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A MORPHOMETRIC AND MULTIVARIATE ANALYSIS APPROACH TO PRIORITIZATION OF SUB-WATERSHED: A CASE STUDY ON MUZAFFARPUR DISTRICT OF BIHAR, INDIA

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ABSTRACT

Aim of the study

The goal of the present study, which was undertaken as a research, was to Prioritization of Sub-Watershed using Morphometric and Multivariate Analysis.

Material and methods

Prioritization of sub-watersheds relying on erosion proclivity is critical in strategic planning when incorporating management practices, especially in vulnerable semi-arid regions. Geomorphometric as well as land use and land cover data sets are essential for determining sub-watershed priorities for integrated watershed management. Prioritizing watersheds entails ranking sub-watersheds according to their susceptibility based on several variables, including the average yearly soil loss, the depletion of water resources, and ecological deterioration. The final sub-watershed prioritization for our study area i.e., Muzaffarpur District, was determined by combining PCA (Principal Component Analysis) with WSA (Weighted Sum Approach). PCA was used to differentiate important parameters, whereas WSA was used to measure compound values for priority ranking, and to determine weights for significant parameters.

Results and conclusion

PCA was effective in obtaining the most crucial values (i.e., WB, Dt, Re, and Rb). A load of each significant parameter was successfully defined by means of the WSA application. Compared to traditional prioritizing procedures, which use numerous criteria in a complex manner and presumptively contribute equally, PCA-WSA integration results in more dynamic, effective, and efficient solutions. The Muzaffarpur District's decision-makers can apply this useful knowledge in establishing management methods that will reduce and perhaps even prevent land degradation.

Keywords: geomorphology, PCA (Principal Component Analysis), WSA (Weighted Sum Approach), LULC (Land Use / Land Cover)

INTRODUCTION

The term "watershed" refers to the region from which runoff from rainfall runs through a single point and into significant streams, lakes, rivers, and seas. A watershed is a naturally occurring hydrologic unit that can be classified according to the surrounding physical, climatic, and topographic conditions (Syed et al., 2017). Natural availability of resources, such as land and water, is dwindling daily as a result of

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increasing population pressure. Therefore, these natural resources must be planned for and managed. For the scientific management and control of these resources, vast amounts of data are required. This is why, when creating regional hydrological models to address a variety of hydrological issues with unmeasured watersheds or insufficient data conditions, the geomorphologic properties of a watershed are frequently used as input (Gajbhiye et al., 2014). The science of measuring and mathematically estimating size, shape, surface, and dimensions of the earth's land formations is known as morphometric analysis (Sharma et al., 2014; Mangan et al., 2019; Sangma and Guru, 2020; Raj et al., 2022; Rawat and Singh, 2023; Bisht and Rawat, 2023a). Geomorphometric factors are mostly used in prioritizing analysis to highlight the natural characteristics of the watershed that are referred to as the principal topic of concern. Perhaps the analysis method could be made more thorough by including management qualities (Setiawan and Nandini, 2021).

Numerous interrelated causes, including both geophysical and social aspects, contribute to the degradation of watersheds. Foley et al. (2005) assert that a region's socioeconomic and geophysical factors have an impact on Land Use / Land Cover (LULC) variation, which itself is recognized as the primary force behind climatic change. Because of this, it is desirable to designate components of all factors contributing to watershed degradation, in order to rank the importance of managing particular watersheds. Prioritizing watersheds entails ranking sub-watersheds according to their susceptibility based on several variables, including the average yearly soil loss, the depletion of water resources, and ecological deterioration. Prioritizing sub-watersheds makes it easier to create methods that effectively manage soil erosion by reducing the amount of sediment produced (Javed et al., 2009; Siddiqui et al., 2020).

The LULC status of the watershed is given particular consideration in the prioritizing of sub-watersheds (Mishra et al., 2007; Javed et al., 2009). It has been determined that the main factor causing environmental changes in the watershed that accelerate soil erosion mostly consists in anthropogenic changes to land use or land cover (Malik and Bhat, 2014). Using the geographic information system, the basin's morphometric parameters have been computed and outlined (Singh et al., 2013). The utilization of remote sensing and geographic information systems (GIS) has become prevalent in prioritizing watersheds (Martin and Saha, 2007; Mahanta et al., 2023; Bisht and Rawat, 2023b).

The analytical method of prioritization has primarily been employed in earlier research with a standard compound value, which is derived by averaging the initial ranks of priority across all parameters (Martin and Saha, 2007). Some investigations have been guided by Principal Component Analysis (PCA) and Weighted Sum Approach (WSA, Shinde et al., 2011; Patil and Mali, 2013; Aher et al., 2014). For instance, the WSA of geomorphometric factors was used by Aher et al. (2014) to prioritize sub-watersheds within the watershed Pimpalgaon Ujjaini in India. Sharma et al. (2014) and Meshram and Sharma (2017) used Principal Component Analysis to determine the sub-watershed, and it was deduced that the technique reduced the complexity of the dataset by taking into account the correlation between the variables. According to these investigations, PCA and WSA turned out both more dynamic and more effective compared to the standard compound value approach. To determine ultimate prioritizing, the traditional compound values technique presupposed that all of the factors were of equal weight. Meanwhile, the fact that each sub-watershed has unique properties means that the significance of the parameters, in practice, may not be the same for all of them. As a result, the union of PCA and WSA demonstrated a promising method for watershed prioritizing.

The goal of the current study is prioritizing the sub-watersheds, derived from the data incorporation of geomorphometric characteristics and land use in the Muzaffarpur district. To be able to rank the sub-watersheds, PCA and WSA approaches were combined.

By the analysis of SRTM DEMs we can pinpoint the precise elevation, and by the analysis of ASTER DEMs we can monitor more details pertaining thereto (Rawat et al., 2014a). To examine the alterations between ASTER and SRTM data and their influence on the time of concentration (TC) of water flow at Moolbari Experimental Watershed, estimations have been made (Rawat et al., 2016). In statistical analysis, non-linear regression and polynomial regression are used, whereas developing data driven models involves the application of artificial neural network (ANN) and fuzzy logic (FL) (Negi et al., 2021). By using different GIS techniques we can monitor various morphometric parameters (Sahu et al., 2020). Sediment Yield Index (SYI) is used to estimate soil loss, which is important for the planning and management of watershed (Rawat et al., 2014b).

MATERIAL AND METHODS

Study area

The Muzaffarpur District is located between latitudes 25° 54’ 00” and 26° 23’ 00” North, and longitudes 84° 53’ 00” and 85° 45’ 00” East. The city is located in a seismically active region of India. Located on a foundation of Himalayan sand and silt, which was carried by the meandering rivers of the Himalayas and the Indo-Gangetic plains of Bihar, is a saucer-shaped settlement with a distinctive low-centered form.

The district’s principal rivers are fed by the area’s drainage system, which rises in the Himalayas. The rivers Burhi Gandak, Baghmati, and Baya, which typically run in a south-easterly direction, are the main drainage systems for the area. Even though the three rivers and all of their tributaries are perennial, they are highly unpredictable during the rainy season and monsoon, when they become extremely destructive and often cause flooding in this region. This unusual characteristic causes the sedimentation rate to spike during the monsoon season close to the riverbanks, leading to the construction of raised upland, and gradually decreasing away from the river channels.

The district experienced 1280 mm of rainfall on average. It is well established that the monsoon season occurs from June through September. According

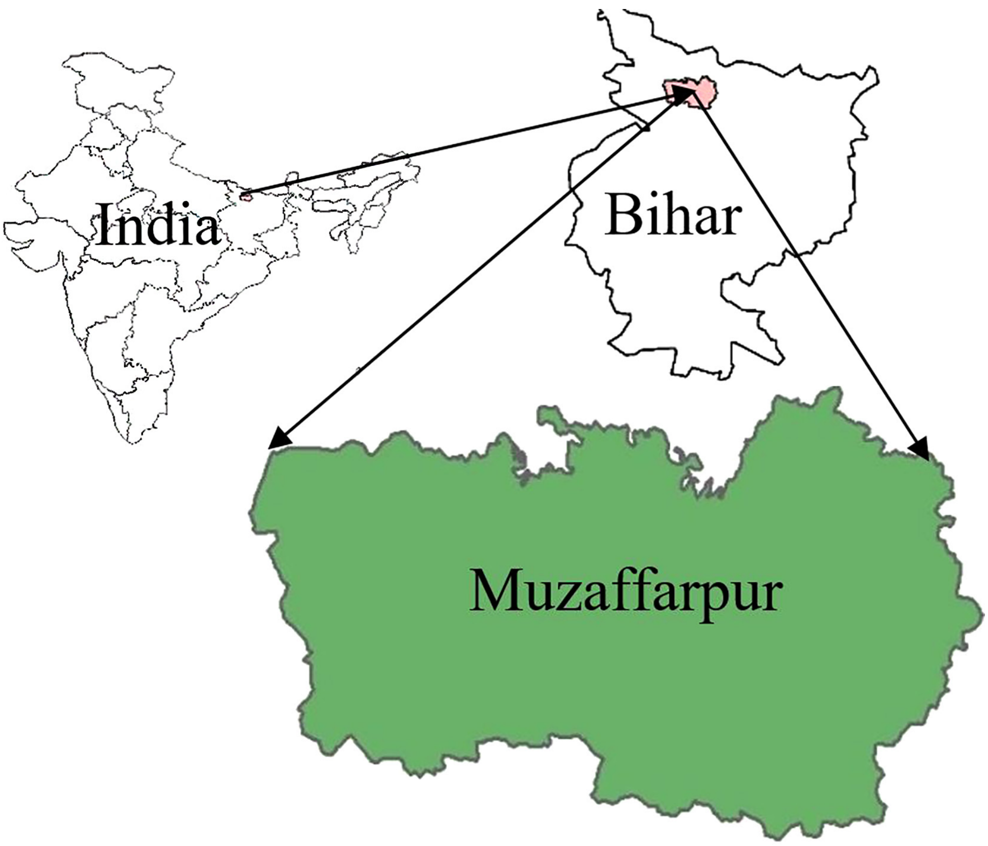

Fig. 1. Study area map of Muzaffarpur District (source: Authors’ own elaboration)

to monthly rainfall data, the monsoon season accounts for 85% of the total precipitation. The district receives the most rainfall in the southwest monsoon season, and a small amount in the northeastern monsoon season.

Alluvium covers the entire district. There are generally four different types of soil in this area. They are subdivided into four categories: sandy loam, clayey, clay soil with sand mixture known as *Bangar*, and lastly the patches of *Usar* land with salt efflorescence known in the local language as *Reh*. The sandy loam variation predominates in the area south of the Burhi Gandak river. The northern region is home to *Bangar* and clayey soils, whereas *Usar* land is scattered throughout the western region. The district's soil becomes more salinized and alkaline as a result of the water logging that is also prevalent in some areas of the district.

Input data collection

The present study employs ASTER Digital Elevation Model (DEM) data, which offers a spatial resolution of 30m. Using the DEM information along the district border, the location of the network of the stream and sub-watershed was determined. Ridgelines, the water divide, and other morphological elements assist the subdivision of the sub-watershed. From the upstream to the watershed outflow, eight sub-watersheds were obtained and given the labels SW1, SW2, SW3, SW4, SW5, SW6, SW7, and SW8. Following Horton's law, a number was assigned to the stream network of each sub-watershed beginning with the first order (Rawat et al., 2013).

GIS software was used to determine the fundamental geomorphometry, as well as stream number (Nu), sub-watershed area (A), stream length (Lu), sub-watershed perimeter (P) and sub-watershed length (Lb), under the sub-watershed boundary and their stream orders. Three types of geometric parameters: linear, areal, and relief were utilized in the sub-watershed prioritizing process. Three linear parameters: bifurcation ratio (Br), stream length (Lu), and average overland flow length (Lg) were employed in the analysis. The seven areal aspect variables used for priority calculations were: compactness coefficient (Cc), form factor (Ff), drainage texture (Dt), drainage density (Dd), elongation ratio (Re), circularity ratio (Rc), and stream frequency (Fs). Additionally, the parameters of the relief aspect utilized in the inspection were the ruggedness number (Rn), relative relief ratio (Rhp), and relief ratio (Rhl), among others. Using GIS software and a formula developed by Miller (1953); Schumm (1956); Strahler (1957) and Rawat et al. (2013), all the geomorphometric parameters were acquired and derived using the fundamental geomorphometric characteristics and DEM data.

By using supervised interpretation and classification of remotely sensed data from Landsat 5 and Landsat 8, it was possible to get Land Use / Land Cover data for the Muzaffarpur district. With the machine learning application, LULC categories used the random forest classification technique. Corresponding to a significant impact on the hydrological procedure in the watershed, six general, key Land Use and Land Cover categories were identified: waterbody (WB), forest (FO), agriculture (AG), urban (UA), barren (BA), and scabland (SC). Due to their tiny areas and assumption that they would not significantly alter the prioritizing, other LULC categories were disregarded.

Geomorphometric and LULC analyses

Each parameter and each sub-watershed were given a Preliminary Rank (PR) formed on the link between the variable and soil erodibility through geomorphometric and LULC analyses. The geomorphometric variables Lu, Lg, Rb, Dd, Dt, Fs, Rhl, Rn, and Rhp all directly affected soil erodibility, whereas the variables that show an inverse correlation to soil erodibility were Ff, Cc, Rc, and Re (Khan et al., 2001; Varade et al., 2013). The geomorphometric factors that directly influenced soil erodibility for each sub-watershed were ranked from 1 for the greatest value, then 2 for the next-greatest value, and so forth. A higher direct effect parameter value indicated a greater likelihood of soil erodibility. The parameter with the lowest value received rank 1, and similarly for each sub-watershed, to rank the factors that have a reverse association to soil erodibility. The minimum value of inverse relationship parameters suggested a strong possibility for soil erodibility (Subrahmanyam and Ahmed, 2005; Thakkar, 2012) by using a methodology used in a prior study, the preliminary rank for LULC was determined (Javed et al., 2011). The meth-

Table 1. The formula used to calculate geomorphological parameters (source: Rawat et al., 2013)

Morphometric Parameters Formula	
Basis aspect	
Area of the basin (A, in)	The region enclosed by the watershed boundary
Perimeter of the basin (P, in km)	Perimeter of the watershed
Number stream order (Nu)	Nu = N1+N2+N3+……Nn
Liner aspect	
Stream length (Lu)	Lu = L1+L2+L3……Ln
Bifurcation ratio (Rb)	Rb = Nu/Nu+1
Length of overland flow (Lg)(km)	Lg = 1/2Dd
Areal aspect	
Form factor (Ff)	$Ff = A/Lb^2$
Drainage texture (Dt)	Dt = Nu/P
Compactness coefficient (Cc)	Cc = 0.282 * P/VA
Circularity ratio (Rc)	$Rc = 4 * \pi \cdot A/P^2$
Elongation ratio (Re)	Re = 1.129 * VA/Lb
Drainage density (Dd) (km/k)	Dd = Lu/A
Stream frequency (Fs)(no/k)	Fs = Nu/A
Relief aspect	
Relief ratio (Rhl)	Rhl = H/Lb
Relative relief ratio (Rhp)	Rhp = H * 100/P
Gradient ratio (Gr)	Gr = (Z-z)/Lb
Ruggedness number (*Rn*)	*Rn* = *Dd* * (H/1000)

od involved ranking the regions with the greatest concentration of agricultural land and bushes. The least quantity of forest was described as being in the highest preliminary rank.

Principal Component Analysis and Weighted Sum Approach

PCA has been utilized to specify important geomorphometric and Land Use / Land Cover factors. PCA is used as a multivariate statistical technique to dimensionally simplify the parameters. It was necessary to normalize the dataset using the z-score approach before PCA calculation because the parameters had different scales (Spitale and Mair, 2017; Siddiqui et al., 2020). Following the conversion of the original data, PCA generates two or more primary components. To select principal components with eigenvalues exceeding 1, the Kaiser criterion and varimax rotation of factor loading were applied (Kaiser, 1958). To improve the correlation in defining the most significant parameters, the factor loading rotation was carried out (Aher et al., 2013). The most significant parameters derived from PCA were then subjected to WSA. Cross-correlation evaluation was used to obtain the weighted quantity of significant parameters represented as Wsp, which is reflected as follows (Malik et al., 2019):

$$Wsp = \frac{(\text{Sum of Correlation coefficient})}{(\text{Total of Correlation})} \qquad (1)$$

The Wsp and PR of critical variables were used to produce the compound values (CV), which were then used to establish the final priority ranking. The following mathematical formula was used for the CV calculation (Aher et al., 2013; Malik et al., 2019):

$$CV = PRsp \times Wsp \tag{2}$$

where: PRsp = Preliminary Ranking of significant parameter; CV = compound value; Wsp = weight of significant parameter. For all sub-watersheds, the CV with the lowest value received priority rank 1, the very next value received priority rank 2, and so on.

RESULTS

Geomorphometric and Land Use / Land Cover analysis

GIS software was used in the geomorphometric investigation of the eight sub-watersheds of the Muzaffarpur district to assess the sub-characteristics of the watershed. The three types of computation used to calculate morphometrics were: linear (Lu, Lg, Rb), areal (Ff, Cc, Dt, Re, Rc, Fs, Dd), and relief (i.e., Rhl, Rn, Rhp). Table 2 displays the numerical measure of the geomorphometric factors.

Although the stream length (Lu) differs, the sub-watersheds in the Muzaffarpur district typically are of fifth stream order. The largest and the smallest sub-watersheds according to total stream length are SW5 (1041.44 km) and SW2, respectively. The initial stream order has the longest stream segment length, which then decreases as the stream order sequence continues.

The watershed's hydrological process and the bifurcation ratio (Rb) are closely related. High overland flow is a sign of high Rb values, and it affects how much erosion is possible. The value of Rb is also influenced by the severity of the structural disruption. As structural disturbance in the watershed increases, the level of control of that disturbance also increases. The Muzaffarpur district's SW6 continues to have the highest likelihood of soil erodibility based on Rb value. The average overland flow measures the amount of time water spends rushing over land before entering a stream (Lg). The maximum erosion susceptibility, as indicated by the Lg value in Table 2, is SW5. Drainage texture is the watershed's relative distance between streamlines. Lithospheric composition, surface material, vegetation, and relief all affect drainage texture. In the Muzaffarpur district, SW1 has the highest Dt value. The longer Lg values provide for greater time for overland flow and erosion processes, according to Ali and Ikbal (2015). The Muzaffarpur district's sub-watershed form factor (Ff) score ranges from 0.17 to 0.57, indicating a flow with a longer du-

Table 2. The geomorphometric qualities of the sub-watersheds (source: Authors' own elaboration)

	Linear			Areal							Relief		
	Lu	Rb	Lg	Ff	Dt	Cc	Rc	Re	Dd	Fs	Rhl	Rhp	Rn
SW1	481.41	7.435	66037.417	0.290	7.055	2.145	0.221	0.615	1.755	3.215	2.471	59.995	0.132
SW2	112.09	8.179	3606.496	0.260	3.236	2.178	0.214	0.575	1.742	3.092	4.005	102.456	0.110
SW3	503.19	8.29	114631.71	0.169	2.677	2.919	0.119	0.457	1.104	1.288	1.482	35.577	0.086
SW4	248.84	12.02	27746.904	0.290	2.430	2.287	0.194	0.608	1.116	1.309	2.311	53.262	0.071
SW5	1041.4	7.50	470762.12	0.230	4.546	2.591	0.151	0.552	1.152	1.378	1.189	26.632	0.084
SW6	169.63	12.2	13330.374	0.528	2.365	2.023	0.248	0.820	1.079	1.342	2.493	48.201	0.046
SW7	372.57	7.91	37970.472	0.416	1.748	2.403	0.176	0.727	1.828	1.035	1.897	34.799	0.077
SW8	185.68	9.32	8830.941	0.567	6.893	1.699	0.352	0.849	1.952	4.226	4.788	106.310	0.121

ration, a lower peak, and a more elongated shape. The ratio of the watershed's surface area to its square area, based on the watershed's length, is the value of Ff. The SW8 has the highest likelihood of erosion of any sub-watershed, while the SW3 has the lowest. The drainage density (Dd) demonstrates a stronger correlation with the length of time it takes water to cross a watershed. Additionally, it addresses permeability of the subsurface components that affect erosion. The district of Muzaffarpur has the highest Dd value, which is SW8. This is indicative of how much more prone to soil erosion the SW8 is. The number of streams per unit area is expressed by a watershed's stream frequency (Fs). The correlation between stream frequency and permeability, infiltration, and relief is strong. SW7 exhibits the lowest Fs value, whereas SW1 exhibits the greatest value. Geomorphometric relief has been investigated as one of the key elements in understanding geomorphometric and erosion interactions. The strength of the slope's erosion is measured by the relief ratio (Rhl). Due to the lower slope and the foundation rock's resistance, the lowest level of Rhl demonstrates reduced soil erodibility. The SW5 and SW8 had the minimum and maximum Rhl levels, respectively, based on this study. This implies that, given this situation, SW8 is much more susceptible to erosion than SW5. It was observed that the SW5 and SW8 had the minimum and the maximum values of the relative relief ratio (Rhp), respectively. The terrain that characterizes the watersheds is also described by the Rhp. High relief with steeper incline and greater erosion susceptibility is indicated by a high Rhp rating. Roughness number (Rn) is another measure of relief that is determined by drainage network and relief or by the proportion of relief to horizontal distance. The high value of Rn suggests that the watershed is typically prone to erosion. The sub-watershed in this study that is most prone to erosion is SW1. The Muzaffarpur district's Land Use/ Land Cover was broadly classified into six essential types: waterbody, forest, agriculture, urban, barren land, and scabland. When classifying specific Land Use / Land Cover types compared to sub-watershed areas, percentages are employed as the measurement unit. The percentage of each sub-watershed and LULC is shown in Table 3 for the Muzaffarpur district.

The correlations between Land Use / Land Cover, geomorphometric parameters and erosion potential were used to estimate the preliminary rank (PR) for every sub-watershed. PR was calculated using the parameters' direct or inverse correlation to erosion. Tables 4 and 5 show the PR of sub-watersheds that meet the geomorphometric and LULC criteria, respectively.

Table 3. The Land Use / Land Cover percentages in sub-watersheds (source: Authors' own elaboration)

	LULC %					
SW	WB	FO	AG	UA	BA	SC
SW1	9.769	27.743	41.125	14.739	5.793	0.831
SW2	11.559	19.560	47.305	14.865	6.233	0.478
SW3	6.099	26.229	36.457	24.026	6.285	0.904
SW4	6.382	19.661	41.969	25.925	5.180	0.882
SW5	10.282	15.702	37.582	19.574	12.176	4.685
SW6	9.302	5.341	25.039	3.759	13.746	42.812
SW7	12.728	10.584	41.436	14.974	16.486	3.790
SW8	52.870	373.525	205.704	433.805	26.383	7.712

Note: SW – sub-watershed; WB – water; FO – forest; AG – agriculture; UA – urban; BA – barren land; SC – scabland

Table 4. Preliminary Rank (PR) of sub-watersheds (source: Authors' own elaboration)

SW	Linear			Areal							Relief		
	Lu	Rb	Lg	Ff	Dt	Cc	Rc	Re	Dd	Fs	Rhl	Rhp	Rn
SW1	3	8	3	4	1	3	6	5	3	2	4	3	1
SW2	8	5	8	3	4	4	5	3	4	3	2	2	3
SW3	2	4	2	1	5	8	1	1	7	7	7	6	4
SW4	5	2	5	5	6	5	4	4	6	6	5	4	7
SW5	1	7	1	2	3	7	2	2	5	4	8	8	5
SW6	7	1	6	7	7	2	7	7	8	5	3	5	8
SW7	4	6	4	6	8	6	3	6	2	8	6	7	6
SW8	6	3	7	8	2	1	8	8	1	1	1	1	2

Table 5. Preliminary Rank (PR) of sub-watersheds according to Land Use / Land Cover (source: Authors' own elaboration)

	Land Use %					
SW	WB	FO	AG	UA	BA	SC
SW1	4	7	5	2	7	7
SW2	6	4	2	3	6	8
SW3	1	6	7	6	5	5
SW4	2	5	3	7	8	6
SW5	5	3	6	5	4	3
SW6	3	1	8	1	3	1
SW7	7	2	4	4	2	4
SW8	8	8	1	8	1	2

Results from PCA and WSA

The PCA was used to determine the connection between all variables, including geomorphometric and Land Use / Land Cover data, to identify the main component, minimize the dimension of the parameters, and identify the most crucial variables. The correlation analysis for all variables is shown in Table No. 6. A strong correlation ($r \geq 0.9$) is noticed between Lg and Lu, Re and Ff, Rc and Cc, Rhp and Rhl, FO and WB, AG and WB, UA and WB. A good correlation ($0.75 \leq r \leq 0.9$) occurs between Cc and Ff, Rc and Ff, BA and Ff, Fs and Dt, Rn and Dt, Re and Rc, Rhl and Rc, Rhp and Rc, WB and Rc, FO and Rc, AG and Rc, UA and Rc, BA and Re, Rhl and Fs, Rhp and Fs, Rn and Fs, WB and Rhl, AG and Rhl, BA and WB, BA and FO, BA and AG, BA and UA. Some moderate correlation ($0.60 \leq , \leq 75$) exists between Cc and Lu, Rhl and Lu, Rhp and Lu, Rn and Rb, WB and Ff, UA and Ff, Sc and Ff, FO and Dt, AG and Dt, Fs and Cc, Rhp and Cc, WB and Cc, FO and Cc, AG and Cc, UA and Cc, WB and Re, SC and Re, Rhl and Dd, Rhl and Dd, Rhp and Dd, Rn and Dd, WB and Dd, WB and Fs, FO and Fs, AG and Fs, UA and Fs, WB and Rhl, FO and Rhl, AG and Rhl, UA and Rhl, WB and Rhp, FO and Rhp, AG and Rhp, UA and Rhp, SC and Rn. The fact that certain parameters are correlated suggests that different parameters may contain various pieces of information. Therefore, utilizing PCA and the correlation matrix, parameter dimension can be reduced for practical reasons.

Four principal components (PCs) were produced by the application of PCA in this investigation (shown in Table 7). These principal components could account for 95.202% of the variation in the starting data since they had eigenvalues > 1.

Table 6. Correlation matrix of variables of Muzaffarpur district (source: Authors' own elaboration)

	Lu	Rb	Lg	Ff	Dt	Cc	Rc	Re	Dd	Fs	Rhl	Rhp	Rn	WB%	FO%	AG%	UA%	BA%	SC%
Lu	1																		
Rb	–0.53	1																	
Lg	0.96	–0.41	1																
Ff	–0.51	0.44	–0.45	1															
Dt	0.17	–0.37	0.12	0.16	1														
Cc	0.60	–0.35	0.51	–0.81	–0.48	1													
Rc	–0.56	0.30	–0.48	0.83	0.55	–0.96	1												
Re	–0.49	0.43	–0.44	0.99	0.17	–0.83	0.82	1											
Dd	–0.33	–0.48	–0.39	0.37	0.49	–0.54	0.54	0.39	1										
Fs	–0.34	–0.24	–0.31	0.31	0.81	–0.69	0.76	0.31	0.72	1									
Rhl	–0.70	0.13	–0.59	0.55	0.43	–0.82	0.86	0.54	0.65	0.85	1								
Rhp	–0.65	0.04	–0.54	0.37	0.45	–0.73	0.76	0.36	0.63	0.88	0.98	1							
Rn	0.00	–0.63	–0.08	–0.13	0.82	–0.28	0.34	–0.11	0.72	0.84	0.50	0.59	1						
WB%	–0.27	–0.02	–0.21	0.66	0.59	–0.67	0.83	0.63	0.60	0.73	0.75	0.66	0.45	1					
FO%	–0.26	0.02	–0.21	0.59	0.61	–0.62	0.80	0.55	0.52	0.73	0.72	0.65	0.47	0.98	1				
AG%	–0.28	–0.01	–0.22	0.58	0.60	–0.63	0.80	0.54	0.57	0.74	0.75	0.68	0.50	0.99	1.00	1			
UA%	–0.26	0.04	–0.20	0.60	0.58	–0.61	0.80	0.56	0.50	0.70	0.71	0.63	0.44	0.98	1.00	1.00	1		
BA%	–0.13	0.03	–0.07	0.81	0.30	–0.55	0.68	0.79	0.45	0.35	0.45	0.29	0.06	0.86	0.78	0.78	0.80	1	
SC%	–0.27	0.62	–0.16	0.62	–0.22	–0.35	0.32	0.61	–0.34	–0.20	0.03	–0.10	–0.61	0.00	0.05	–0.10	–0.04	0.29	1

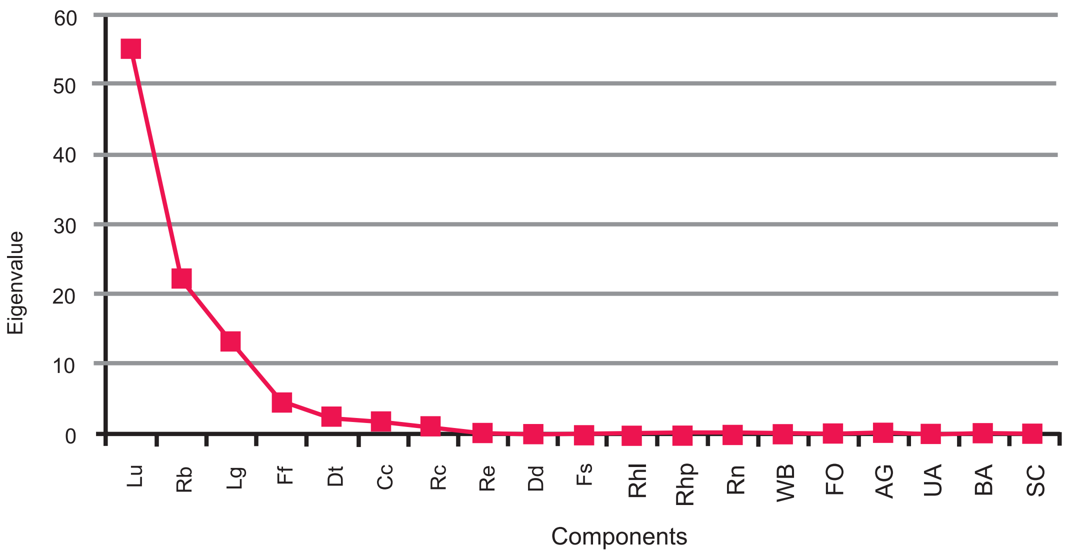

Fig. 2. The graph between principal components and eigenvalues (source: Authors' own elaboration)

Table 7. Total variance of principal components for the Muzaffarpur district (source: Authors' own elaboration)

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Lu	10.478	55.147	55.147	10.478	55.147	55.147
Rb	4.194	22.072	77.219	4.194	22.072	77.219
Lg	2.523	13.280	90.500	2.523	13.280	90.500
Ff	0.893	4.702	95.202	.893	4.702	95.202
Dt	0.443	2.334	97.536			
Cc	0.309	1.627	99.164			
Rc	.159	.836	100.000			
Re	.000	.000	100.000			
Dd	.000	.000	100.000			
Fs	.000	.000	100.000			
Rhl	.000	.000	100.000			
Rhp	.000	.000	100.000			
Rn	.000	.000	100.000			
WB	.000	.000	100.000			
FO	.000	.000	100.000			
AG	.000	.000	100.000			
UA	.000	.000	100.000			
BA	.000	.000	100.000			
SC	.000	.000	100.000			

The initial factor-loading matrix produced by PCA also depicts the correlation between the variables in each principal component, shown in Table 8. The initial PC and AG exhibited a strong ($r \geq 0.9$) and good correlation ($0.75 \leq r \leq 0.9$) with Lu, Lg, Cc, Rc,Rhl, Rhp, WB, FO, UA, and BA, and a moderate correlation ($0.60 \leq r \leq 75$) with Ff, Re, Dd, and Fs. The second PC had a strong correlation to Rn, a good correlation to Rb and Dt, and a moderate correlation to Fs. The third PC only had a moderate correlation with Ff, Re, and SC.

The initial factor-loading matrix revealed that certain parameters had strong correlations with PC, some had good correlations with PC, others had moderate correlations with PC, and yet others lacked any principal component correlation. As a result, it might be difficult to pinpoint the key features of any PC. To obtain greater correlation and meaningful parameters, it is important to rotate the first factor-loading matrix. Table 9 shows the rotated factor-loading framework. Lu, Lg, WB, AG, and BA had the first PC's strongest correlation. Fs, Ff, and Re, respectively, had the strongest correlations with the second PC and third PC. These factors are also recognized as essential variables and are utilized for sub-watershed prioritization and WSA.

Table 8. First factor-loading matrix of all parameters (source: Authors' own elaboration)

	Component			
	1	**2**	**3**	**4**
Lu	**0.89**	0.34	0.28	–0.07
Rb	–0.33	**–0.77**	0.18	0.47
Lg	**0.85**	0.29	0.39	0.04
Ff	–0.69	–0.26	0.60	–0.20
Dt	–0.25	**0.81**	0.37	0.20
Cc	**0.85**	–0.08	–0.47	–0.06
Rc	**–0.84**	0.17	0.48	0.13
Re	–0.69	–0.24	0.62	–0.24
Dd	–0.63	0.58	–0.03	–0.52
Fs	–0.67	0.70	0.12	0.18
Rhl	**–0.89**	0.29	0.08	0.16
Rhp	**–0.83**	0.39	–0.04	0.24
Rn	–0.31	**0.93**	–0.16	0.01
WB	**0.88**	0.23	0.38	–0.09
Fo	**0.85**	0.41	0.03	0.23
AG	**0.95**	0.24	0.20	0.05
UA	**0.88**	0.29	0.17	0.20
BA	**0.86**	0.11	0.43	–0.14
Sc	0.29	–0.53	0.68	0.04

Strong correlation ($r > 0.90$); good correlation ($0.90 \geq r > 0.75$); moderate correlation ($0.75 \geq r > 0.60$)

Table 9. Rotated factor-loading matrix of all parameters (source: Authors' own elaboration)

	Component			
	1	2	3	4
Lu	**0.96**	–0.11	–0.22	0.11
Rb	–0.42	–0.20	0.31	**–0.80**
Lg	**0.97**	–0.07	–0.14	–0.04
Ff	–0.30	0.13	**0.92**	–0.06
Dt	0.27	**0.88**	0.14	0.18
Cc	0.39	–0.55	**–0.70**	0.06
Rc	–0.35	0.65	0.67	–0.08
Re	–0.29	0.13	**0.94**	–0.03
Dd	–0.31	0.47	0.28	**0.77**
Fs	–0.23	0.93	0.16	0.22
Rhl	–0.56	**0.70**	0.33	0.05
Rhp	–0.54	**0.76**	0.15	0.06
Rn	–0.02	**0.81**	–0.22	0.52
WB	**0.96**	-0.18	–0.11	0.05
Fo	**0.81**	0.05	–0.53	–0.04
AG	**0.92**	–0.18	–0.33	–0.03
UA	**0.87**	–0.05	–0.39	–0.11
BA	**0.94**	–0.28	–0.01	0.01
Sc	0.41	–0.39	0.53	–0.48

The CV value, which was produced using the initial order and weight of pertinent qualities, was employed in the ultimate sub-watershed prioritising phase (WB, Dt, Re, Rb). An analysis of the four parameters' cross-correlations was used to establish the parameters' relevance (Table 10). An equation based on the weighted sum of the significant variables was used to calculate the CV.

$$CV = (0.321 \text{ x PR of WB}) + (0.203 \text{ x PR of Dt}) + (0.325 \text{ x PR of Re}) + (0.152 \text{ x PR of Rb})$$

Table 10. Cross-correlation between the crucial variables of Muzaffarpur district (source: Authors' own elaboration)

	WB	Dt	Re	Rb
WB	1	0.59	0.63	–0.02
Dt	0.59	1	0.17	–0.37
Re	0.63	0.17	1	0.43
Rb	–0.02	–0.37	0.43	1
Sum	2.2	1.39	2.23	1.04
Grand Total	6.86	6.86	6.86	6.86
WSA	0.321	0.203	0.325	0.152

PCA and WSA are used to prioritize sub-watersheds. Using CV values, Table 11 presents the priority ranking of the sub-watersheds. The pattern of priority rank across the spatial watershed is shown in Figure 3.

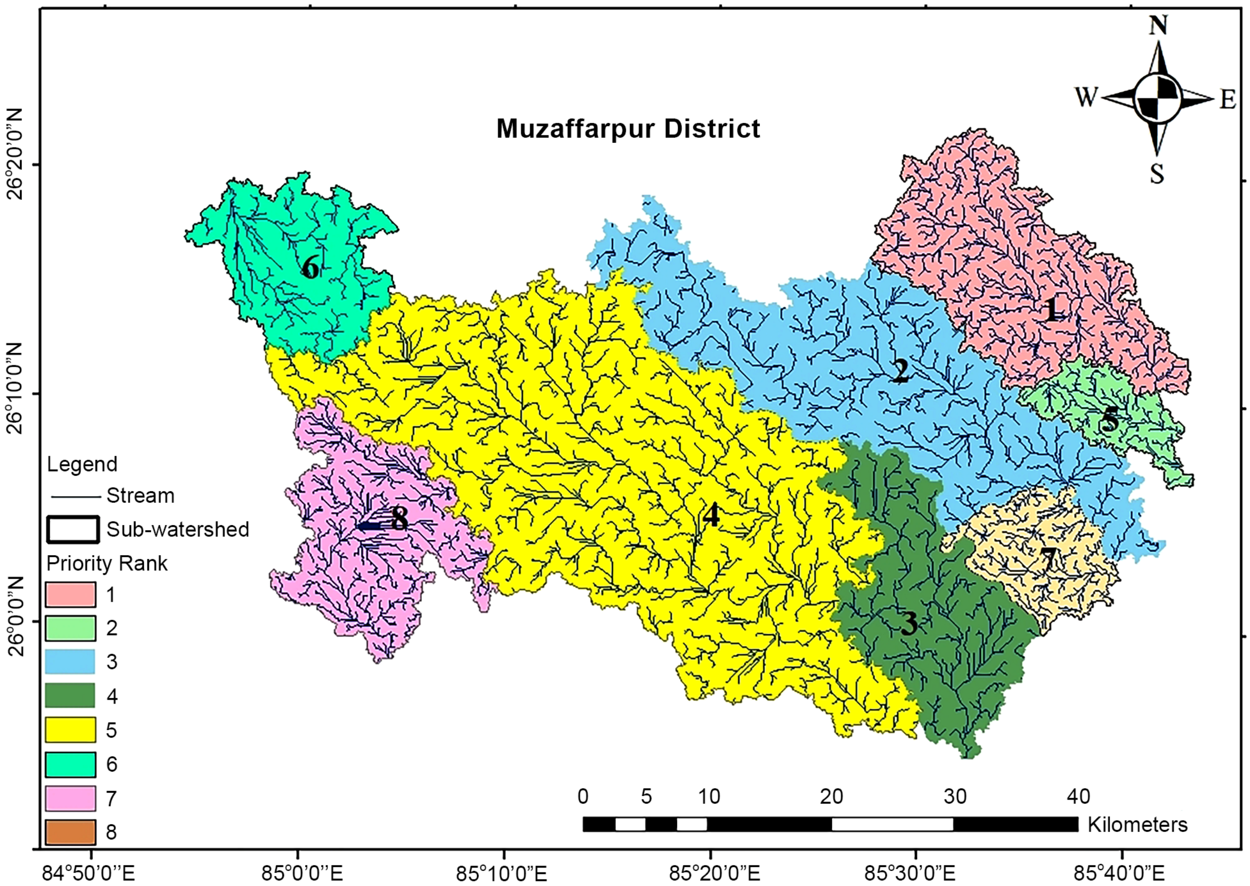

Fig. 3. Sub-watershed priority ranking map (source: Authors' own elaboration)

Table 11. Priority rank for sub-watersheds of Muzaffarpur district (source: Authors' own elaboration)

	Compound Value (CV)	Priority Rank
SW1	4.3	1
SW2	4.5	5
SW3	2.3	2
SW4	3.5	3
SW5	3.9	4
SW6	4.8	6
SW7	6.7	8
SW8	6.0	7

Subject to CV values, the priority rank was assigned. The three groups of the priority category are classified as: low (CV > 4.40), medium (3.40 ≤ CV ≤ 4.40), and high (CV < 3.30). SW3 is listed in the high category in Table 12; SW1, SW4, and SW5 are listed within the medium category; while SW2, SW6, SW7, and SW8 are listed within the low category. Muzaffarpur district's high category takes up roughly 2.27 hectares of space. The priority category map for the Muzaffarpur district is shown in Figure 4.

The high category area (Block Bochaha, villages Balia Indarjit, and Borwara) are identified as having a high flood hazard index as per Flood Hazard Atlas of Bihar, prepared by the National Remote Sensing Centre, Indian Space Research Organisation, Dept. of Space, Govt. of India, July-2020). Flood hazards can intensify soil erosion as rushing water erodes and carries away topsoil. Prioritizing not only reveals an area with a high potential for erosion but also one where soil and water conservation might be applied.

Table 12. The sub-watersheds' of the Muzaffarpur district priority categories (source: Authors' own elaboration)

No	Compound Value (CV)	Priority Category	Sub Watershed (SW)	Area (ha)	Percentage of area (%)
1	< 3.300	High	SW3	2.27	6.29
2	3.40-4.40	Medium	SW1, SW4, SW5	11.71	32.52
3	> 4.40	Low	SW2, SW6, SW8, SW7	22.03	61.19

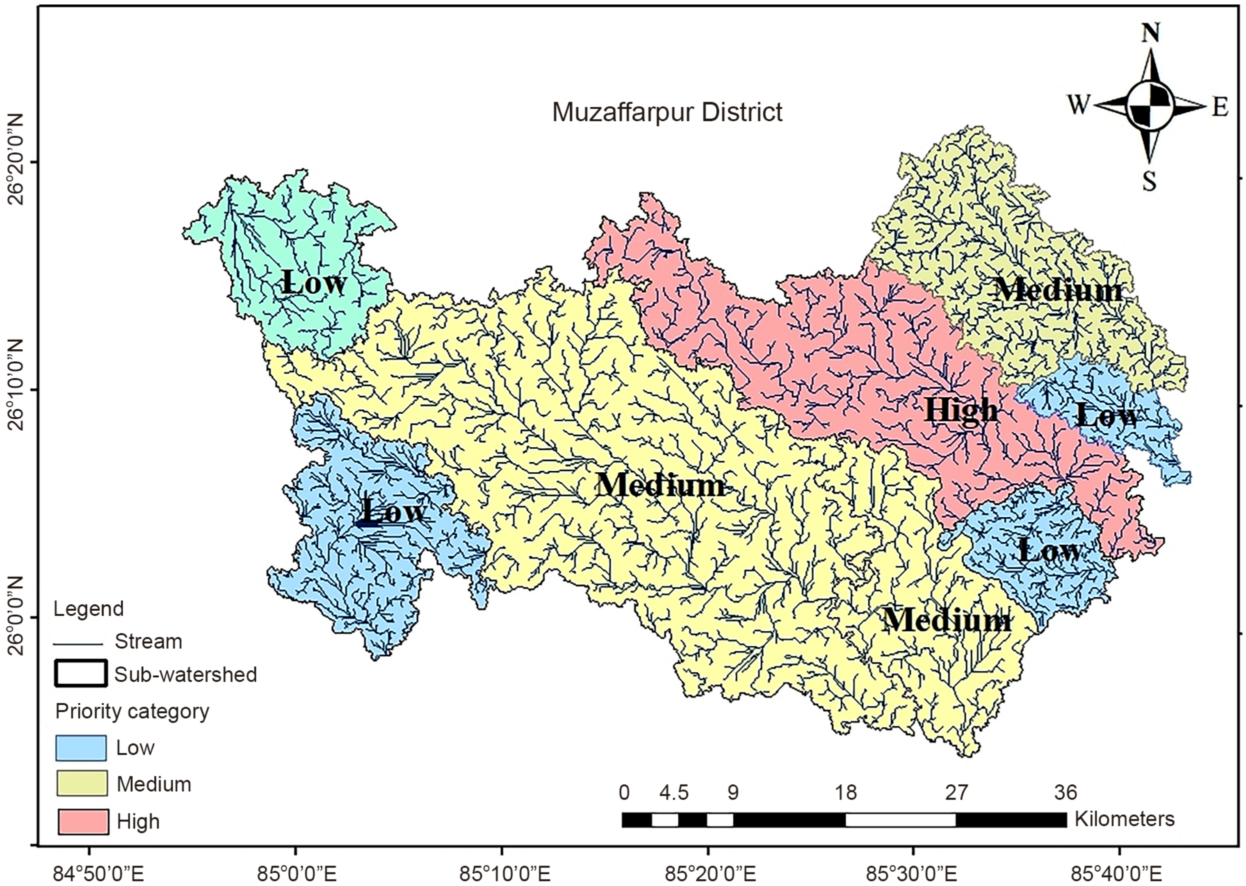

Fig. 4. Priority map for sub-watersheds (source: Authors' own elaboration)

Areas in a medium priority category (Block Aurai, villages such as Bishunath, Chainpur, Chihuta, Dharampur, Dharopatti, Ganguli, Jiusar, Maheswara, Mahisautha, Mathurapur, Rampur, etc.) exhibit very high flood hazard index. Additionally, villages like Asmanpur, Bahuara, Banauli, Bara Buzurg, Borwara Garib, Basua, Deora Asli, etc., within the same block demonstrate a high flood hazard index. Similarly, in Block Katra, villages including Aghari, Raipur Aghari, Ankhauli, Bandhpura, Basant, Bel Pakauna, Bhagwanpur, Chak Bhabda, Chak Mohiuddin, Dhubauli, Khangura Dih, Madaripur, Pahsaul, Pindauli, Sahnauli, etc., are classified with a very high flood hazard index, while Marwa, Madhaipura, Tehwara, Marwa, Kopi, Jitwara, Dhanaur, Chanauli, etc., have a high flood hazard index. In these areas, as per Flood Hazard Atlas of Bihar, prepared by the National Remote Sensing Centre, Indian Space Research Organisation, Dept. of Space, Govt. of India, July-2020, it is advised to maintain and safeguard the current vegetation coverage and high-category revegetation. It is necessary to conserve vegetation, soil, and water in the medium category sub-watersheds to prevent erosion, especially sheet and rill erosion.

In turn, the low priority category villages such as Sahebganj, Mamrezpur, Faridpur, Mahuwara etc. were demonstrated to have an adequate geomorphometric characteristic and current Land Use / Land Cover. Structured soil and water conservation methods are used in the high-category mitigation strategies to reduce the sub-watersheds' susceptibility to erosion.

DISCUSSION OF THE RESULTS

The primary goal was to reduce the dimensionality of parameters and identify critical variables for sub-watershed prioritization and WSA. PCA is a statistical technique used to uncover patterns in complex datasets (Behera et al., 2023). In most research work, RS data is integrated in GIS platform with simple weighted analysis for prioritization (Sharma et al., 2015; Kadam et al., 2016; Farhan et al., 2017; Gajbhiye and Sharma, 2017), while in the present study we drive the morphometric parameters from earth observational data and then apply PCA and WSA statistical tools for the prioritization of the study area. Using PCA and WSA analyses renders the results of prioritization more precise. In this study, these tools were employed to reduce the dimensionality of the data, and to identify the primary components. This helped to simplify the analysis and focus on the most significant variables. Moreover, it revealed that four principal components explained an impressive 95.202% of the variation in the initial data. Eigenvalues exceeding 1 confirmed the robustness of the analysis.

The initial factor-loading matrix provided insights into the relationships between variables within each principal component. This revealed that different parameters held distinct information, confirming the utility of PCA and the correlation matrix for dimension reduction. The first principal component displayed strong correlations with several variables, including AG, Lu, Lg, Cc, Rc, Rhl, Rhp, WB, FO, UA, and BA. This component provided valuable insights into the dominant factors driving the data's variation. To refine the understanding of each principal component, a rotation of the factor-loading matrix was performed. This revealed the essential variables strongly correlated with each PC. For instance, Lu, Lg, WB, AG, and BA were found to have the strongest correlation with the first PC. These variables were considered crucial for further analysis.

CV value, which incorporated the initial order and weight of relevant attributes, was employed in sub-watershed prioritization. Factors such as WB, Dt, Re, and Rb were considered, and their cross-correlations were used to establish their significance. The resulting CV equation allowed for the calculation of priority rankings for sub-watersheds.

PCA and WSA were then used to prioritize sub-watersheds based on the CV values. This categorization was divided into low, medium, and high priority, indicating the level of susceptibility to erosion. SW3 was identified as a high-priority sub-watershed, suggesting a significant risk of erosion in that area. Medium-priority sub-watersheds included SW1, SW4, and SW5, which required attention to prevent erosion, particularly sheet and rill erosion. SW2, SW6, SW7, and SW8 were classified as low priority, indicating more stable geomorphometric characteristics and land use.

PCA and WSA are valuable tools for prioritization and decision-making in a wide range of applications. PCA reduces data complexity by highlighting key components, while WSA helps assign importance to different criteria. When used together, these techniques provide a holistic approach to effective prioritization, ensuring that decisions are based on data-driven insights and the relative significance of various factors. Whether in finance, healthcare, or any other field, the combination of PCA and WSA offers a strong framework for making informed choices and optimizing outcomes. Compared to traditional prioritizing procedures, which use numerous criteria in a complex manner and presumptively equal contributions, PCA-WSA integration results in more vibrant, useful, and efficient solutions (Sharma et al., 2015; Kadam et al., 2016; Farhan et al., 2017; Gajbhiye and Sharma, 2017).

CONCLUSIONS

The present research illustrates the holistic approach, deploying remote sensing and GIS as well as advanced statistical techniques. In most research work, RS data is integrated in GIS platform with simple weighted analysis in GIS platform for prioritization (Sharma et al., 2015; Kadam et al., 2016; Farhan et al., 2017; Gajbhiye and Sharma, 2017), while in the present study we drive the morphometric parameters from earth observational data, and then apply PCA and WSA statistical tools for the prioritization of the study area. Using PCA and WSA analysis produces more precise results of prioritization.

The Muzaffarpur District has several measures to lessen soil erosion-related land degradation. Due to biophysical and socioeconomic constraints, the sub-watershed unit needs to prioritize the implementation of the programs in terms of space. In this study, sub-watersheds were prioritized using geomorphometric variables that represent "natural" characteristics and Land Use / Land Cover data that indicate "management" characteristics. PCA and WSA were combined as the calculation's approach. The PCA was effective at obtaining the most crucial values (i.e., WB, Dt, Re, and Rb). The weight of each significant parameter was successfully defined by the WSA application. It is consistent with the actual situation that the involvement of parameters does not equate natural phenomena, such as erosion. Compared to traditional prioritizing procedures, which use numerous criteria in a complex manner and presume their equal contributions, PCA-WSA integration results in more vibrant, useful, and efficient solutions (Sharma et al., 2015; Kadam et al., 2016; Farhan et al., 2017; Gajbhiye and Sharma, 2017). SW3 is assigned top priority in the Muzaffarpur District sub-watershed, under the methods used there. SW2, SW6, SW7, and SW8 are given low priority, whereas SW1, SW4, and SW5 are given medium priority. The Muzaffarpur District's decision-makers can apply this useful knowledge to establish management methods that will lessen and prevent land degradation. It is advisable to take socioeconomic factors into account while setting priorities for future employment. It is anticipated that using different parameters (such as social economics and biophysics) will produce a more accurate conclusion. The methods adopted in this study can be used to address other vulnerabilities or major problems, such as drought, groundwater potential, and flash floods.

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PODEJŚCIE DO USTALANIA PRIORYTETOWYCH DZIAŁÓW WODNYCH METODĄ ANALIZY MORFOMETRYCZNEJ I WIELOCZYNNIKOWEJ: STUDIUM PRZYPADKU REGIONU MUZAFFARPUR W STANIE BIHAR W INDIACH

ABSTRAKT

Cel pracy

Celem przedstawionej pracy, która została podjęta w formie badań, było ustalenie priorytetowych działów wodnych z wykorzystaniem metody analizy morfometrycznej i wieloczynnikowej.

Materiał i metody

Ranking działów wodnych (zlewni) w zależności od ich podatności na erozję ma kluczowe znaczenie w planowaniu strategicznym i praktycznym zarządzaniu, szczególnie w regionach klimatu półsuchego. Gromadzenie danych geomorfologicznych oraz dotyczących zagospodarowania i pokrycia terenu jest niezbędne do określenia priorytetowych podzlewni, w których najpilniej należy podjąć działania w ramach zintegrowanej gospodarki wodnej. Nadanie priorytetu poszczególnym działom pociąga za sobą uszeregowanie podzlewni według ich podatności na podstawie zmiennych, w tym średniej rocznej utraty gleby, wyczerpywania się zasobów wodnych i degradacji ekologicznej. Ostateczne uszeregowanie podzlewni dla naszego obszaru badawczego, tj. regionu Muzaffarpur, doprecyzowano przy użyciu podejścia łączącego PCA (analizę głównych składowych) i WSA (metodę sumy ważonej). Do różnicowania istotnych parametrów zastosowano narzędzie PCA, natomiast do pomiaru wartości złożonych w celu ustalenia rankingu priorytetów i określenia wag dla istotnych parametrów użyto narzędzia WSA.

Wyniki i wnioski
Analiza PCA okazała się skuteczna w określaniu najbardziej istotnych parametrów (WB, Dt, Re i Rb), zaś metoda WSA pozwoliła zdefiniować wagi poszczególnych z nich. W porównaniu do tradycyjnych procedur ustalania priorytetów, które w złożony sposób wykorzystują wiele kryteriów, zakładając ich jednakową wagę, integracja PCA-WSA skutkuje bardziej dynamicznymi, skutecznymi i wydajnymi rozwiązaniami. Decydenci w dystrykcie Muzaffarpur mogą wykorzystać tę pożyteczną wiedzę do udoskonalenia metod zarządzania, co pozwoli na zmniejszenie i zapobieganie degradacji gleby.

Słowa kluczowe: geomorfologia, analiza głównych składowych PCA, metoda sumy ważonej WSA, użytkowanie gruntów / pokrycie terenu