Applied Water Science (2022) 12:153
https://doi.org/10.1007/s13201-022-01644-0

ORIGINAL ARTICLE

Morphometric deterministic model for prediction of sediment yield index for selected watersheds in upper Narmada Basin

Sarita Gajbhiye Meshram[1] · Chandrashekhar Meshram[2] · Mohd Abul Hasan[3] · Muhammad Arshad Khan[4] · Saiful Islam[3]

Received: 13 July 2021 / Accepted: 8 March 2022 / Published online: 9 May 2022

Abstract

Soil erosion is common and has a wide range of spatiotemporal variability. It is crucial in determining sediment output, which is essential for proper watershed management. In this research, we propose morphometric deterministic models (MDM) for prediction of sediment yield index using morphometric parameters of 49 watersheds from Upper Narmada Basin of Madhya Pradesh state, India. For this purpose, Shuttle Radar Topography Mission generated Digital Elevation Model was used to extract and analyze 12 morphometric parameters including linear, aerial, and relief parameters. Principle Component Analysis has been applied for the most effective parameter estimation. The linear and nonlinear MDM were discovered to be suitable for the field of sediment research due to the high value of R^2 (over 70%). The sediment yield forecasting is critical for taking the appropriate management measures in the watershed to reduce the sediment load in the reservoir and extend the life of the structure.

Keywords Unguaged watersheds · Morphological parameters · Sediment yield index · PCA

Abbreviations

AISLUS	All India soil and land use survey
Ba	Bamhan
C_c	Compactness coefficient
D_d	Drainage density
DEM	Digital elevation model
F_s	Drainage frequency
GIS	Geographic information system
HI	Hypsometric index
km	Kilometers
km^2	Square kilometer
L_o	Length of overland flow
MDM	Morphometric deterministic models
Ma	Manot
Mo	Mohgaon
MAE	Mean absolute error
NSE	Nash–Sutcliffe efficiency
PCA	Principle component analysis
R^2	Correlation coefficient
RS	Remote sensing
R_e	Elongation ratio
R_f	Form factor
R_h	Relief ratio
R_r	Relative ratio
R_N	Ruggedness number
R_c	Circularity ratio
R_b	Bifurcation ratio
SYI	Sediment yield index
SRTM	Shuttle radar topography mission
SPR	Sediment production rate

✉ Sarita Gajbhiye Meshram
gajbhiyesarita@gmail.com

Chandrashekhar Meshram
cs_meshram@rediffmail.com

Mohd Abul Hasan
mohad@kku.edu.sa

Muhammad Arshad Khan
moakhan@kku.edu.sa

Saiful Islam
sfakrul@kku.edu.sa

1 Water Resources and Applied Mathematics Research Lab, Nagpur 440027, India

2 Department of Mathematics, Jaywanti Haksar Government P. G. College, Chhindwara University, Betul, M.P., India

3 Civil Engineering Department, College of Engineering, King Khalid University, P.O. Box 394, Abha 61321, Saudi Arabia

4 Department of Chemical Engineering, College of Engineering, King Khalid University, P.O. Box 394, Abha 61321, Saudi Arabia

S_a	Average slope of watershed
T	Drainage texture
WI	Willmott's index

Introduction

Basin is an ideal unit to manage natural resources and reduce the impact on sustainable development from natural disasters (Abdul Rahaman et al. 2015). Planning for the basin management highlights river erosion management techniques (Gajbhiye et al. 2015a, b). The assessment was also performed in sub watersheds to assess the natural hazards and threats (soil erosion, floods, slide etc.). Water soil erosion is recognized as a major cause of earth deterioration throughout the world. Soil erosion in general, particularly in the Narmada River basin watershed is not a recent problem in the country. Environmental degradation is environmental degradation induced by the loss of resources such as air, water and soil; ecosystem destruction and the extinction of biodiversity. It is characterized as any changes or disruptions perceived to be deleterious or unwelcome to the environment. The issue of environmental degradation affects the countries of the world in general and the Narmada basin in particular.

Many additional threats to climate change emerge in this dynamic environment, including extreme land degradation and prolonged droughts. Unfortunately, these challenges, in conjunction with other environmental developments like as water and air pollution, are becoming increasingly important drivers of environmental degradation (Choudhary et al. 2015; Cramer et al. 2019). Among the examples of environmental degradation, the negative effect of risk of water erosion in the watershed. Land degradation is a complex series of processes in surfaces (Fadhil Al-Quraishi 2003) the example of land degradation in Narmada basin watershed is water erosion risk, which is a natural process. Defining the vulnerable field of soil erosion and identifying the key areas of erosion is critical for the prioritization and delineation of these areas of management.

The morphometric parameters represent nearly the entire watershed's causative variables affecting rainfall-generated runoff and sediment, either directly or indirectly. Prior to using any sophisticated instrument to track watershed responses in relation to any of the hydrologic processes operating on it, the surface highlights are the most important analysis units. As a result, these criteria can be used to determine watershed planning goals in terms of proper soil and water management. An examination of silt load data from India and other parts of the world showed that not all watersheds are equally vulnerable to erosion (Nikam et al. 2014). As a result, in order to be handled on a priority basis, it is important to define a vital watershed. In this way, morphometric parameters combined with satellite-based land cover data of watersheds can be useful in prioritizing sub watersheds in the absence of extensive hydrological data.

The Remote Sensing (RS) and Geographic Information System (GIS) can serve as useful tools to monitor and assess land loss and soil erosion, helping to develop appropriate and reasonable strategies for management (Fadhil Al-Quraishi 2003). The watershed by its geographic position is vulnerable to several natural risks (flooding, landslide, drought, water erosion, forest fires, etc.). This study focus on the risk of 'water erosion'. Several factors such as rainfall, lithology, slopes and plant cover must be prioritized, analyzed and treated by the approach of morphometric analysis. Morphometric mapping in combination with the Remote Sensing (RS) and Geographical Information System (GIS) which can serve as useful resources for monitoring and evaluating land loss and soil erosion, helping to establish appropriate and reasonable management strategies (Fadhil Al-Quraishi 2003; Benzougagh et al. 2020, 2022a, b; Meshram et al. 2022a, b). The morphometric analysis including linear, areal and drainage parameters. Morphometric watershed research is an important first step towards a clearer appreciation of watershed dynamic characteristics. Therefore, morphometric analysis is an important method for prioritizing sub-watershed growth and the management of natural resources (Biswas and Chakraborty 2016; Benzougagh et al. 2016, 2017). The results of the production of an erosion danger map are a powerful resource for planning to minimize the problems of soil erosion induced by potential and current sustainable growth programs in the research region as well as in other regions.

Recent studies have shown that remote sensing (RS) and geographic information system (GIS) tools and techniques are highly efficient and useful for improving and monitoring watersheds, as well as prioritizing sub-watersheds in soil and water management (Sarma and Saikia 2012; Ahmed and Rao 2015; Khadse et al. 2015; Makwana and Tiwari 2016; Khanday and Javed 2016; Farhan et al. 2017; Jharia et al. 2018; Kadam et al. 2019; Arefin et al. 2020). In the ongoing decades, numerous scientists have concentrated on deterministic or regression modeling. Koutsoyiannis (2001) proposed a system for coupling stochastic models of hydrologic measures applying to various time scales with the goal that the time arrangement produced by various model is reliable. Singh et al. (2001) created local stream span models for enormous number of un-checked Himalayan catchments. They announced that the factual methodology of quantile assessment performed acceptably in alignment just as in approval. Kumar and Rastogi (2005) analyzed hydrologic data for the year 1977–1985 for development of sub area routing model for estimation of sediment yield on storm basis from Gagas watershed, Ramganga reservoir catchment. Caissie et al. (2007) used a deterministic model to predict water temperatures in Miramichi River catchments (New Brunswick, Canada). When researching rivers of various sizes and thermal conditions, they concluded that deterministic water temperature models are useful tools for forecasting river water temperatures. Gupta and Singh (2010) multivariate statistical techniques were used to create dimensionally homogeneous and statistically optimal models for annual runoff and Sediment Production Rate (SPR) prediction from the Mahi catchment's limited watersheds. The developed models can be used to forecast runoff and SPR in small un-gauged watersheds in the Mahi catchment that have similar physiographic characteristics. Singh et al. (2007) used deterministic modeling of annual runoff and sediment production rate for small watersheds of Chambal Catchment. Amoudry and Souza (2011) reviewed and discussed the deterministic coastal morphological and sediment transport modeling. Shojaeezadeh et al. (2018) introduced a parsimonious probabilistic model to describe the relationship between Suspended Sediment Load (SSL) and discharge volume. This model, rooted in multivariate probability theory and Bayesian Network, infers conditional marginal distribution of SSL for a given discharge level.

Watershed management is needed for the proper and efficient use of land and water resources. As a result, it is often preferable to begin management steps from the most sensitive sub-watershed. To make accurate predictions, comprehensive data are needed for proper scientific planning and management of the watershed. Many watersheds in India are not measured for such situations. Deterministic morphometric modeling is a fundamental method for studying a basin's hydrologic activity. A deterministic model can be constructed using dimensionless morphometric characteristics and the sediment yield index. Models built in this way can be used to predict sediment yield in watersheds with similar physiographic conditions. Considering such approach the present study was undertaken. However, the basin's understanding of the aforementioned facts has yet to be discussed, and no such scientific tests for a basin have been published thus far. As a result, the findings of this study are novel and significant to the water resource authorities concerned.

Material and methods description

Study area and data used

The Narmada is the Indian peninsula's largest west-flowing river. It is one of India's most powerful rivers. The Narmada River rises at an elevation of 1057 m above mean sea level in the Amarkantak Plateau of the Maikala range in the Shahdol district of Madhya Pradesh, at a latitude of 22° 40′ N and a longitude of 81° 45′ E. The river flows for 1312 km before crashing into the Gulf of Cambay in the Arabian Sea near Bharuch, Gujarat. The first 1079 km of its run are in Madhya Pradesh. The river forms the border between the states of Madhya Pradesh and Maharashtra for the next 35 km. It then forms the border between Maharashtra and Gujarat for the next 39 km (Gajbhiye et al. 2013a, b). The last length of 159 km lies in Gujarat. The Narmada basin covers 98,796 km^2 and is located between longitudes 72° 32′ E and 81° 45′ E, and latitudes 21° 20′ N and 23° 45′ N. For model application, three watersheds were selected based on the availability of morphometric parameter and sediment yield index data, a brief description of which is given below:

Bamhani watershed (Ba), Manot watershed (Ma), Mohgaon watershed (Mo) in Mandla district, India. In this research, morphometric parameter of 49 sub-watersheds across upper Narmada Basin Mandla, Madhya Pradesh State, India. The location map of the study watershed shown in Fig. 1.

In order to develop morphometric deterministic model (MDM), we have taken the morphometric parameter and sediment yield index for the 49 sub-watershed (Ba, Ma, Mo) (Table 1) from the previous studies of Gajbhiye et al. (2014a, b).

Methodology

The used procedure in this study can be summarized in the following stages:

1. Establishing morphometric parameters and sediment yield index
2. Applying the principal component analysis (PCA) for redundancy of morphometric parameter
3. Develop morphometric deterministic model (MDM).
4. Parameter estimation.
5. Qualitative evaluation of model performance.

Morphometric parameters

Stream network is a basic requirement of any morphometric study and the prioritization of watersheds. Digital Elevation Model (DEM) (30*30 m) generated by Shutter Radar Topography Mission (SRTM) data is a common tool to define a stream network and sub-watershed map. Different drainage network parameters, i.e., numbers and lengths and watershed area, perimeter, width and length were determined in GIS environment (Meshram et al. 2019, 2020a, b, 2021). Then using standard formulae stream frequency, drainage density, circulatory ratio, form factor and elongation ratio were estimated. Sediment yield index is calculated using the AISLUS (1991) formulae.

Principal component analysis

Most of the time there is relationship between the morphometric parameters such that some of the parameters share the

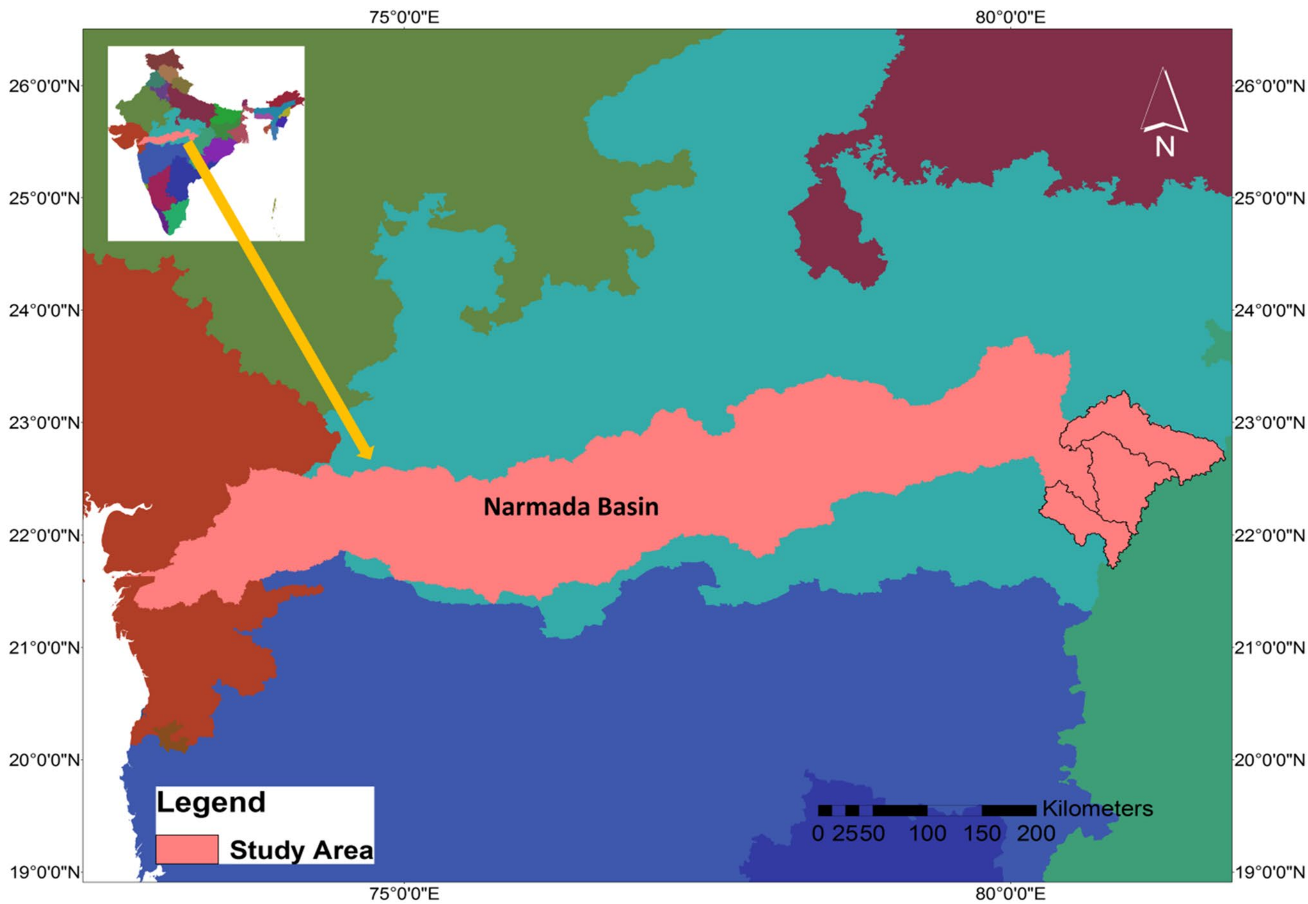

Fig. 1 Location map of the study area

same information. In performing component analysis, the coordinates axis is transformed to a new reference frame within the total variable space. This involves assigning new principal components to each variable either through an uncorrelated or an orthogonal transformation. These components are unique in that they consider the maximum variance between the variables. The correlation matrix and principal components are thus obtained from the principal component analysis performed on the geomorphic variables (Gajbhiye et al. 2015c; Gajbhiye and Sharma 2017). The analysis employs the first factor and rotated the factor loading matrices. The product of the square of a parameter's loading and the percent of the rotated factor covariance gives the order of importance of a parameter. Thus, computation is derived from the most commonly used transformation technique involving rotated factor loading matrices based on the varimax criteria (Singh 2006).

The proposed morphometric deterministic model

SPSS 16.0 software was used to create dimensionally homogeneous and statistically optimal models of the following linear (Eq. 1) and nonlinear (Eq. 2) form after redundancy of morphometric parameters into physically significant components.

$$\mathcal{Y} = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \ldots + a_nx_n \tag{1}$$

$$\mathcal{Y} = a_0 x_1^{a_1} x_2^{a_2} x_3^{a_3} \ldots x_n^{a_n} \tag{2}$$

where $\mathcal{Y}$ is the dependent variable (Sediment yield index) and $x_1, x_2, \ldots, x_n$ are the independent variables (Morphometric parameter), $a_0, a_1, \ldots, a_n$ are the regression co-efficients.

Parameter estimation

The SPSS Statistical Package was used to analyze the data in Windows version 22.0. For multi-step regression, one-way multivariate analyses were used to depart from the morphometric parameter and SYI parameters. In the MDM, sediment yield index was dependent variable and morphometric parameter (most effective) was independent variables.

Table 1 Morphometric parameter of the study area Gajbhiye et al. (2014a, b)

Sub-watershed	R_h	R_r	R_N	R_b	D_d	F_s	R_c	R_f	R_e	T	L_o	C_c	S_a	HI	SYI
Ba-1	0.012	0.003	0.450	3.485	2.498	3.983	0.313	0.375	0.691	5.979	0.200	0.024	3.871	0.500	1070.47
Ba-2	0.012	0.003	0.148	2.917	1.415	2.609	0.859	0.91	0.989	3.287	0.353	0.052	2.16	0.500	1159.31
Ba-3	0.022	0.006	0.374	3.792	2.337	3.764	0.634	0.601	0.875	4.658	0.214	0.046	4.027	0.500	1107.11
Ba-4	0.019	0.006	0.948	3.662	2.369	3.949	0.418	0.348	0.666	8.954	0.211	0.015	8.519	0.500	1279.04
Ba-5	0.017	0.003	0.386	3.432	2.410	3.953	0.443	0.945	0.987	6.762	0.208	0.024	4.676	0.485	1094.39
Ba-6	0.008	0.002	0.485	4.676	2.425	4.161	0.352	0.603	0.877	12.742	0.206	0.009	4.538	0.500	914.97
Ba-7	0.008	0.002	0.237	4.353	2.372	3.901	0.425	0.677	0.929	7.547	0.211	0.019	2.387	0.500	796.42
Ba-8	0.018	0.005	0.369	4.889	1.942	3.125	0.671	0.632	0.898	4.441	0.257	0.038	4.428	0.500	969.15
Ba-9	0.034	0.009	0.593	3.167	1.852	3.132	0.683	0.767	0.989	4.112	0.270	0.044	6.229	0.500	1062.07
Ba-10	0.022	0.004	0.683	4.945	2.626	4.603	0.364	0.722	0.959	4.475	0.190	0.022	6.647	0.565	1013.29
Ba-11	0.010	0.002	0.948	5.657	2.494	3.812	0.228	0.383	0.699	11.831	0.201	0.007	6.467	0.500	923.82
Ba-12	0.014	0.004	0.395	3.846	2.466	4.001	0.568	0.584	0.863	7.184	0.203	0.025	5.045	0.500	971.02
Ba-13	0.019	0.005	0.838	3.588	2.465	3.97	0.312	0.424	0.735	7.309	0.203	0.018	5.796	0.500	1154.44
Ba-14	0.018	0.006	0.368	2.971	1.800	3.148	0.665	0.496	0.795	4.068	0.278	0.044	3.791	0.500	1177.68
Ba-15	0.006	0.002	0.490	4.101	2.449	4.131	0.287	0.276	0.593	10.165	0.204	0.011	4.621	0.500	1032.71
Ba-16	0.015	0.004	0.591	4.096	2.287	3.78	0.329	0.382	0.698	6.035	0.219	0.023	6.801	0.500	1115.03
Ba-17	0.017	0.005	0.594	4.015	2.475	3.967	0.491	0.423	0.734	7.055	0.202	0.023	9.125	0.500	1264.42
Ba-18	0.012	0.002	0.337	3.867	2.408	4.033	0.384	0.761	0.985	6.943	0.208	0.022	3.731	0.500	840.95
Ba-19	0.019	0.005	0.391	3.329	1.886	3.182	0.448	0.595	0.87	3.958	0.265	0.038	6.139	0.595	1054.24
Ba-20	0.008	0.002	0.410	4.927	2.560	4.245	0.357	0.416	0.728	9.182	0.195	0.015	5.04	0.595	901.41
Ma-1	0.016	0.003	0.923	3.715	3.075	7.689	0.386	0.76	0.984	21.707	0.163	0.010	5.139	0.500	991.61
Ma-2	0.014	0.003	1.206	4.314	3.053	6.846	0.393	0.761	0.984	27.599	0.164	0.006	3.928	0.406	987.42
Ma-3	0.017	0.003	1.368	4.345	3.109	7.55	0.347	0.681	0.931	27.34	0.161	0.007	4.313	0.541	986.82
Ma-4	0.019	0.004	1.237	3.827	3.256	7.624	0.331	0.644	0.905	19.998	0.154	0.011	7.047	0.500	1032.24
Ma-5	0.014	0.003	1.287	4.216	3.065	7.264	0.213	0.431	0.741	18.188	0.163	0.009	4.109	0.364	1173.33
Ma-6	0.029	0.003	1.249	3.859	3.286	7.548	0.259	0.512	0.807	17.72	0.152	0.011	6.349	0.500	1088.42
Ma-7	0.026	0.004	0.933	4.405	3.111	7.21	0.298	0.678	0.930	14.082	0.161	0.016	5.232	0.500	1031.08
Ma-8	0.031	0.005	1.033	4.032	3.060	6.722	0.317	0.631	0.897	10.438	0.163	0.023	7.002	0.500	1099.92
Ma-9	0.016	0.003	1.104	4.080	3.247	7.404	0.318	0.730	0.964	22.918	0.154	0.008	5.155	0.500	940.97
Ma-10	0.023	0.004	1.231	3.967	3.292	7.611	0.440	0.773	0.993	24.225	0.152	0.009	4.489	0.500	1030.19
Ma-11	0.009	0.002	1.159	3.956	3.220	7.567	0.252	0.260	0.575	22.209	0.155	0.008	4.812	0.500	1347.6
Ma-12	0.018	0.004	1.094	3.696	3.217	7.592	0.300	0.504	0.801	15.278	0.155	0.015	7.187	0.500	1238.36
Ma-13	0.011	0.003	1.315	6.574	3.130	7.636	0.322	0.510	0.806	32.416	0.160	0.005	2.816	0.500	1007.85
Ma-14	0.015	0.002	1.260	4.372	3.198	7.573	0.151	0.716	0.955	18.055	0.156	0.008	3.918	0.500	925.38
Mo-1	0.037	0.009	0.961	3.339	2.418	6.277	0.551	0.7	0.944	9.382	0.207	0.032	9.523	0.393	1252.84
Mo-2	0.016	0.004	1.298	5.019	3.091	7.854	0.435	0.584	0.863	28.542	0.162	0.008	13.253	0.413	973.76
Mo-3	0.024	0.006	0.924	4.147	2.888	7.692	0.379	0.569	0.852	13.195	0.173	0.022	12.108	0.393	1109.84
Mo-4	0.023	0.005	1.014	3.869	3.17	8.058	0.483	0.702	0.946	18.324	0.158	0.016	9.797	0.5	965.63
Mo-5	0.01	0.002	1.044	5.558	2.269	7.892	0.219	0.31	0.628	26.127	0.22	0.006	10.532	0.42	943.09
Mo-6	0.011	0.003	1.107	4.234	2.914	7.835	0.362	0.332	0.65	27.554	0.172	0.007	11.843	0.5	1054.65
Mo-7	0.014	0.003	1.109	4.407	3.082	7.388	0.227	0.287	0.605	13.776	0.162	0.015	10.033	0.5	1322.99
Mo-8	0.01	0.002	1.276	3.951	3.357	8.016	0.268	0.376	0.692	26.151	0.149	0.007	7.558	0.557	938.59
Mo-9	0.016	0.005	1.028	3.907	2.942	7.671	0.476	0.348	0.665	18.205	0.17	0.015	9.132	0.551	1259.42
Mo-10	0.034	0.008	0.909	3.306	3.247	7.623	0.484	0.72	0.958	10.376	0.154	0.035	6.461	0.561	1148.61
Mo-11	0.016	0.002	1.117	4.14	3.102	7.758	0.16	0.658	0.916	15.943	0.161	0.011	9.101	0.5	846.58
Mo-12	0.015	0.005	0.849	3.759	3.144	7.637	0.462	0.356	0.674	15.095	0.159	0.019	9.586	0.375	1337.36
Mo-13	0.013	0.003	0.875	4.375	2.918	7.929	0.299	0.47	0.773	18.82	0.171	0.012	4.303	0.5	956.43
Mo-14	0.012	0.003	0.98	4.624	3.266	8.053	0.353	0.563	0.847	24.382	0.153	0.009	9.002	0.443	915.91
Mo-15	0.008	0.002	0.936	4.904	3.119	7.633	0.227	0.25	0.564	18.687	0.16	0.01	10.1	0.443	1052.09

Bamhani-Ba; Manot-Ma; Mohgoan-Mo

Evaluation of model performance

The accuracy of prediction models was evaluated using three error measures in this paper: Mean Absolute Error (MAE) (Chai and Draxler 2014) (Eq. 3), Nash–Sutcliffe Efficiency (NSE) (Nash and Sutclife 1970) (Eq. 4), and Willmott's Index (WI) (Willmott 1981) (Eq. 5).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{\mathrm{n}} \left|\mathcal{X}_i - \mathcal{Y}_i\right| \tag{3}$$

$$\mathrm{NSE} = \left|1 - \left[\frac{\sum_{i=1}^{\mathrm{n}} \left(\mathcal{Y}_i - \mathcal{X}_i\right)^2}{\sum_{i=1}^{\mathrm{n}} \left(\mathcal{Y}_i - \overline{\mathcal{Y}}\right)^2}\right]\right| \tag{4}$$

$$\mathrm{WI} = \left|1 - \left[\frac{\sum_{i=1}^{\mathrm{n}} \left(\mathcal{Y}_i - \mathcal{X}_i\right)^2}{\sum_{i=1}^{\mathrm{n}} \left(\left|\mathcal{X}_i - \overline{\mathcal{Y}}\right| + \left|\mathcal{Y}_i - \overline{\mathcal{Y}}\right|\right)^2}\right]\right| \tag{5}$$

where is the total number of data; $_i$ and $_i$ are the observed and predicted sediment yield index data; and, $\overline{\mathcal{Y}}$ is the average of observed data.

Results and discussion

Morphometric parameters of upper Narmada basin watersheds adapted from Gajbhiye et al. (2014a, b) are presented in Table 1. For redundancy of morphometric parameter, PCA has been applied. A hierarchical tree from the most effective morphometric results is used to prioritize the sub-watersheds.

The SPSS 22.0 software is employed to assess the inter-co-relationships of morphometric variables through a correlation matrix (Table 2). Very high correlations ($R > 0.9$) exist between the elongation ratio (R_e) and form factor (R_f); L_o and D_d. In addition, moderately high correlations ($R > 0.70$) are observed between; R_h and R_r; R_N and $D_d/F_s/T/L_o/C_c$ and between D_d and $F_s/T/C_c$, F_s and T/L_o; R_c and C_c; T and C_c; L_o and C_c. Because there are no significant correlations between R_r, R_b, S_a and HI with any of the parameters under consideration, it is practically impossible to put the parameters into component groups. Therefore, the subsequent step makes use of the principal component analysis technique.

The correlation matrix obtained from the previous step is used to generate the first unrotated factor loading matrix (Table 3). The results show that about 84.57% of the total explained variance is attributed to the combination of the first three components with eigen values above one. It is observed that a strong correlation ($R > 0.9$) between C_c and the first component (Table 4A). Relatively high correlations ($R > 0.7$) are also found between the first component and each of the variables; L_o, D_d, T, F_s, R_N, R_c. On the other hand, R_h has high correlations with second component. S_a and HI have high correlation with third and fourth component correspondingly. No significant correlations exist between the R_b, R_e, R_r and R_f with any one of the component.

Redistribution of the observed variance is performed so that better factor loadings can be obtained. This is done by carrying out analytical rotations those components whose eigen value exceeds one. The outcome of varimax rotation is shown in Table 4B.

Table 2 Inter-correlation matrix of the morphometric parameters

Correlation matrix														
	R_h	R_r	R_N	R_b	D_d	F_s	R_c	R_f	R_e	T	L_o	C_c	S_a	HI
R_h	1	0.820	0.126	−0.424	0.031	0.061	0.322	0.433	0.483	−0.246	−0.010	0.440	0.161	−0.018
R_r	0.820	1	−0.113	−0.480	−0.250	−0.171	0.595	0.208	0.254	−0.387	0.243	0.632	0.223	−0.076
R_N	0.126	−0.113	1	0.313	0.817	0.858	−0.579	−0.173	−0.120	0.826	−0.765	−0.703	0.381	−0.255
R_b	−0.424	−0.480	0.313	1	0.255	0.259	−0.465	−0.278	−0.235	0.473	−0.319	−0.575	0.110	−0.099
D_d	0.031	−0.250	0.817	0.255	1	0.887	−0.626	−0.116	−0.061	0.733	−0.968	−0.723	0.278	−0.136
F_s	0.061	−0.171	0.858	0.259	0.887	1	−0.525	−0.125	−0.084	0.833	−0.823	−0.651	0.439	−0.288
R_c	0.322	0.595	−0.579	−0.465	−0.626	−0.525	1	0.424	0.389	−0.475	0.692	0.813	−0.171	0.058
R_f	0.433	0.208	−0.173	−0.278	−0.116	−0.125	0.424	1	0.979	−0.147	0.192	0.338	−0.364	0.069
R_e	0.483	0.254	−0.120	−0.235	−0.061	−0.084	0.389	0.979	1	−0.117	0.123	0.306	−0.344	0.076
T	−0.246	−0.387	0.826	0.473	0.733	0.833	−0.475	−0.147	−0.117	1	−0.676	−0.784	0.261	−0.258
L_o	−0.010	0.243	−0.765	−0.319	−0.968	−0.823	0.692	0.192	0.123	−0.676	1	0.765	−0.307	0.142
C_c	0.440	0.632	−0.703	−0.575	−0.723	−0.651	0.813	0.338	0.306	−0.784	0.765	1	−0.220	0.167
S_a	0.161	0.223	0.381	0.110	0.278	0.439	−0.171	−0.364	−0.344	0.261	−0.307	−0.220	1	−0.320
HI	−0.018	−0.076	−0.255	−0.099	−0.136	−0.288	0.058	0.069	0.076	−0.258	0.142	0.167	−0.320	1

Table 3 Total variance explained

Total variance explained									
Component	Initial eigen values			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	6.293	44.952	44.952	6.293	44.952	44.952	5.358	38.271	38.271
2	2.724			2.724	19.456	64.408	2.865	20.465	58.736
3	1.811	12.935	77.343	1.811	12.935	77.343	2.317	16.548	75.284
4	1.013	7.234	84.577	1.013	7.234	84.577	1.301	9.292	84.577
5	0.635								
6	0.513	3.665	92.778						
7	0.426	3.045	95.823						
8	0.27	1.93	97.753						
9	0.154	1.1	98.853						
10	0.064	0.458	99.312						
11	0.05	0.358	99.67						
12	0.027	0.191	99.86						
13	0.013	0.094	99.954						
14	0.006	0.046	100						

Extraction method: principal component analysis

The first component is very highly correlated with F_s and highly correlated with D_d, L_o, F_s and R_N. The second component is very highly correlated with R_r, the third component is very highly correlated with R_f, R_e and the fourth component is very highly correlated with HI. A strong correlation also exists between the first component with T and C_c, while second component with R_h. For the model development, we selected the morphometric parameter (D_d, L_o, F_s, R_N, R_r, R_f, R_e, HI) that's very highly correlated ($R > 0.90$) with the component.

The sediment yield index models based on morphometric parameter were developed for the Narmada basin watersheds. The morphometric deterministic model (linear and nonlinear) was developed by considering the 34 sub-watershed dataset (Morphometric parameter and SYI). The linear and nonlinear MDM in form of Eq. 6 and 7 were derived on the basis of sub-watershed dataset. The value of coefficient of multiple regressions (R^2) for linear MDM was (0.81). Whereas, R^2 value for the nonlinear MDM was 0.89. This shows the applicability of morphometric deterministic models. The linear and nonlinear MDM developed by (34 sub-watershed) datasets are:

$$\begin{aligned} \mathrm{SYI} = {} & 4391.73 + 61603.38\left(R_{\mathrm{r}}\right) - 23.67\left(R_{\mathrm{N}}\right) \\ & - 343.78\left(D_{\mathrm{d}}\right) - 123.99\left(F_{\mathrm{s}}\right) \\ & - 1080.08\left(R_{\mathrm{f}}\right) + 361.56\left(R_{\mathrm{e}}\right) \\ & - 7618.15\left(L_{\mathrm{o}}\right) - 86.30(\mathrm{HI}) \\ R^2 = {} & 0.81 \end{aligned} \tag{6}$$

$$\begin{aligned} \mathrm{SYI} = {} & 18.35 R_{\mathrm{r}}^{0.298} R_{\mathrm{N}}^{0.075} D_{\mathrm{d}}^{-8.45} F_{\mathrm{s}}^{-0.767} R_{\mathrm{f}}^{-2.72} R_{\mathrm{e}}^{4.70} L_{\mathrm{o}}^{-8.77} \mathrm{HI}^{-0.006} \\ R^2 = {} & 0.89 \end{aligned} \tag{7}$$

The linear and nonlinear MDMs were applied tohe sub-watershed dataset to test and verify their applicability for the study region. The comparison of observed and expected values using the evolved model with the remaining data set (15 sub-watershed) is presented in graphical form in Fig. 2, along with graphical validation in Fig. 3. Table 5 also shows the values of qualitative parameters for the built model. It was discovered that the model performs well in terms of predicting the sediment yield index, which is critical for effective soil conservation programs.

Table 4 Varimax method of the first factor loading matrix (unrotated) and rotated factor loading matrix of morphometric parameters

	Component			
	1	2	3	4
(A) Unrotated component matrix				
C_c	0.924			
L_o	0.865	−0.305		
D_d	−0.857	0.376		
T	−0.852			
F_s	−0.842	0.429		
R_N	−0.835	0.405		
R_c	0.807			
R_b	−0.553	−0.348		
R_h	0.307	0.838		
R_e	0.376	0.634	0.625	
R_r	0.501	0.623	−0.500	
S_a	−0.381		−0.706	
R_f	0.418	0.586	0.636	
HI			0.330	−0.788
(B) Rotated component matrix				
D_d	0.962			
L_o	−0.937			
F_s	0.917			
R_N	0.906			
T	0.788	−0.342		
C_c	−0.752	0.556		
R_c	−0.659	0.445	0.319	
R_r		0.911		
R_h		0.888		
R_b		−0.633		
R_f			0.952	
R_e			0.948	
S_a	0.343	0.33	−0.518	0.456
HI				−0.902

Morphometric deterministic model (MDM) validation

The linear and nonlinear MDM were validated for the remaining sub-watershed (Mo 1–15) dataset. The value of the (R^2) coefficient of determinations for all the linear and nonlinear models observed to be 0.88 and 0.95, respectively. The values of NSE, MAE and WI of linear models were found of (88.09, 42.77, 0.96), nonlinear model were (94.73, 25.91, 0.98), respectively (Table 6). Validation statistics of all the models were found best fit to satisfy the criteria of a good model (Table 6).

Table 5 Estimated values of regression parameters linear and non-linear MDM, and coefficient of determination (R^2) for the dependent and independent variables

Regression parameter	Morphometric deterministic model (MDM)			
	Linear MDM		Non-linear MDM	
	$\mathcal{Y} = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \ldots + a_nx_n$	R^2	$\mathcal{Y} = a_0x_1^{a_1}x_2^{a_2}x_3^{a_3}\ldots x_n^{a_n}$	R^2
$\dashv_0$	4391.73	0.81	18.35	0.89
$\dashv_1$	61,603.40		0.29	
$\dashv_2$	−23.68		0.075	
$\dashv_3$	−343.78		−8.45	
$\dashv_4$	−123.99		−0.77	
$\dashv_5$	−1080.10		−2.72	
$\dashv_6$	361.56		4.71	
$\dashv_7$	−7618.80		−8.77	
$\dashv_8$	−86.31		−0.006	

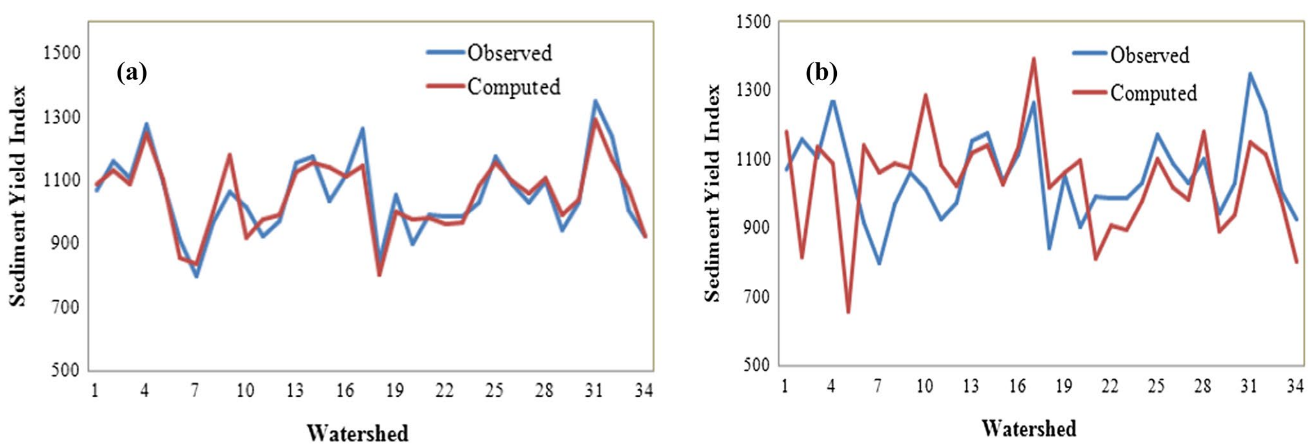

Fig. 2 Comparison of observed and predicted sediment yield Index during calibration stage **a** Linear model; **b** Nonlinear morphometric deterministic model

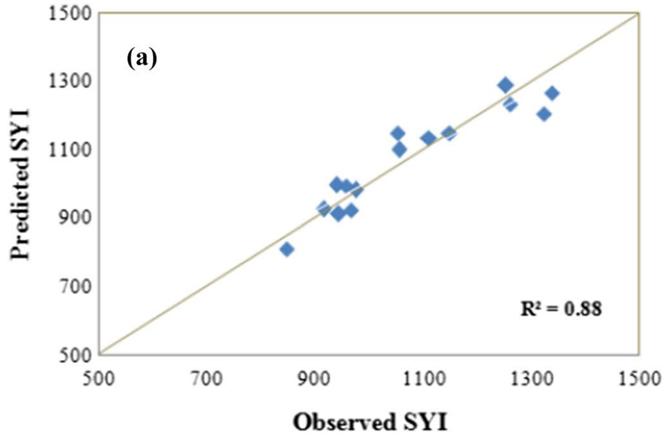

Fig. 3 Comparison of observed and predicted sediment yield Index during validation stage **a** Linear model; **b** Nonlinear morphometric deterministic model

Table 6 Performance evaluation of linear and nonlinear MDM

	NSE	MAE	WI
Linear	88.09	42.77	0.96
Non-linear	94.73	25.91	0.98

Conclusions

The aim of this study was to develop a morphometric deterministic model using input parameters such as morphometric parameter (R_r, R_N, D_d, F_s, R_f, R_e, L_o, HI). The established linear and nonlinear morphometric deterministic models performed admirably. As a result, the best performance model for nonlinear MDM has been declared. The study area was found to be suitable for the deterministic models constructed using the most powerful morphometric parameter. Independent variables of morphometric parameters have a major impact on sediment yield forecasting.

Acknowledgements The authors thankfully acknowledge the Deanship of Scientific Research, King Khalid University, Abha, Kingdom of Saudi Arabia, for funding the project research grant number RGP.2/43/1443.

Declarations

Conflict of interest All Authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

Abdul Rahaman S, Aruchamy S, Jegankumar R, Abdul Ajeez S (2015). Estimation of annual average soil loss, based on RUSLE model in Kallar watershed, Bhavani basin, Tamil Nadu, India. ISPRS annals of the photogrammetry, remote sensing and spatial information sciences, Volume II-2/W2, 2015 joint international geoinformation conference 2015, 28–30 October 2015, Kuala Lumpur, Malaysia. 10.5194/isprsannals-II-2-W2-207-2015

Ahmed F, Rao KS (2015) Prioritization of sub-watersheds based on morphometric analysis using remote sensing and geographic information system techniques. Int J Remote Sens GIS 4(2):51–65. https://doi.org/10.1007/s12524-009-0016-8

AISLUS (1991) Methodology of Priority Delineation Survey, All India Soil & Land Use Survey Technical Bulletin 9. Department of Agriculture and Cooperation, New Delhi, India

Amoudry LO, Souza AJ (2011) Deterministic coastal morphological and sediment transport modeling: a review and discussion. Rev Geophys 49(RG2002):1–21. https://doi.org/10.1029/2010RG000341

Arefin R, Mohir MMI, Alam J (2020) Watershed prioritization for soil and water conservation aspect using GIS and remote sensing: PCA-based approach at northern elevated tract Bangladesh. Appl Water Sci 10:91. https://doi.org/10.1007/s13201-020-1176-5

Benzougagh B, Dridri A, Boudad L, Kodad O, Sdkaoui D, Bouikbane H (2017) Evaluation of natural hazard of Inaouene watershed river in northeast of Morocco: application of morphometric and geographic information system approaches. Int J Innov Appl Stud 19(1):85–97

Benzougagh B, Meshram SG, Dridri A, Boudad L, Sadkaoui D, Mimich K, Khedher KM (2020) Mapping of soil sensitivity to water erosion by RUSLE model: case of the Inaouene watershed

(northeast Morocco). Arab J Geosci 13:1153. https://doi.org/10.1007/s12517-020-06079-y
Benzougagh B, Boudad L, Dridri A, Sdkaoui D (2016) Utilisation du Sig dans l'analyse morphométrique et la prioritisation des sous-bassins versants de Oued Inaouene (nord-est du Maroc). Eur Sci J 12(6):283–306. https://doi.org/10.19044/esj.2016.v12n6p283
Benzougagh B, Meshram SG, Dridri A, Boudad L, Baamar B, Sadkaoui D, Khedher KM (2022a) Identification of Critical Watershed at Risk of Soil Erosion using Morphometric and Geographic Information System Analysis. Appl Water Sci 12:8. https://doi.org/10.1007/s13201-021-01532-z
Benzougagh B, Meshram SG, El Fellah B, Mastere M, Dridri A, Sadkaoui D, Mimich K, Khedher KM (2022b) Combined use of Sentinel-2 and Landsat-8 to monitor water surface area and evaluated drought risk severity using Google Earth Engine. Ear Sci Inform. https://doi.org/10.1007/s12145-021-00761-9
Biswas MR, Chakraborty S (2016) Watershed prioritization based on geo-morphometry and land use parameters–an approach to watershed development using remote sensing and GIS, Neora Watershed, Darjeeling and Jalpaiguri Districts, West Bengal, India. J Appl Geol Geophys 4(3):36–49. https://doi.org/10.9790/0990-0403013649
Caissie D, Satish MG, El-Jabi N (2007) Predicting water temperatures using a deterministic model: application on Miramichi river catchments (New Brunswick, Canada). J Hydrol 336:303–315. https://doi.org/10.1016/j.jhydrol.2007.01.008
Chai T, Draxler RR (2014) Root mean square error (RMSE) or mean absolute error (MAE)? Arguments against avoiding RMSE in the literature. Geosci Model Dev 7:1247–1250. https://doi.org/10.5194/gmd-7-1247-2014
Choudhary MP, Chauhan GS, Kushwah YK (2015) Environmental degradation: causes, impacts and mitigation. Conference: national seminar on recent advancements in protection of environment and its management issues (NSRAPEM-2015). Maharishi Arvind College of Engineering and Technology, Kota, Rajasthan
Cramer W, Guiot J, Fader M, Garrabou J, Gattuso JP, Iglesias A, Lange MA, Lionello P, Lla-sat MC, Paz S, Peñuelas J, Snoussi M, Toreti A, Tsimplis MN, Xoplaki E (2019) Climate change and interconnected risks to sustainable development in the Mediterranean. Nat Clim Chang 8:972–980. https://doi.org/10.1038/s41558-018-0299-2
Fadhil Al-Quraishi AM (2003) Soil erosion risk prediction with RS and GIS for the north western part of Hebei province. China Pak J Appl Sci 3(10–12):659–669. https://doi.org/10.3923/jas.2003.659.669
Farhan Y, Anbar A, Al-Shaikh N, Mousa R (2017) Prioritization of semi-arid agricultural watershed using morphometric and principal component analysis, remote sensing, and GIS techniques, the Zerqa river watershed, northern Jordan. Agric Sci 8:113–148. https://doi.org/10.4236/as.2017.81009
Gajbhiye S, Sharma SK (2017) Prioritization of watershed through morphometric parameters: a PCA based approach. Appl Water Sci 7:1505–1519. https://doi.org/10.1007/s13201-015-0332-9
Gajbhiye S, Mishra SK, Pandey A (2013a) Effect of seasonal/monthly variation on runoff curve number for selected watersheds of Narmada basin. Int J Environ Sci 3(6):2019–2030. https://doi.org/10.6088/ijes.2013030600021
Gajbhiye S, Mishra SK, Pandey A (2014a) Prioritizing erosion-prone area through morphometric analysis: an RS and GIS perspective. Appl Water Sci 4(1):51–61. https://doi.org/10.1007/s13201-013-0129-7
Gajbhiye S, Sharma SK, Tignath S, Mishra SK (2015a) Development of a geomorphological erosion index for Shakkar watershed. Geol Soc India 86(3):361–370. https://doi.org/10.1007/s12594-015-0323-3
Gajbhiye S, Mishra SK, Pandey A (2015b) Simplified sediment yield index model incorporating parameter CN. Arab J Geosci 8(4):1993–2004. https://doi.org/10.1007/s12517-014-1319-9
Gajbhiye S, Mishra SK, Pandey A (2013b). A procedure for determination of design runoff curve number for Bamhani watershed. IEEE-International conference on advances in technology and engineering (ICATE), Bombay, 23–25 January 2013b, 1(9):23–25, ISBN: 978–1–4673–5618–3. https://doi.org/10.1109/ICAdTE.2013b.6524755
Gajbhiye S, Sharma SK, Meshram C (2014b) Prioritization of watershed through sediment yield index using RS and GIS approach. Int J u e Serv Sci Technol 7(6):47–60. https://doi.org/10.14257/ijunesst.2014.7.6.05
Gajbhiye S, Sharma SK, Awasthi MK (2015c) Application of principal components analysis for interpretation and grouping of water quality parameters. Int J Hybrid Inf Technol 8(4):89–96. https://doi.org/10.14257/ijhit.2015.8.4.11
Gupta Y, Singh PK (2010) Deterministic modelling of annual runoff and sediment production rate for small watersheds of Mahi catchment. Indian J Soil Conserv 38(3):142–147
Jharia DC, Kumar T, Pandey HK (2018) Watershed prioritization based on soil and water hazard model using remote sensing, geographical information system and multi-criteria decision analysis approach. Geocarto Int 35(2):188–208. https://doi.org/10.1080/10106049.2018.1510039
Kadam AK, Jaweed TH, Kale SS, Umrikar BN, Sankhua RN (2019) Identification of erosion-prone areas using modified morphometric prioritization method and sediment production rate: a remote sensing and GIS approach. Geomat Nat Haz Risk 10(1):986–1006. https://doi.org/10.1080/19475705.2018.1555189
Khadse GK, Vijay R, Labhasetwar PK (2015) Prioritization of catchments based on soil erosion using remote sensing and GIS. Environ Monit Assess 187:333. https://doi.org/10.1007/s10661-015-4545-z
Khanday MY, Javed A (2016) Prioritization of sub-watersheds for conservation measures in a semi arid watershed using remote sensing and GIS. J Geol Soc India 88:185–196. https://doi.org/10.1007/s12594-016-0477-7
Koutsoyiannis D (2001) Coupling stochastic models of different time scale. Water Resour Res 37(2):379–391. https://doi.org/10.1029/2000WR900200
Kumar V, Rastogi RA (2005) Sub area routing model for estimation of sediment yield from a mountainous watershed. Hydrology and watershed management. Himanshu Publication, Udaipur, pp 98–105
Makwana J, Tiwari MK (2016) Prioritization of agricultural sub-watersheds in semi arid middle region of Gujarat using remote sensing and GIS. Environ Earth Sci 75:137. https://doi.org/10.1007/s12665-015-4935-0
Meshram SG, Alvandi E, Singh VP, Meshram C (2019) Comparison of AHP and fuzzy AHP models for prioritization of watersheds. Soft Comput 23(24):13615–13625. https://doi.org/10.1007/s00500-019-03900-z
Meshram SG, Alvandi E, Meshram C, Kahya E, Fadhil Al-Quraishi AM (2020a) Application of SAW and TOPSIS in prioritizing watersheds. Water Resour Manag 34:715–732. https://doi.org/10.1007/s11269-019-02470-x
Meshram SG, Singh VP, Kahya E, Alvandi E, Meshram C, Sharma SK (2020b) The feasibility of multi-criteria decision making approach for prioritization of sensitive area at risk of water erosion. Water Resour Manag. https://doi.org/10.1007/s11269-020-02681-7
Meshram SG, Adhami M, Kisi O, Meshram C, Duc PA, Khedher KM (2021) Identification of critical watershed for soil conservation using game theory-based approaches. Water Resour Manag. https://doi.org/10.1007/s11269-021-02856-w

Meshram SG, Singh VP, Kahya E, Sepehri M, Meshram C, Hasan MA, Islam S, Duc PA (2022a) Assessing Erosion Prone Areas in a Watershed Using Interval Rough-Analytical Hierarchy Process (IR-AHP) and Fuzzy Logic (FL). Stochastic Environ Res Risk Assessment. https://doi.org/10.1007/s00477-021-02134-6

Meshram SG, Tirivarombo S, Meshram C, Alvandi E (2022b) Prioritization of soil erosion–prone sub-watersheds using Fuzzy based Multi Criteria Decision Making Methods in Narmada basin. Int J Environ Sci Technol, India. https://doi.org/10.1007/s13762-022-04044-8

Nash JE, Sutclife JV (1970) River flow forecasting through conceptual models part I—a discussion of principles. J Hydrol 10(3):282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Nikam BR, Kumar P, Garg V, Thakur PK, Aggarwal SP (2014) Comparative evaluation of different potential evapotranspiration estimation approaches. Int J Res Eng Technol 3(6):544–552

Sarma S, Saikia T (2012) Prioritization of sub-watersheds in Khanapara-Bornihat area of Assam-Meghalaya (India) based on land use and slope analysis using remote sensing and GIS. J Indian Soc Remote Sens 40:435–446. https://doi.org/10.1007/s12524-011-0163-6

Shojaeezadeh SA, Nikooa MR, McNamarab JP, Kouchak AA, Sadegh M (2018) Stochastic modeling of suspended sediment load in Alluvial rivers. Adv Water Resour 119:188–196. https://doi.org/10.1016/j.advwatres.2018.06.006

Singh RD, Mishra SK, Choudhary H (2001) Regional flow duration models for large number of ungauged Himalayan catchment for planning mocro hydro projects. J Hydrol Eng 6(4):310–316. https://doi.org/10.1061/(ASCE)1084-0699(2001)6:4(310)

Singh CV (2006) Pattern characteristics of Indian monsoon rainfall using principal component analysis (PCA). Atmos Res 79(3–4):317–326. https://doi.org/10.1016/j.atmosres.2005.05.006

Singh PK, Kumar V, Purohit RC (2007) Deterministic modeling of annual runoff and sediment production rate for small watersheds of Chambal catchment. J Agric Eng 44(4):8–15

Willmott CJ (1981) On the validation of models. Phys Geogr 2:184–194. https://doi.org/10.1080/02723646.1981.10642213