L_g (0.983). Likewise, S finds a strong positive correlation with R_n (0.97), while, R_e espy is negatively correlated with L_b (−0.752), respectively. The SM represents the conflict created. Among the criteria parameters, HI was assigned the highest relative priority (15.14%), while L_g was provided the least (6.9%). Table 3 illustrates the SM, C_j, and W_{cj} for the criteria parameters.

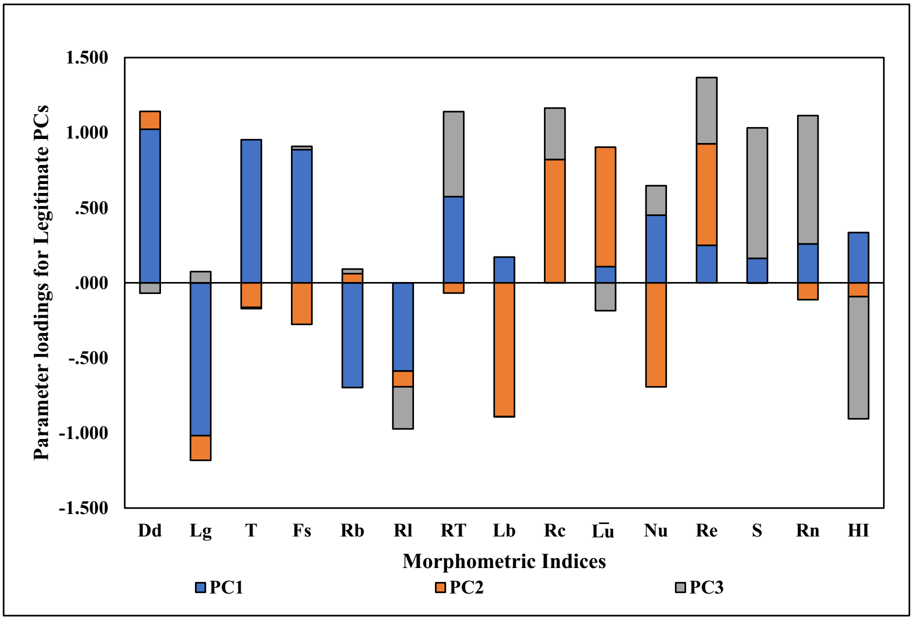

Fig. 5 Stacked column for loading scores of input indices on legitimate PCs

Table 3 SM with W_{cj} for criteria parameters

Criteria para	D_d	T	F_s	L_g	R_c	E_u	L_b	S	R_n	HI	Sum	SD (NDM)	C_j	W_{cj} (%)
D_d	0.000	0.039	0.108	0.017	0.988	0.933	0.738	0.639	0.529	0.922	4.912	0.289	1.418	6.92
T	0.039	0.000	0.027	0.061	1.193	1.181	0.533	0.639	0.497	0.885	5.056	0.298	1.505	7.35
F_s	0.108	0.027	0.000	0.101	1.242	1.387	0.483	0.668	0.508	0.846	5.372	0.270	1.448	7.07
L_g	0.017	0.061	0.101	0.000	0.912	0.994	0.806	0.661	0.550	0.903	5.007	0.282	1.414	6.90
R_e	0.988	1.193	1.242	0.912	0.000	0.495	1.752	0.700	0.801	1.439	9.522	0.289	2.750	13.42
E_u	0.933	1.181	1.387	0.994	0.495	0.000	1.532	1.000	1.126	1.198	9.846	0.294	2.894	14.12
L_b	0.738	0.533	0.483	0.806	1.752	1.532	0.000	1.063	0.930	0.786	8.624	0.279	2.403	11.73
S	0.639	0.639	0.668	0.661	0.700	1.000	1.063	0.000	0.030	1.530	6.930	0.269	1.865	9.10
R_n	0.529	0.497	0.508	0.550	0.801	1.126	0.930	0.030	0.000	1.545	6.517	0.259	1.689	8.24
HI	0.922	0.885	0.846	0.903	1.439	1.198	0.786	1.530	1.545	0.000	10.054	0.308	3.102	15.14

Table 4 Sub-watersheds with W_{mk} values

Criteria Para	D_d	T	F_s	L_g	R_c	E_u	L_b	S	R_n	HI	Sum	SD (NDM)	C_j	W_{cj} (%)
D_d	0.000	0.039	0.108	0.017	0.988	0.933	0.738	0.639	0.529	0.922	4.912	0.289	1.418	6.92
T	0.039	0.000	0.027	0.061	1.193	1.181	0.533	0.639	0.497	0.885	5.056	0.298	1.505	7.35
F_s	0.108	0.027	0.000	0.101	1.242	1.387	0.483	0.668	0.508	0.846	5.372	0.270	1.448	7.07
L_g	0.017	0.061	0.101	0.000	0.912	0.994	0.806	0.661	0.550	0.903	5.007	0.282	1.414	6.90
R_e	0.988	1.193	1.242	0.912	0.000	0.495	1.752	0.700	0.801	1.439	9.522	0.289	2.750	13.42
E_u	0.933	1.181	1.387	0.994	0.495	0.000	1.532	1.000	1.126	1.198	9.846	0.294	2.894	14.12
L_b	0.738	0.533	0.483	0.806	1.752	1.532	0.000	1.063	0.930	0.786	8.624	0.279	2.403	11.73
S	0.639	0.639	0.668	0.661	0.700	1.000	1.063	0.000	0.030	1.530	6.930	0.269	1.865	9.10
R_n	0.529	0.497	0.508	0.550	0.801	1.126	0.930	0.030	0.000	1.545	6.517	0.259	1.689	8.24
HI	0.922	0.885	0.846	0.903	1.439	1.198	0.786	1.530	1.545	0.000	10.054	0.308	3.102	15.14

W_{cj} values were then utilized to compute W_{mk} for the sub-watersheds using normalized values of criteria parameters as stated in Eq. (4). The sub-watershed SB11 was assigned the highest relative priority with W_{mk} of 10.839, while the SB3 was allocated the least, with W_{mk} value of 7.353, respectively. Table 4 represents the normalized criteria parameter with W_{mk} values for each sub-watershed.

3.4 Landuse and soil based prioritization

Using the Sentinel-2A data seven types of landuse classes, namely, waterbody (419.03 sq. km), forest (402.35 sq. km), flooded vegetation (4.02 sq. km), cropland (24,396.68 sq. km), built-up/ settlement (4441.63 sq. km), bare ground (205.79 sq. km), and grassland/ pastures (1422.78 sq. km), were observed in the AOI. Figure 6 (1) represents the landuse map for the AOI. Based on the characteristics of landuse class towards generating sediment and surface runoff integer weights (from 1 to 11) were assigned to each of them depending upon the percentage area of each class in the given sub-watershed. The results illustrated that the sub-watershed SB3 has the lowest score (4.833), while the SB9 has the highest (7.667) in the context of prioritization using landuse. Using the digital soil map of the world eight (08) soil types, namely, SNUM 3675 (38.15%), 3685 (2.83%), 3739 (5.32%), 3772 (0.87%), 3785 (3.50%), 3798 (5.05%), 3810 (20.56%), and 3812 (23.72%), were identified for the study area. Textural class for all the soil types was reported to be loam except for SNUM 3772 and 3785 which were categorized under sand-clay loam and sandy loam, respectively. Soil with SNUM 3675 & 3785 was classified under Hydrologic Soil Group (HSG) C, while the remaining soil type was placed in HSG D. Towards assigning integer ratings (1 to 9) to the soil types USLE K factor was employed, with higher K-factor corresponding to greater rating and vice-versa. The K or soil erodibility factor characterizes soil detachability and transportability due to various soil properties (Chang, 2013). Following Eq. (5) final soil-based prioritization scores (W_{sk}) were computed for each sub-watershed with SB4 (0.854) getting the least relative priority while the SB5 (7.431) getting the highest. Figure 6 (2) depicts the soil map for the study area, while Table 5 illustrates land use and soil statistics for the sub-watersheds.

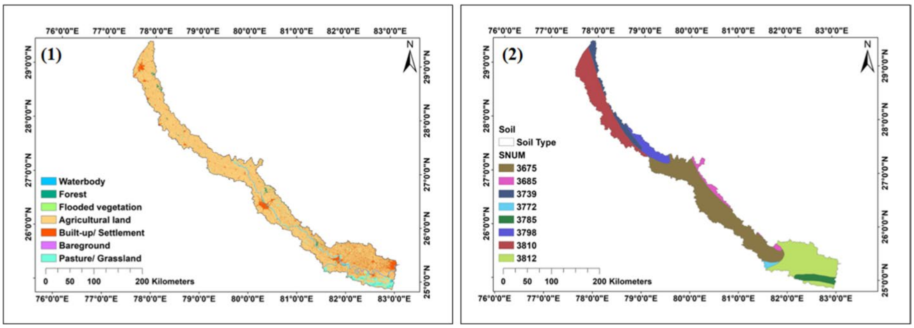

Fig. 6 (1) Landuse and (2) Soil map for the study area

Table 5 Landuse and soil statistics along with W_{lk} & W_{sk} scores for the sub-watershed

Sub-Water-shed	Landuse														Soil SNUM								
	Flooded vegetation	Forest		Waterbody		Cropland		Built-up		Bareground		Pasture		W_{lk}	3675 (sq. km)	3685 (sq. km)	3739 (sq. km)	3772 (sq. km)	3785 (sq.km)	3798 (sq. km)	3810 (sq.km)	3812 (sq.km)	W_{sk}
	%	%	Score	%	Score	%	Score	%	Score	%	Score	%	Score										
SB1	NA	12.77	4	2.00	8	9.94	5	9.66	7	0.03	2	0.27	4	5.000	NA	NA	615.31	NA	NA	NA	2300.35	NA	4.722
SB2	NA	5.84	6	0.06	11	4.05	10	2.66	2	NA	1	0.01	2	5.333	NA	NA	NA	NA	NA	NA	1131.28	NA	1.231
SB3	NA	12.37	5	0.10	10	5.36	9	2.98	3	NA	1	0.00	1	4.833	NA	NA	341.77	NA	NA	NA	1147.37	NA	2.481
SB4	NA	2.50	10	0.33	9	2.85	11	1.69	1	0.82	4	0.15	3	6.333	NA	NA	NA	NA	NA	NA	784.87	NA	0.854
SB5	0.24	4.12	8	3.27	6	10.08	4	5.76	5	0.63	3	0.71	5	5.167	2.13	NA	706.65	NA	NA	979.91	1068.45	NA	7.431
SB6	NA	3.25	9	12.31	5	10.25	3	5.62	4	12.06	6	5.26	7	5.667	2016.66	306.67	NA	NA	NA	590.46	0.02	NA	4.471
SB7	21.40	19.39	2	13.63	4	13.67	2	9.81	8	12.31	7	6.93	8	5.167	3707.26	312.05	NA	NA	NA	10.48	NA	NA	3.002
SB8	71.60	20.64	1	22.50	2	19.71	1	20.49	10	23.25	9	19.44	10	5.500	5559.00	265.19	NA	NA	NA	NA	NA	401.11	3.742
SB9	NA	1.86	11	3.25	7	9.42	6	21.01	11	1.87	5	1.98	6	7.667	NA	1.78	NA	NA	NA	NA	NA	3281.18	1.776
SB10	0.18	4.44	7	17.21	3	6.25	8	8.67	6	20.58	8	12.55	9	6.833	651.69	NA	NA	272.05	NA	NA	NA	1296.20	2.971
SB11	6.58	12.81	3	25.35	1	8.43	7	11.66	9	28.44	10	52.70	11	6.833	NA	NA	NA	NA	1093.722	NA	NA	2446.15	4.318

NA: Not Applicable

3.5 Final relative prioritization

The final score of prioritization (W_{fk}) was computed by taking the arithmetic average of W_{mk}, W_{lk}, and W_{sk} for each sub-watershed. Subsequently, 04 classes of relative priority, namely, low, moderate, high, and very high, were developed using the W_{fk} values following a quartile-based approach. These classes account for 3405.29 sq. km, 6249.73 sq. km, 12,422.06 sq. km, and 9212.68 sq. km area, respectively. The sub-watersheds SB2, SB3 & SB4 were classified in low ($W_{fk} < Q_1$ (5.449)), while SB7 and SB10 categorized in moderate class ($Q_1 \leq W_{fk} < Q_2$ (6.272)), respectively. Similarly, the sub-watersheds SB6, SB8 & SB9 are under high ($Q_2 \leq W_{fk} < Q_3$ (6.475)), while SB1, SB5 & SB11 were placed in very high class ($Q_3 \leq W_{fk}$) of relative priority, respectively. The 'high' and 'very high' class cumulatively accounts for 69.15% of the total geographical area of the catchment. Figure 7 represents the relative prioritization map of the study area.

4 Conclusion

The presented work is an attempt to prioritize sub-watersheds using morphometry, landuse, and soil statistics. It is a pre-requisite to the implementation of any catchment conservation program as it optimizes sub-watersheds in regards to the identification of drainage systems that exigencies for prompt application of conservation measures. The study shall prove useful, especially in scenarios where there are fiscal and manpower limitations and adequate meteorological data is not available to run and subsequently calibrate and validate hydrologic models. Additionally, the study provides a resolution on the selection of

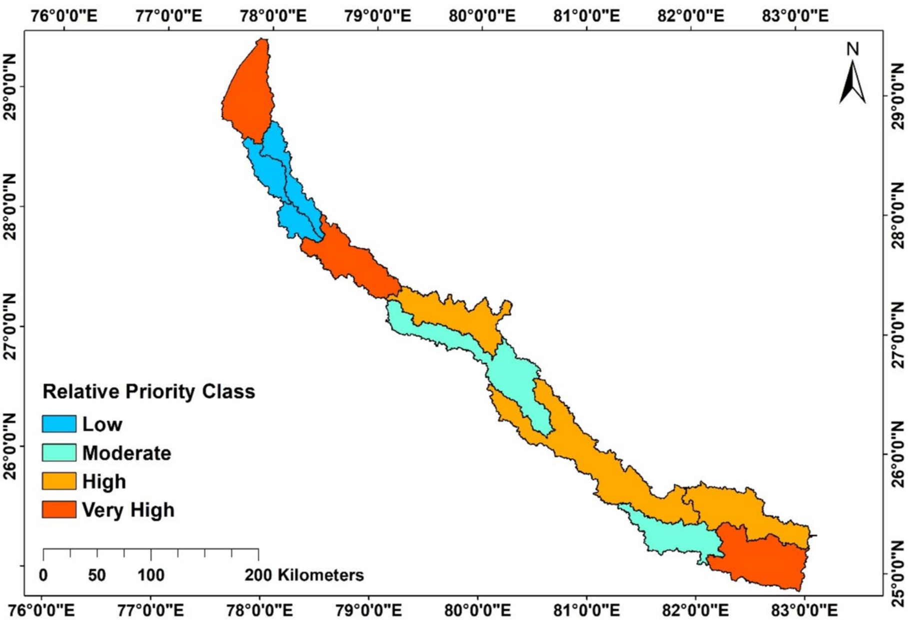

Fig. 7 Relative prioritization map for the sub-watersheds

the most influencing morphometric parameters, which otherwise largely remain elusive, following a statistical (PCA) and multi-criteria (CRITIC) framework. The outcomes determined that approximately 21,636 sq. km of the study area is under the class of very high and high relative priorities suggesting prompt implementation of catchment conservation measures for sustentation of water and soil resources. While the adopted procedure is statistically elegant and provides a comprehensive prioritization of sub-watersheds the outputs are relative and limited to the sub-watershed level only. This lumping of data may mask finer-scale variations within the sub-watersheds that could provide more precise insights into areas requiring conservation interventions. Further, the study primarily relies on static data for morphometry, land use, and soil characteristics. However, dynamic processes such as land use change, seasonal variations, and climate impacts could alter the prioritization outcomes over time. To overcome the same, the study recommends using a suitable semi-distributed hydrologic model (based on the approach of hydrologic response units) for sub-watersheds under very high & high classes of relative priorities. This shall not only lead to the avoidance of data granularity and temporal variability but shall also assist in the identification of specific locations where prompt implementation of soil & water conservation interventions is required within the concerned sub-watersheds. Moreover, the use of more fine data, especially soil, can prove more insightful and could potentially yield more detailed and accurate prioritization. This limitation may affect the precision of the prioritization, particularly in areas where soil heterogeneity plays a crucial role in runoff and erosion processes. The adapted methodology can be adopted as a Standard Operating Procedure (SOP) by various government & non-government agencies, and policymakers toward designing programs for watershed and soil resource conservation. Nevertheless, the illustrated study is not only a direct contribution towards sustainable land & water resource management but also accords towards combating climate change impacts on land and water resources.

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Authors contribution MAA conceptualization, investigation, monitoring, data curation, writing of final draft, review and editing; NR, MS conceptualization, investigation, review, and editing; HJ Data curation, data analysis, modeling, writing of original draft; MR Data curation, data analysis, review and editing; AKP, RKJ, RS investigation, review and editing; SK, ASP conceptualization, review and editing, project administration; MK Data curation.

Data availability statement The data that supports the findings such as geo-processed maps, etc., under this manuscript can be made available upon request to the first or the corresponding author(s). Additionally, the quantitative data associated with the manuscript (mostly in the tabular form) is provided under the supplementary information.

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization/entity with any financial interest in the subject matter as discussed in this manuscript. The authors concede that to the best of their knowledge, the submitted manuscript has no conceivable ethical contentions. Further, no known personal relationship has appeared to influence the deliberated study under the contemplated manuscript.

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