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Original Article

Modeling of Soil Erosion using SWAT and Linking Land-Cover Pattern to Soil Erosion in Upper Krishna Sub-Basin

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Abstract - *The soil erosion modeling in any watershed is controlled by the attribute related to hydro-meteorological and geospatial data. Following these principles, the study is conducted to simulate soil erosion through the Soil and Water Assessment Tool and topographic link pattern to soil erosion through Partial Least square regression (PLSR). The study involved a model run of 10-year calibration and 5-year validation in response to observed soil erosion. The sensitivity of the basin parameter was assisted through SIMCA-P and SUFI-2 algorithms. The soil erosion model performed well by displaying R^2>0.70 for daily and monthly simulation. The catchment was delineated into 25 sub-basins and was further distributed in different erosion severity zones. The ranks are allotted to the SWAT parameters, which show higher sensitivity towards soil erosion through SUFI-2 analysis. In contrast, the sensitivity of parameters from PLSR towards soil erosion is evaluated through weight analysis. Identifying highly sensitive parameters towards soil erosion and finding the ability of landscape metrics to acquire a close association of soil erosion with the land cover pattern are the important findings of this study.*

Keywords - *Erosion modeling, GIS, PLSR, SWAT, Sensitivity Analysis.*

1. Introduction

During the ecosystem's supply of goods to humans, soil plays a major role. Of all the rewards obtained through nature, the soil is more important than anything to humans. The contribution of soil in providing services and goods to humans is incredible; hence the ecosystem needs to stay high. Soil erosion is a natural process, but it is expelled worldwide by anthropogenic tasks such as farming, desertification, and urbanization. Substantial erosion leads to challenges such as land deterioration, siltation of rivers, and aquatic ecosystem. Even though the terminology erosion was in service in the 19th century, the terminology soil erosion was proposed afterward, at the outset of the 20th century. It did not come into general use until the 1930s. The term soil erosion, in many instances, indicates the eradication of soil by the action of water and wind. Many writers who engaged with the challenges of soil erosion utilized the events associated with humanity's degradation. Some researchers feature soil erosion as simply erosion provoked by precipitation, while the rest of the authors include erosion provoked by natural and manufactured factors. Currently, soil erosion is a top-rated debated issue in the circle of environmentalists today, considering that it can damage agriculture and the natural environment to a higher extent.

Empirical models are hinged on determining crucial aspects by means of field observations, experiments, measurements, and statistical techniques in terms of soil loss (Petter). Several benefits from a functional perspective characterize them, but they require prolonged statistical data (Elirehema). Physical models are proposed to exhibit the erosion proceeding by addressing the corresponding equations. The distinct components of these models can affect the entire erosion process. Also, they had the skill to determine spatial and temporal instability of degradation processes (Bhattarai and Dutta). Computer-based hydrologic models are an important aspect of water resource planning and enhancement because they empower long-lasting simulations of the outcomes of watershed processes and monitoring activities. On top of that, these models enhance the simulation of numerous conservation programs. They can certainly be utilized to produce regulation to minimize water and soil quality deterioration by figuring out appropriate conservation programs for distinct watershed perspectives.
By having the enhancement of computational potentials and criteria upheld with recently offered disseminated databases like remote sensing and satellite imaging in the form of digital elevation models (DEMs) to assist decision-makers in getting the solution to water resources problems. The demand for the scientific technique to monitor sediment

carriers in catchment operations is a rising concern. Currently, the application of the hydrological model conjugate with satellite data access tools is more popular. Currently, a physical model has command over another type of model. It deeply understands the irregularity of catchment attributes. Several multidisciplinary models have been developed to illustrate erosion, water resource, and sedimentation processes. These models summarize the physical techniques regulating the makeover of runoff via precipitation, while modeling of soil erosion is set up to understand the activities that occurred in the natural landscape through physical laws (Onori and Grauso; Halkude and Katdare).

Over the past few years, the composition of LULC has emerged as a critical aspect of research studies of geomorphologic activities associated with erosion. The De-intensification of topographic cover management has forced environmental progression in the last few years, which considerably influenced erosion risk in the area(Ismanto et al.). Land cover patterns are portrayed by utilizing a range of landscape metrics; looking forward to this positive aspect, a deep study of landscape metrics has been done in the last few years (Feng et al.). Remarkably, many researchers have made use of regression techniques on multi-variable to explore soil erosion to various land cover managements. The fundamental constraints of conventional multivariate regression techniques in dealing with multi-collinear and riotous data are eliminated by employing strategies formed on the multivariate analytical forecast, such as partial least-square regression (PLSR) and principal component regression (PCR). PLSR is a contemporary method developed by incorporating attributes of the multiple linear regression techniques and principal component analysis (PCA) (Abdi). The PLSR method manages incredibly riotous data by clearly speculating the responsibility among parameters and predicting the underlying framework, which combines the real parameters. An earlier study done by (Ganasri and Ramesh; Dabral et al.; Kalambukattu and Kumar) had focused on the quantifying the loading of nutrients for planning the watershed management strategies, but they had their limitations; on the contrary, PLSR could quantify the sensitivity of landscape parameters concerning soil erosion which will help to overcome the limitations for planning the watershed management strategies.

The physical-based model SWAT was applied since it is a distributed watershed simulation model commenced to estimate runoff and loadings from rural watersheds, notably where cultivation is predominant (Himanshu et al.; Dutta and Sen). The ability of SWAT to simulate the loading on a monthly and a daily scale had given the researcher the luxury to study the parameters responsible for soil erosion on a daily and a monthly scale(Venkatesh et al.; Prabhanjan et al.; Vigiak et al.). SWAT-CUP is programmed to evaluate the prediction uncertainty of calibration and validation results obtained through SWAT. SUFI-2 algorithm is inbuilt in SWAT-CUP and is used to acquire parameter sensitivity through model evaluation criteria (Abbaspour et al.; Arnold et al.). The interpretation and the scaling of results obtained in soil erosion studies have emerged as the topic of effective research over the past few years (Abbaspour). The interpretation of uncertainty multi-variable cum site procedure to get effective outcomes of SWAT model have been determined in few watersheds. Counsel of sensitivity analysis, calibration, and validation are principal aspects of cutting down output uncertainty and intensifying user confidence in model potential, making the simulation more reliable. The parameters associated with Hydrological Response Unit, Groundwater, Soil, and Slope aspect available in SWAT-CUP Software were monitored by (Gholami, Tripathi, et al.) during the study of soil erosion over the watershed. (Hassen M Yesuf et al.) had successfully identified the SWAT-CUP parameters responsible for soil erosion from the landscape and channel to have proper soil conservation measures in the watershed. However, very few researchers have promoted SWAT-CUP analysis of soil erosion daily to overcome these gaps. This study is executed with the following objectives. a) To evaluate the performance of SWAT in predicting soil erosion b) Use of SWAT-CUP with SUFI-2 algorithm for calibration and validation of SWAT model c) To monitor the sensitivity of soil erosion parameters using sensitivity analysis on global scaled) Use of partial least square regression technique in identifying the relationship of landscape metrics and soil erosion.

2. Study Area

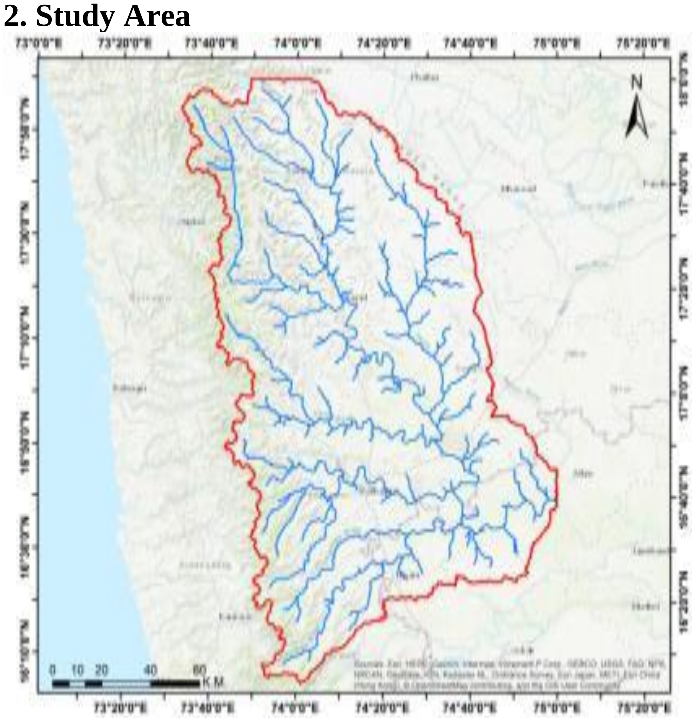

Fig. 1 Location map of Upper Krishna Sub-Basin

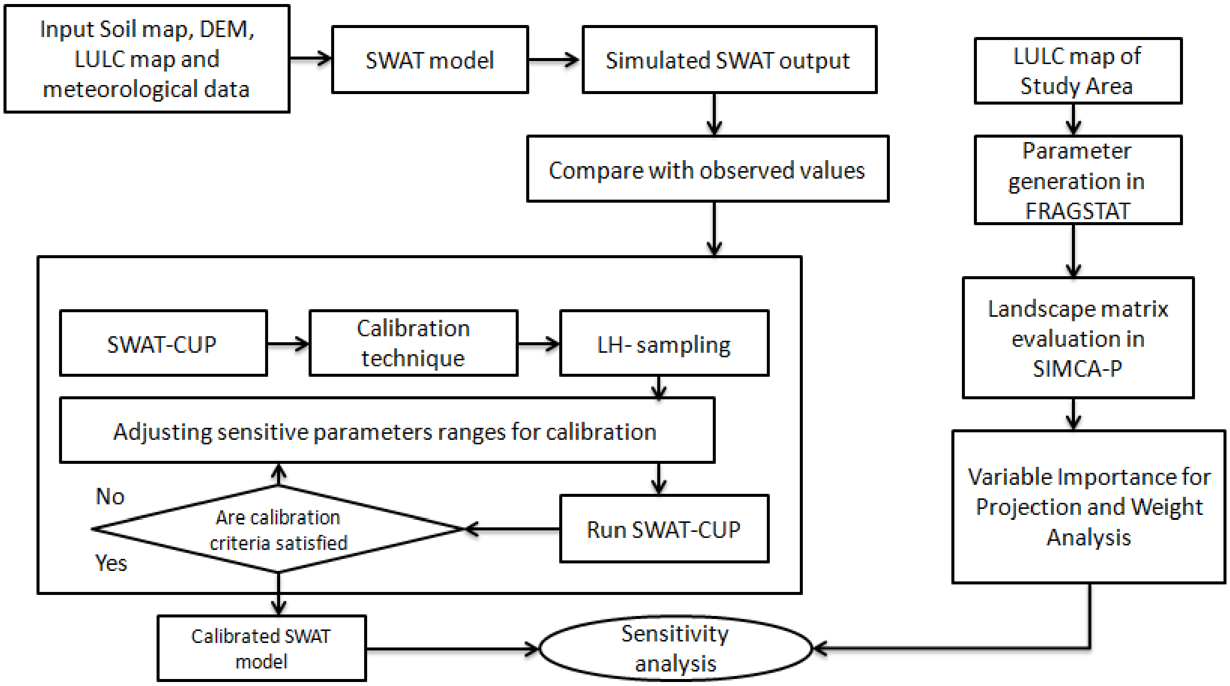

Fig. 2 Methodology flow chart

The present study took place in the Upper Krishna Sub-Basin (K1) is one of the largest sub-basin of the upper Krishna basin. The upper Krishna sub-basin is confined between latitudes 16°0' N & 18° 0' N and the longitudes 73°40'E and 75°0'E and has a geographical area of about 1906 km². Krishna river is the main river that flows throughout this basin along with its tributaries such as Koyna, Panchganga, Dudhganga, and Warna. The upper Krishna sub-basin annually encounters a monsoon for four months, and the precipitation lies within 580mm to 140mm. Also, precipitation of 30 to 70 days is reported yearly, out of which 90% is acquired within four months (June to September). Sediment data of duration 1998-2014
(16 yrs) The Karad Gauge on river Krishna was received via the central water commission.

3. Methodology

3.1. Upper Krishna Sub-Basin DEM

The webpage of the U.S. Geological Survey is used to retrieve the Digital Elevation Model (DEM) of the upper Krishna sub-basin. The elevation of 490-1458m is observed in the DEM of the upper Krishna sub-basin. The multifunction feature of DEM is used for generating slope maps and flow accumulation maps of the Upper Krishna Sub-Basin.

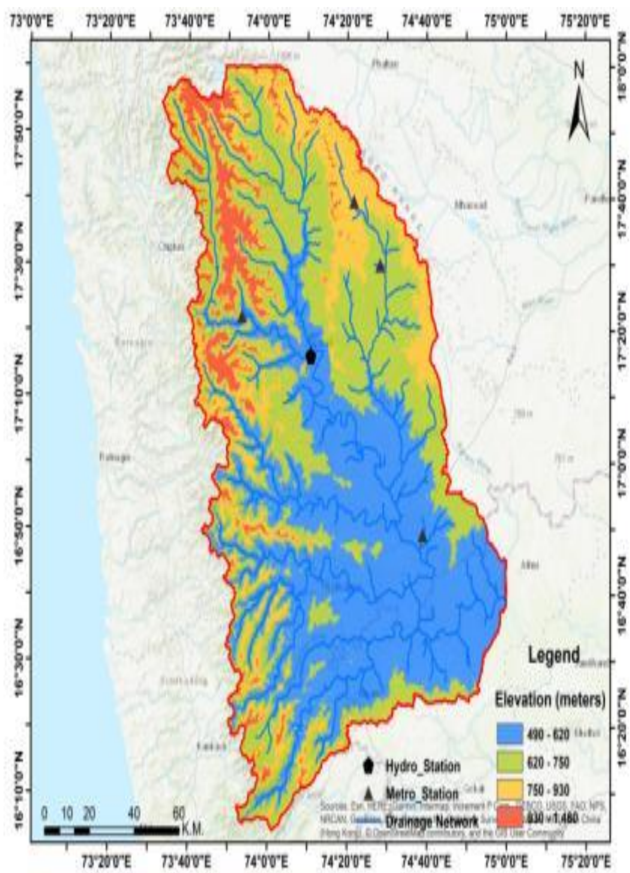

Fig. 3 Digital Elevation Model of Upper Krishna Sub-Basin

3.2. Analysis of SWAT Model

Soil Water Assessment Tool (SWAT) is a physical-based distributed model which relies on the physical activities of components present in watersheds. SWAT model cut down the watershed into sub-units called Hydrological Response Units (HRUs). SWAT model predicts soil erosion with the algorithm run on the below equation:

$$SW_t = SW_o + \sum_{n=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \quad (1)$$

Where SW_t is the final amount of soil water (mm), SW_o is planted water intake (mm), R_{day} is precipitation (mm), Q_{surf} is surface runoff (mm), E_a is evapotranspiration (mm), W_{seep} is percolation (mm), Q_{gw} is low flow (days).

3.3. Input Data

Weather data for 23 years (1/1/1995- 12/31/2014) which includes precipitation, solar radiation, temperature (max/min), and wind speed daily, is used in this work; apart from it, DEM is used as the base map for LULC, slope and soil map of Upper Krishna Sub-basin is also utilized.

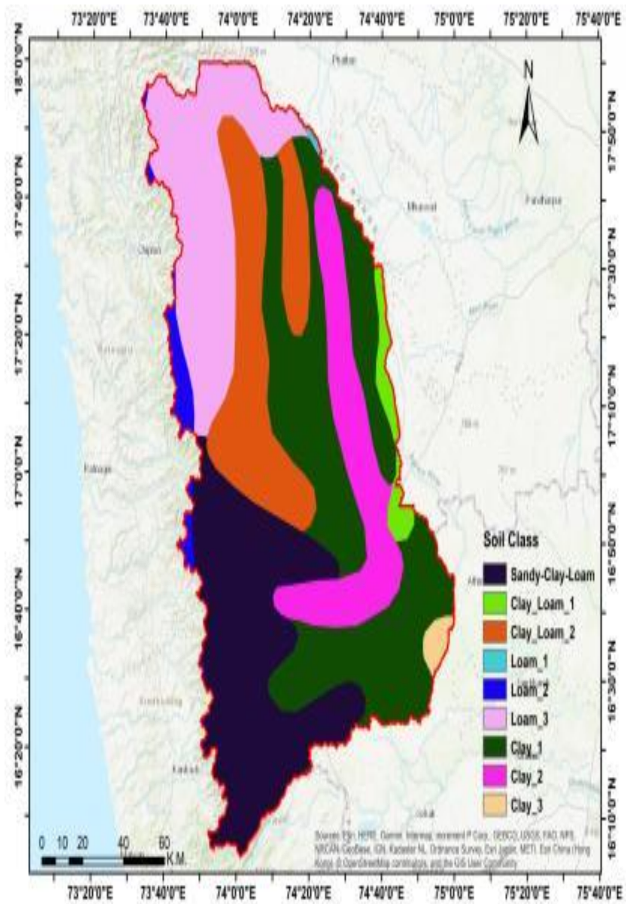

Fig. 4 Soil map of Upper Kriahna Sub-basin

Soil map of Upper Krishna Sub-basin is collected from (NBSS & LUP), Nagpur, which was digitized in ERDAS Software for reclassification. The SOIL-FAO database is used to upgrade the soil data of the Upper Krishna Sub-basin, and it was inserted in the look-up table of the soil section of the SWAT interface. In this reclassification process soils were identified as Sandy-Clay-Loam, Clay-Loam_1_2, Loam_1_2_3 and, Clay_1_2_3.

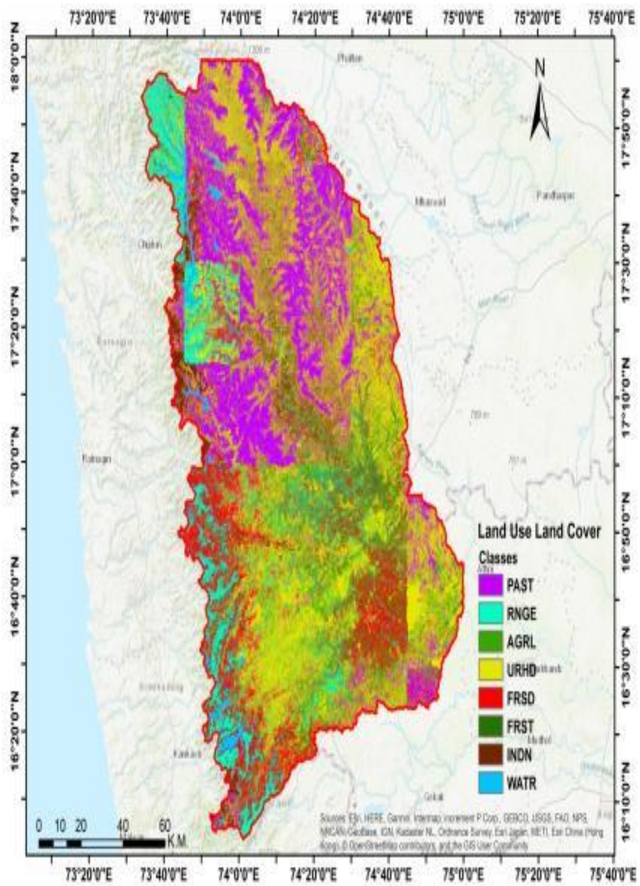

Fig. 5 LULC map of Upper Krishna Sub-basin

Land-use map leads the current status of land use in the area of the project, the reference of the SWAT database is taken to upload the land use land cover classes in look up table of LULC section of SWAT interface. Upper Krishna Sub-basin is covered by forest, pasture, agricultural and rangeland areas, and urban areas can also be seen in most parts of the watershed.

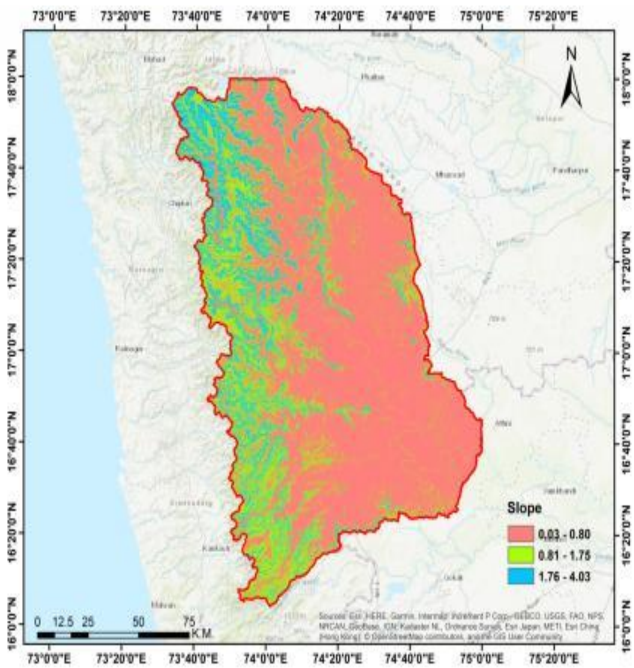

Fig. 6 Soil map of Upper Krishna Sub-basin

Slope Map: It is created in Arc-GIS Software using the slope tool. The slope classification is put up in the look-up table of the Slope section in the SWAT interface. It shows a high slope in the Western Ghats, whereas a plane area is observed in the southern part of the study area.

3.4. Delineation of basin and HRU definition

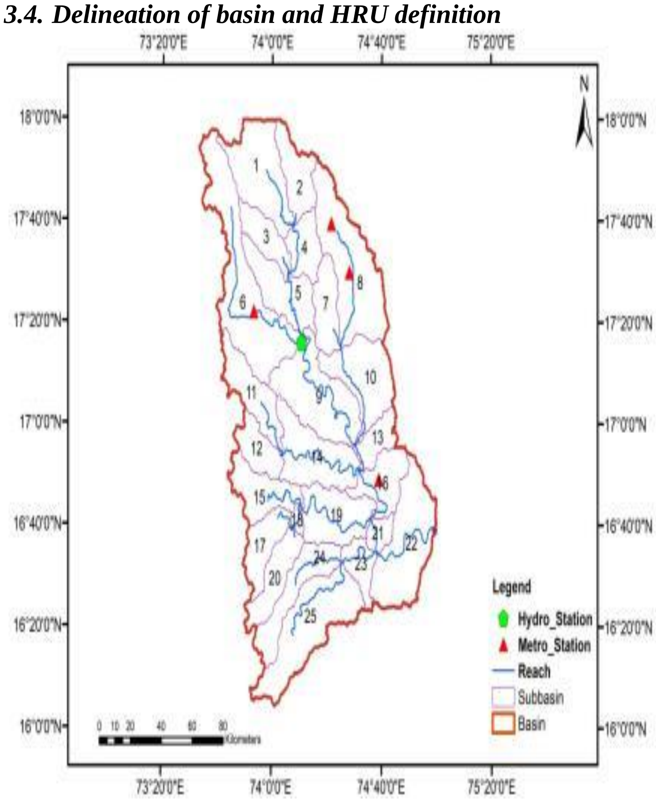

Fig. 7 Delineated Upper Krishna Sub-basin

In the initial step, the study area is delineated by taking DEM as an input; 25 sub-basins were generated through the delineated process. In the further step, overlaid analysis of Land use, soil, and slope map is carried out to create Hydrologic Response Unit (HRU). A composition of features available in soil, slope, and land use is detected in HRU. By applying a command, threshold of 5% to land-use and soil, 10% to slope, 141 HRUs were generated. Daily hydro metrological data is put up for SWAT Run in the third stage. In the SWAT run, daily soil erosion output and monthly soil erosion output are obtained for 1995-2014, including the early couple of years as a warm-up period.

3.5. Analysis of SWAT-CUP model

The SUFI-2 algorithm inbuilt in SWAT-CUP interfaces of Arc-SWAT is utilized in this study, considering that it is such a technique that can deliver the largest insignificant specification unpredictability intervals of model parameters. The uncertainty between actual and simulated parameters is revealed in the SUFI-2 algorithm. It also develops the uncertainty band among the parameters by grouping them concerning their calibration uncertainty analysis. The features of SUFI-2 are unique, i.e., uncertainty distribution within sensitivity parameters is uniform. Gradation of model performance is done by 3 indices, as below.

$$R^2 = \left\{ \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y^{mean}\right)\left(Y_i^{sim} - Y^{pre\_mean}\right)}{\left[\sum_{i=1}^{n}(Y_i^{obs} - Y^{mean})^2\right]^{0.5}\left[\sum_{i=1}^{n}(Y_i^{sim} - Y^{pre\_mean})^2\right]^{0.5}} \right\}^2 \quad (2)$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - Y^{mean})^2} \quad (3)$$

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right) * 100}{\sum_{i=1}^{n}\left(Y_i^{obs}\right)} \quad (4)$$

Y_i^{obs} is the ith real-time data Y_i^{sim} is the ith predicted data, Y^{mean} is the mean of observed data, Y^{pre_mean} is the mean of model prediction, and n is the total number of observations.

A phase from 1995-2009, including 3 years, i.e., 1995-1998, as a warm-up period is used for calibration. Seven parameters were identified in SWAT-CUP through an objective function to perform calibration, and the model was run 500 times (Ref. Table No.1). A unique feature, i.e., Sensitivity analysis inbuilt in SWAT-CUP, evaluates the performance of model output which is directly proportional to the vitality of input given to the model. Validation of the model was conducted to evaluate the model performance for five years (2010-2014) of data.

Table 1. SWAT-CUP Parameters with their description

Sr.No.	Parameter	Description
1	SURLAG	Lag time of Surface Runoff
2	LAT_SED.hru	The concentration of sedimentation in lateral and groundwater flow
3	CN2	Curve Number of Runoff
4	V_CH_COV1	Channel Erodibility factor
5	HRU_SLP.hru	Mean slope steepness (m/m)
6	USLE_K (..).sol	Erodibility factor of soil
7	USLE _P.mgt	Support practice factor

3.6. Landscape matrix and Partial Least-Square Regression

The study area's landscape map with high precision is extracted from the USGS website for 1995, 2005, and 2019. Multiple landscape maps are organized to compute landscape metrics. Even though numerous landscape metrics have been put forward to implement and evaluate landscape patterns or characteristics, from total metrics, few are used for pattern layout, and some metrics are used for mapping units.

15 metrics were figured out to illustrate the landscape characteristic (Table 2). In a few research studies, soil erosion from land-cover patterns was studied through these metrics(Nie et al.). Few metrics corresponding to aspects of land-use planning were selected based on performance through trial and error and further implemented to evaluate soil erosion at the watershed scale. FRAGSTAT 4.0 program is used in this study to evaluate landscape metrics (McGarigal et al.), which is available software in the public domain for landscape metrics identification. The PLSR method is utilized to identify the impact of soil erosion through metrics. PLSR follows the same principle on which Principal Component Analysis (PCA) works, i.e., few linear mathematical combinations are used in PLSR. The impact of land-cover patterns on soil erosion is the main approach in PLSR. This study uses the SIMCA-P program to perform the PLSR procedure.

The landscape metrics are programmed in the PLSR model. These metrics represent an independent variable, whereas soil erosion is a dependent variable in the PLSR model. A set of simulations of new PLSR models were executed, and through new analysis, inclusion and exclusion of new variables are undertaken to achieve the best PLSR model. Some metrics have shown a strong correlation, as shown in table no 3, in which the Patch density (PD) has shown strong relation with Edge density (ED), area ratio in average form (PARA_MN), Cohesion index at patch level (COHESION) had shown a strong relationship with Mean Shape index (SHAPE_MN). Patch average size (AREA_MN) has shown strong relation with the Patch index at the largest scale (LPI), and Simpson's diversity index (SIDI) has shown a strong relationship with the Landscape shape index (LSI).

Table 2. SIMCA software landscape metrics (Shi et al.)

Sr.No.	Metrics	Abbreviation	Descriptions
1	Simpson’s diversity index	SIDI	The landscape contains only 1 patch.
2	Aggregation index	AI	Land-use type adjacency.
3	Area ratio in average form	PARA_MN	Land cover’s area
4	Perimeter-area fractal dimension	PAFRAC	Patch shape index in complexity form
5	Patch density	PD	Volume of patches
6	Shannon’s diversity index	SHDI	Diversity of patches in a landscape.
7	Landscape shape index	LSI	Measurement of complete edge
8	Euclidian nearest-neighbor distance	ENN_MN	Edge to edge distance
9	Largest patch index	LPI	Patch has the largest landscape
10	Mean shape index	SHAPE_MN	Compact shape area
11	Contagion	CONTAG	Aggregated patch type
12	Interspersion and juxtaposition index	IJI	Adjacency index
13	Edge density	ED	Edge segment total length
14	Patch average size	AREA_MN	Land cover area
15	Cohesion index at patch level	COHESION	Connecters of different patch

Table 3. PLSR analysis landscape metrics correlation

Metrics	*PD*	*LPI*	*ED*	*LSI*	*AREA_MN*	*SHAPE_MN*	*PARA_MN*	*PAFRAC*	*ENN_MN*	*CONTAG*	*IJI*	*COHESION*	*SHDI*	*SIDI*	*AI*
PD	1														
LPI	-0.33	1													
ED	0.94	-0.63	1												
LSI	0.29	-0.97	0.57	1											
AREA_MN	-0.52	0.64	-0.6	-0.77	1										
SHAPE_MN	-0.12	0.97	-0.43	-0.98	0.64	1									
PARA_MN	0.64	0.43	0.4	-0.53	0.25	0.64	1								
PAFRAC	-0.4	-0.68	-0.11	0.76	-0.44	-0.84	-0.95	1							
ENN_MN	-0.12	0.93	-0.41	-0.98	0.75	0.98	0.67	-0.86	1						
CONTAG	0.77	0.21	0.59	-0.33	0.12	0.45	0.97	-0.86	0.5	1					
IJI	-0.31	-0.75	-0.01	0.82	-0.47	-0.9	-0.92	0.99	-0.9	-0.8	1				
COHESION	0.43	0.65	0.15	-0.73	0.42	0.82	0.97	-1	0.84	0.88	-1	1			
SHDI	-0.4	-0.67	-0.11	0.75	-0.43	-0.84	-0.96	1	-0.86	-0.86	0.99	-1	1		
SIDI	0.07	-0.96	0.4	0.96	-0.55	-0.99	-0.65	0.84	-0.96	-0.45	0.89	-0.81	0.84	1	
AI	-0.38	-0.69	-0.09	0.77	-0.45	-0.85	-0.95	1	-0.87	-0.85	1	-1	1	0.85	1

4. Results and Discussion

4.1. Soil Erosion Index

The result from SWAT display non-uniform distribution of soil erosion throughout the Upper Krishna Sub-Basin. Basin on the left bank of Krishna stream had shown moderate erosion class due to less percentage of slope present in this area. In contrast, the basin present on the right bank had shown a higher class of erosion index due to the steep mountains in this region.

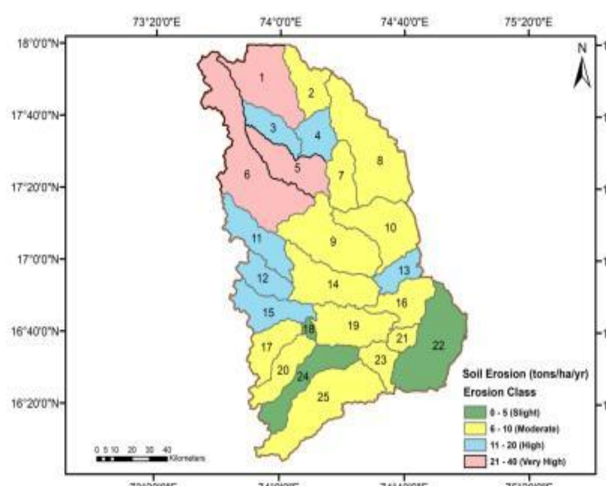

Fig. 8 Soil Erosion Zones in Upper Krishna Sub-Basin

Sub-watershed within the study area is classified into four soil erosion grades (Singh et al.) (Ref. Table 4).

Table 4. Erosivity Index in Upper Krishna Sub-Basin

Sediment loss (tons/ha/yr)	Soil Erosion Class	Percentage of Area
0-5	Slight	10
6-10	Moderate	55
11-20	High	15
21-40	Very High	20

Steep slope and Loamy Soil had caused a high rate of soil severity in the basin, which was accomplished in the zone of the Western Ghats, i.e., watershed no. 1,5,6,11,12,15, and the lowest erosion rates are observed in the sub-watershed located at the moderate slope, i.e., watershed no. 22,19,23,21. About 35% area falls in more than moderate soil erosion class.

4.2. Sensitivity Analysis

The simulations obtained at the preliminary stage, along with default parameters, displayed poor results. Hence the sensitivity analysis of SWAT output and calibration and validation was executed. At the initial stage, simulated values struggle to lie in 95 PPU. Still, by making the changes in SWAT-CUP parameters, i.e., by setting the Curve Number of Runoff (CN2) value at 75.01 and 77.84 for monthly and daily scale slow down infiltration rate, Lag time of Surface Runoff SURLAG was set to a value of 1.93 and 2.08 for monthly and daily scale which helps to control total available water reach. The value of the Support practice factor (USLE_P) was set to 0.83 on a monthly and daily scale, which reduces human activity impact over LULC of the basin. The erodibility factor of soil (USLE_K) was fitted with 0.35 & 0.30 for monthly and daily scales to control sediment formation. Channel Erodibility factor (CH_COV1) is fitted in the value of 0.07 and 0.05 monthly. The daily scale to get linear influence over soil loss and Mean slope steepness (HRU_SLP) is set to 0.22 monthly. Daily scale to increase the percentage of slope in the watershed and Concentration of sedimentation in the lateral. Groundwater flow (LAT_SED) was fitted to 49.95 to increase the infiltration rate for monthly and daily scales.

The sensitivity of all parameters towards soil erosion are indulged through an objective function such as t-stat and p-values obtained for the parameters, and their rank is allotted as given in table no.5 and 6. The criteria lesser the p-value greater the sensitivity is set for allotment of rank to parameters. The parameters like USLE support practice factor and runoff curve number are more sensitive in calibration and validation in SWAT-CUP, whereas Surface runoff lag time, Channel cover, and Sediment concentration in lateral and groundwater flow have lesser sensitivity towards soil erosion.

Table 5. SWAT parameters for soil erosion (Monthly Basis)

Parameter	Min Value	Max Value	Fitted Value	t-stat	p-value	Rank
V_USLE _P.mgt	0.7	0.9	0.83	-11.62	0.00	1
V_CN2.mgt	75	85	75.01	-13.03	0.00	2
V_HRU_SLP.hru	0.2	0.3	0.22	-19.68	0.00	3
V_USLE_K (..).sol	0.3	0.4	0.35	-23.40	0.00	4
V_SURLAG.hru	1	4	1.93	-2.51	0.48	5
V_CH_COV1.rte	0.01	0.2	0.07	0.43	0.59	6
V_LAT_SED.hru	0	50	49.95	1.17	0.39	7

Table 6. SWAT parameters for soil erosion (Daily Basis)

Parameter	Min Value	Max Value	Fitted Value	t-stat	p-value	Rank
V_CN2.mgt	75	85	77.84	-9.73	0.00	1
V_USLE _P.mgt	0.7	0.9	0.83	-5.51	0.00	2
V_HRU_SLP.hru	0.2	0.3	0.21	-14.17	0.00	3
V_USLE_K (..).sol	0.3	0.4	0.3	-7.12	0.00	4
V_SURLAG.hru	1	4	2.08	-0.80	0.42	5
V_CH_COV1.rte	0.01	0.2	0.05	0.72	0.46	6
V_LAT_SED.hru	0	50	49.95	1.13	0.25	7

4.3. Evaluation of Model Calibration

In developing the soil erosion model, which displays ground truth data precisely, calibration plays an important role in the progress of such a model. Initial fourteen years are used for calibration from (1995-to 2009), including 3 years of warm-up, i.e., 1995-1998, by comparing sediment concentration measured at gauge station with simulated sediment concentration (Fig.10),(Fig.11). The calibration is undertaken on a monthly scale and a daily scale. The simulated value had under-predicted the observed value at both scales throughout the calibration phase, but the peak value was simulated effectively. The scatter plot shows the model had performed well for monthly scale R^2= 0.76(Fig.11) and daily scale R^2=0.73(Fig.13). The evaluation criteria like PBIAS=25.3 for the monthly scale and PBIAS=40.9 for the daily scale, NSE=0.67 for the monthly scale and NSE=0.60 for the daily scale, p-factor=0.58 for the monthly scale, and p-factor=0.40 for daily scale, r-factor=1.16 for monthly scale and r-factor=1.37 for daily scale had also displayed that model had performed well in calibration for both the scale.

4.4. Evaluation of Model Validation

After using 70% of the data for calibration, proceeding validation is conducted with the rest of the data (2010-2014) in the SWAT-CUP model by contemplating the measured and simulated sediment concentration. The validation is carried out on a monthly and daily scale. The simulated value had under-predicted the observed value on both scales in the validation phase. Still, the simulation value followed the momentum of the observed value throughout the phase. The scatter plot shows the model had improved on a daily scale of R^2=0.77, and a slight drop in performance on a monthly scale of R^2=0.66 is observed. The evaluation criteria for validation like PBIAS=6.5 for the monthly scale and PBIAS=30.5 for the daily scale and NSE=0.65 for the monthly scale and NSE=0.64 for the daily scale, p-factor=0.64 for the monthly scale and p-factor=0.47 for daily scale, r-factor=1.40 for monthly scale and r-factor=1.56 for daily scale had allowed us to observe improvement in model performance in the validation phase.

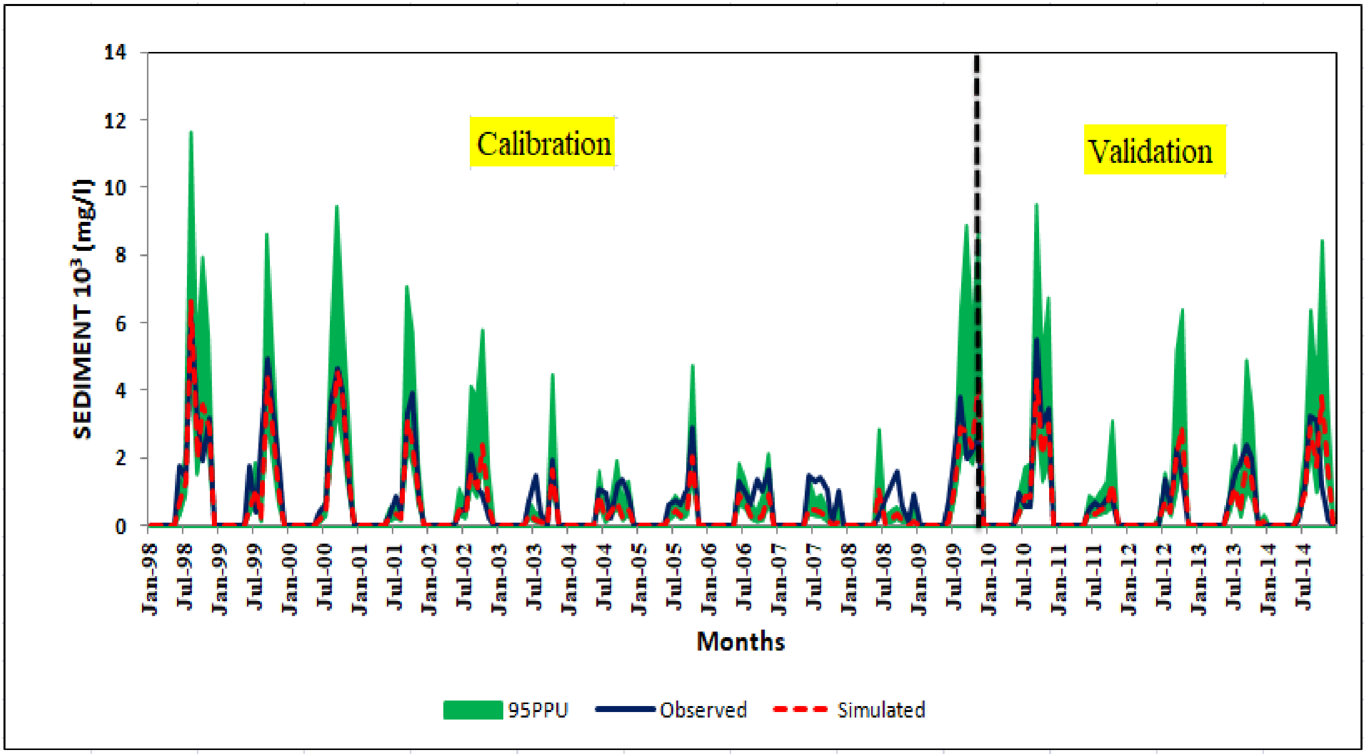

Fig. 9 Graph for monthly observed versus simulated soil erosion in Upper Krishna Sub-basin

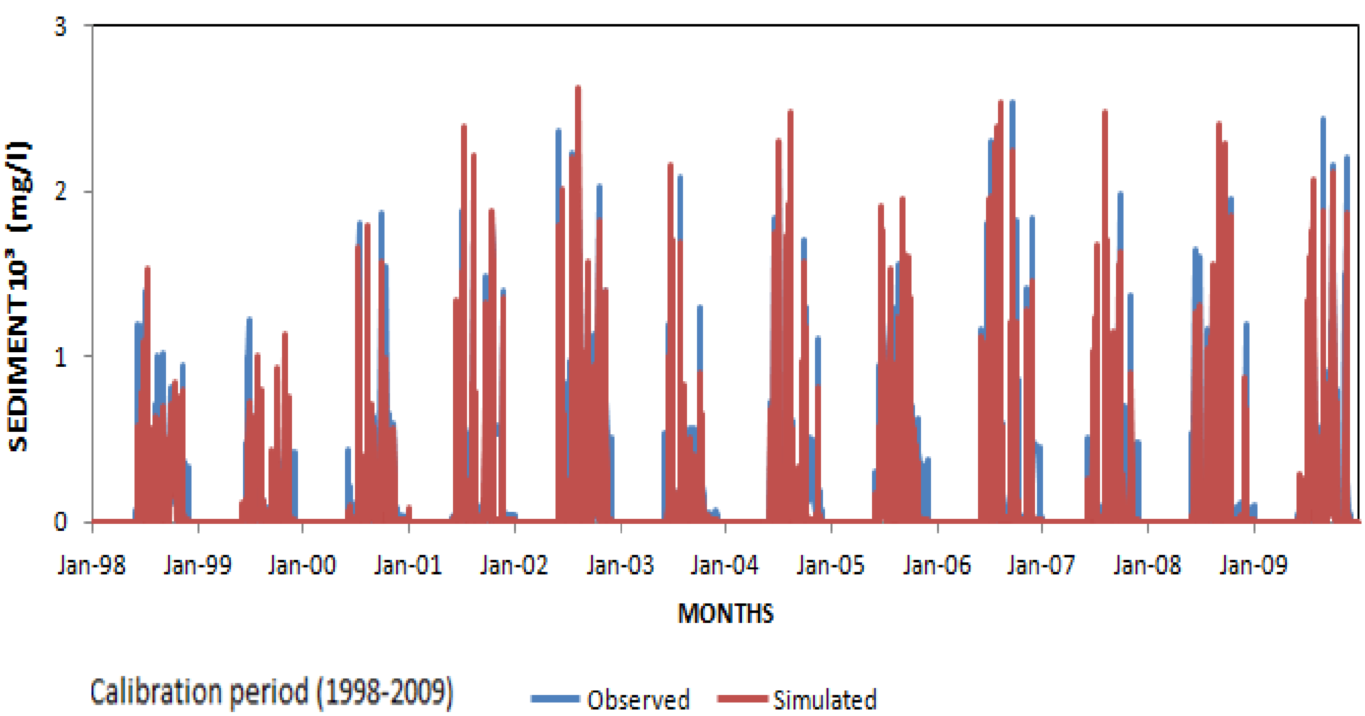

Fig. 10 Graph for daily Observed versus Simulated soil erosion Upper Krishna basin

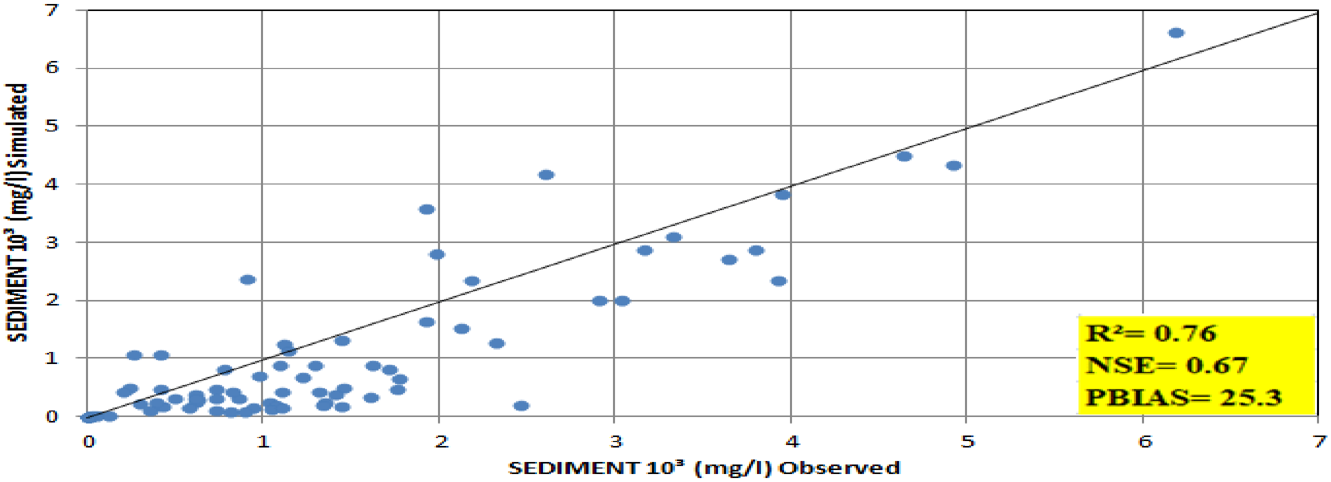

Fig. 11 Scatter Plot of monthly scale Calibration for Upper Krishna basin

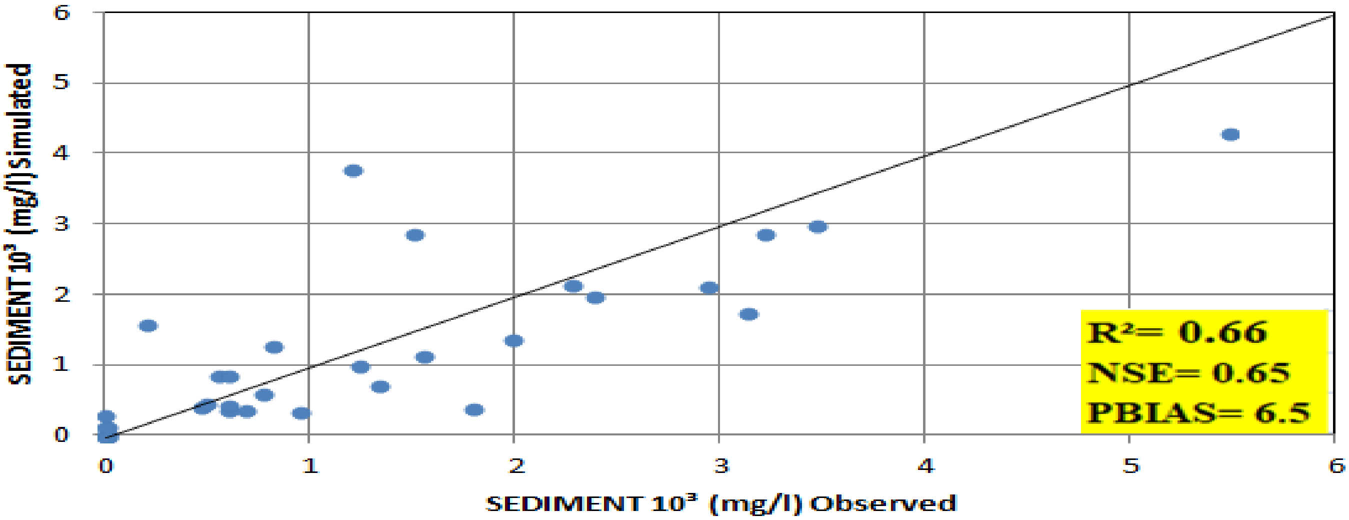

Fig. 12 Scatter Plot of monthly scale Validation for Upper Krishna basin

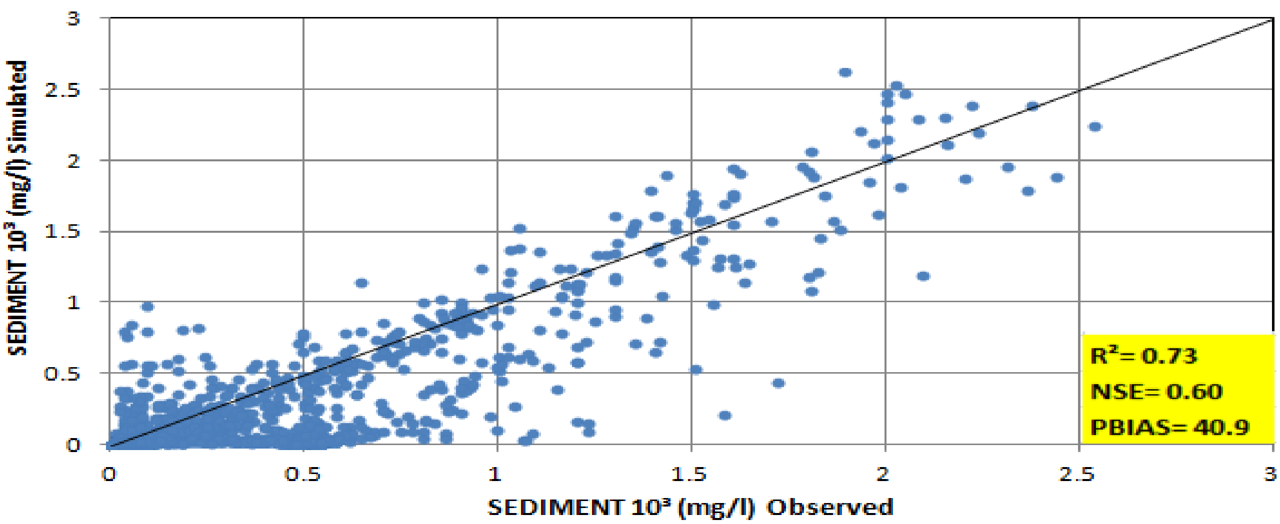

Fig. 13 Scatter Plot of daily scale Calibration for Upper Krishna basin

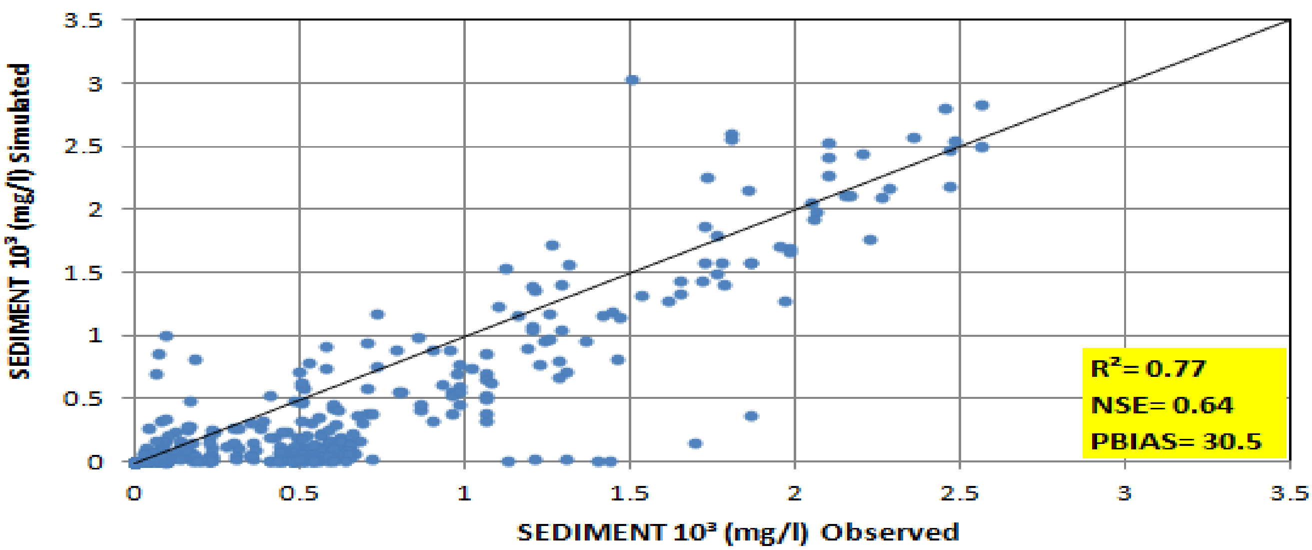

Fig. 14 Scatter Plot of daily scale Validation for Upper Krishna basin

Table 7. Statistical evaluation of model performance

Parameter	Soil Erosion							
	Observed				Simulated			
	Daily		Monthly		Daily		Monthly	
	Calib	Valid	Calib	Valid	Calib	Valid	Calib	Valid
Avg (mg/l)	312.75	593.64	1346.5	1217.7	184.74	412.38	1006.5	1138.1
SD	398.28	606.74	1274.8	1273.7	387.33	647.17	1316.9	1145.4
PBIAS					40.9	30.5	25.3	6.5
NSE					0.60	0.64	0.67	0.65
R^2					0.73	0.77	0.76	0.66
p-factor					0.40	0.47	0.58	0.64
r-factor					1.37	1.56	1.16	1.40

4.5. Pattern Analysis of Landscape metrics

The loading of the landscape matrix shown in fig.13 shows that parameters like (IJI), (AI), and (SHDI) falls under negative weight loading on both scale also the Variable Importance for Projection, as shown in fig.14 of this matrix is less than 1 both these results indicates that these matrices are having a minimum impact over soil erosion.

Parameters like the Sum of the proportion of area in average form (PARA_MN) and Largest Patch Index (LPI) falls under positive weight loading, as shown in fig.13; hence they have a strong influence on the soil erosion. Parameters like Mean patch size (AREA_MN), Simpson's diversity index (SIDI), and Patch cohesion index (COHESION) have negative weight loading, as shown in fig.13. Still, their Variable Importance for Projection value is more than 1, as shown in fig.14; hence, they strongly influenced soil erosion within the watershed.

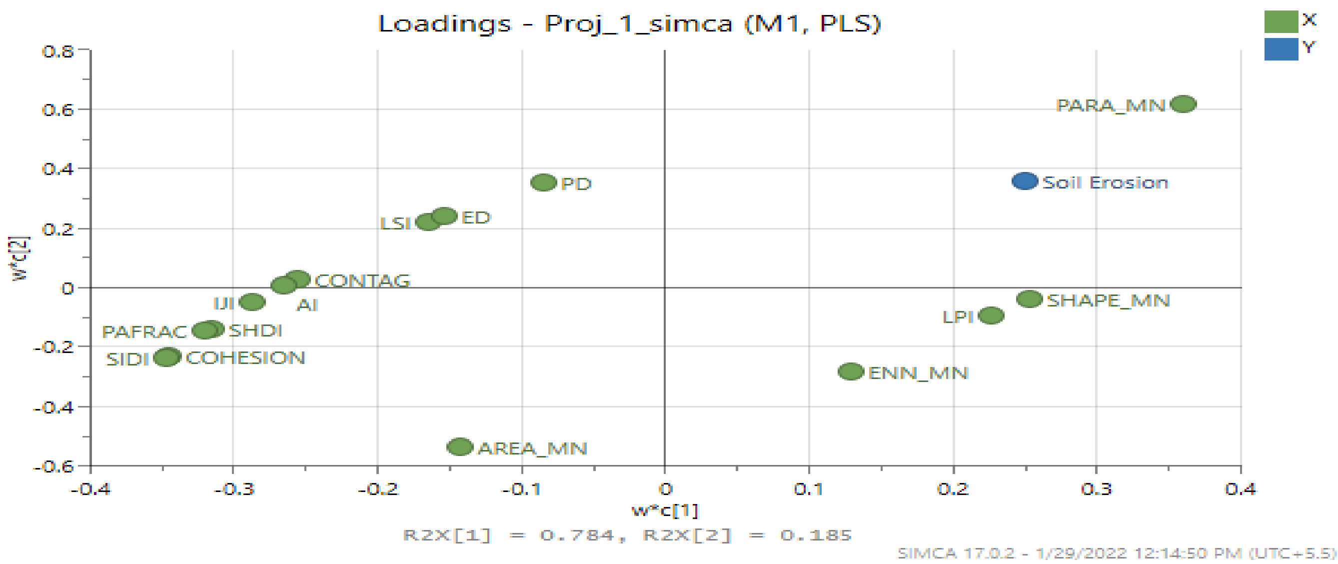

Fig. 15 Loading of landscape matrix concerning soil erosion.

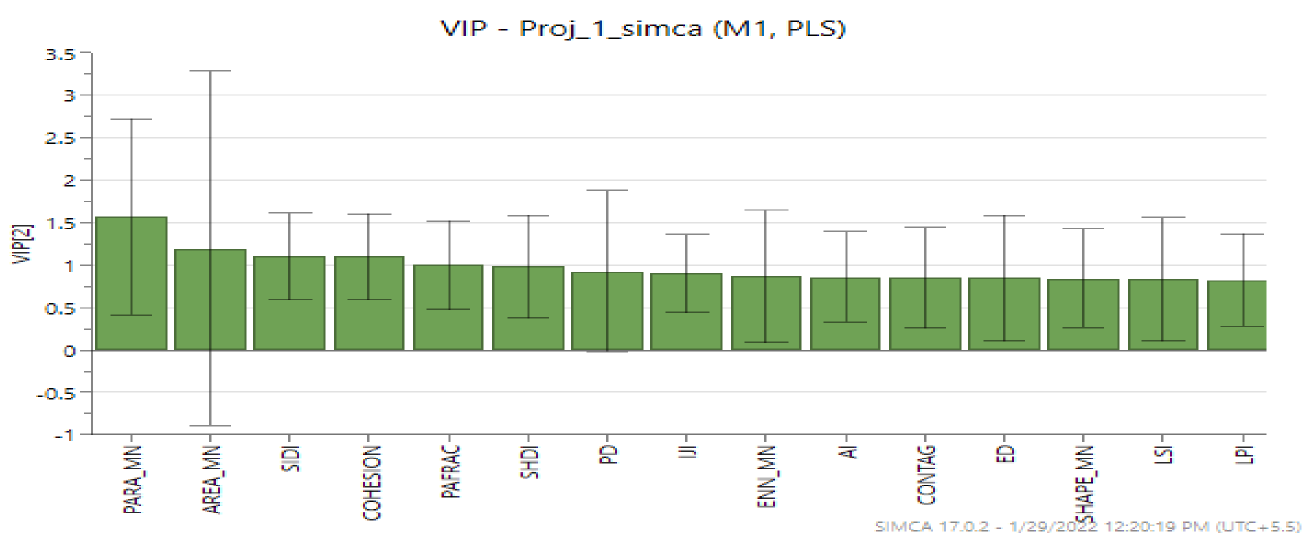

Fig. 16 Variable Importance for Projection

Table 8. Landscape metrics soil erosion results

Landscape metrics	**Soil erosion**		
	VIP	**W'[1]**	**W'[2]**
PARA_MN	1.6	0.35	0.6
AREA_MN	1.2	-0.15	-0.5
SIDI	1.15	-0.35	-0.35
COHESION	1.15	-0.35	-0.39
LPI	0.6	0.21	-0.1

5. Conclusion

Satisfactory remark was assigned to model if R²>0.50 (Hassen M. Yesuf et al.)for soil erosion modeling on a monthly scale. Our SWAT-CUP model had successfully satisfied this criterion; additionally, quantifying the soil erosion on a regular scale proved better than (Himanshu et al.).Sensitivity analysis reveals that the Support practice factor (USLE_P), Curve Number of Runoff (CN2), and Mean slope steepness (HRU_SLP) are highly sensitive parameters toward soil erosion on a monthly scale and daily scale in the SWAT-CUP model. After undertaking different testing phases, the SWAT model's ability to simulate soil erosion is remarked as good in Upper Krishna Sub-basin. This study has traced erosion severity zones in different parts of the Upper Krishna basin that will benefit from implementing management practices. The use of the PLSR model has shown a positive association of landscape metrics such as (PARA_MN) with soil erosion and also the influence of (AREA_MN), Simpson's diversity index (SIDI), (COHESION), and (LPI) over the soil erosion were also identified. Riverbank and hill slope parameters had dominated the soil erosion in the basin. This study noted that SWAT-CUP had limited parameters in its database that could recognize soil erosion effectively. Still, the introduction of new parameters from the PLSR model, which influenced soil erosion in the Upper Krishna Sub-basin, had boosted the soil erosion modeling study in the future.

Conflicts of Interest

The author Mr. Pravin V. Desai declares that there is no conflict of interest regarding the publication of this paper.

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