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Original Article

Soil Erosion Modeling and Sensitivity Analysis using SWAT and PLSR Technique in Upper Bhima Sub-Basin

Pravin V. Desai [1], Suresh K. Ukarande [2]

[1] *Department of Civil Engineering, Anjuman -I- Islam's Kalsekar Technical Campus, Maharashtra, India.*
[2] *K.J. Somaiya Institute of Engineering and Information Technology, Maharashtra, India.*

[1] *Corresponding Author : pravindesai610@gmail.com*

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Abstract *- Carrying out calibration properly is the important phase to enhance the model's credibility. Due to unique features to support decisions about alternative management strategies regarding soil erosion, distributed watershed models have been used quite effectively in a few watersheds. The execution of the Soil and Water Assessment Tool in simulating soil erosion and sensitivity analysis of landscape parameters concerning soil erosion via partial least square regression (PLSR) is put forward in this work. Model run for 2014 and 2005 is carried out in this work; each model holds 10 years of calibration and 5 years of validation by placing soil erosion as a dependent parameter. SIMCA-P and SUFI-2 algorithms were used to evaluate the sensitivity of basin parameters. The use of the SUFI-2 algorithm uplifted model efficiency for monthly and daily scales by displaying NSE>0.60 and R^2>0.60. Within the watershed, on the scale of the sub-watershed, the soil erosion severity zone was organized effectively. The SWAT parameters recognized to be highly sensitive toward soil erosion are placed in higher orders after the evaluation done through the SUFI-2 method. In contrast, PLSR parameters that are highly sensitive toward erosion are placed in a higher order after the evaluation done through weight analysis. The PLSR technique introduced in this work is valuable, as it provides a unique pattern through which the association between soil erosion and land cover pattern can be recognized closely, also determining highly sensitive parameters towards soil erosion through SWAT-CUP will allow working effectively towards watershed management practices at erosion hotspot in Upper Bhima Sub-Basin.*

Keywords *- Soil characteristics, Hydrologic response, Spatial configuration, Land Use Pattern, SUFI-2 algorithm.*

1. Introduction

Over the last decade, increased human activities and drastic climate change have distributed the hydrological cycle to some extent, leading to land degradation worldwide. Soil acts as a transit medium between the ecosystem and humans, where the benefits of the ecosystem are delivered to human beings. The disintegration of soil present in natural form is sloth full process. Also, factually, it is proved soil played an important role in the creation of earth splitting and the hauling technique of soil particles is observed in erosion caused by water. The disintegration of runoff recorded at peak rate is important to decrease soil erosion. Also, social programs like land management, construction of soil and water conservative structure and study of soil and climatic condition of several aspects present in watersheds play a vital role. To overcome these problems, researchers are working on the movement of debris from watershed land to the outlet of the stream network. Past studies have shown concern over the increase in the capacity of sediment transportation of a stream network from watershed to sea. Because of poor management of land resources and water in many areas drop in human health and welfare is observed.

The ability of the empirical model to select a proper characteristic approach toward parameter specification was recognized by a few researchers and is thoroughly used in the research work (Petter). The best soil quality supports agriculture productivity and climate regulation (Elirehema). The catchment characteristics are represented as an equation variable in the physical model. The association between dependent and independent variables can be studied through this model. This model follows conservation regulation of density and energy for sediment yield simulation. Also, these models consider rainfall events as an independent variable during the modeling process. The necessity of an enormous quantity of samples is the deficiency of this model(Wu and Chen). For better investigation of the hydrology and soil erosion processes, advanced technique is needed; also, the technique should be relevant for executing proper measures over the issues related to soil erosion. The present technology available in the market includes hydrological and soil erosion models and geographic information systems. Using this advanced technique accelerates the conservative soil programs, which lead to the control of soil quality and quantity damage in a watershed. The most affected erosion-prone area of the catchment can be defected by adopting a computer hydrological model merged with the GIS database. The computer-based hydrological model is very popular due to its user-friendly nature. This model can also design policies concerning the deterioration of loose by suggesting conservative schemes within watersheds(Zhu and Kuang). Hydrological models have been made popular in the last several decades. Its configuration and satellite data can bring more accuracy to the soil erosion modeling work. This kind of model's key benefit is truthfully working with the spatial irregularity of catchment attributes. To study erosion, water resources and sedimentation processes, multidisciplinary models have been produced in the last few years. The strategies governing the makeover of runoff via precipitation are regulated through these models, while physical laws in the natural landscape regulate the soil erosion modeling (Onori and Grauso).

Through proper judgment, PLSR reads the relation among the parameters and properly understands the framework set for the real parameters (Feng et al.). Through the perception of landscape ecology, the hydrological connectivity technique is arranged through the pattern of LULC; also, the landscape parameters show the sensitivity toward soil erosion (Boongaling et al.). A study by (Shen et al.) explored the influence of landscape configuration on watershed parameters and found lulc related to erosion. From the landscape point of view, a detailed study of the association between landscape patterns and soil erosion is important to achieve rescheduling and management of watersheds. Also, it is essential for executing of landscape in the watershed. It highlights the impact of landscape patterns over the entire watershed (Palang et al.). The impactful nature of landscape patterns towards soil erosion was identified through PLSR by (Shi et al.); in this work, PLSR successfully identified controlling the watershed soil erosion. Few authors evaluated four landscape metrics of the PLSR model, which were responsible for hillside and stream bank erosion.

The existing SWAT includes the new features unavailable in the old version; it is also included in pre-and post-processing software, which also consists of ArcGIS SWAT, available in ArcGIS software, where farming had the upper hand (Oeurng et al.). Some authors have displayed SWAT in the assessment-based analysis, which can predict soil erosion in the large complex watershed. The performance check of the SWAT model is successfully done by running the program in SWAT-CUP software (Abbaspour et al.; Rane and Jayaraj). The SUFI-2 method in SWAT-CUP software is used at a large scale to evaluate parameter sensitivity and uncertainty in watershed modelling. Using a minimum number of model simulations in the SUFI-2 technique is a good quality of calibration and uncertainty results. The model calibration technique is a difficult process, which relies on input parameters, model complexity and few iterations. Using SA and UA techniques, uncertainties imposed on model parameters and structure can be reduced. The model potential is assisted through sensitivity analysis, calibration and validation. Few researchers previously promoted soil erosion analysis work daily using SWAT-CUP to overcome this gap. The objective of this study is a) soil erosion estimation by SWAT model at watershed scale b) Soil erosion output obtain by SWAT model through SUFI-2 algorithm c) Identification of watershed parameter, having influence over soil erosion d) Finding out the relationship between landscape matrix and soil erosion using partial least square regression.

2. Study Area

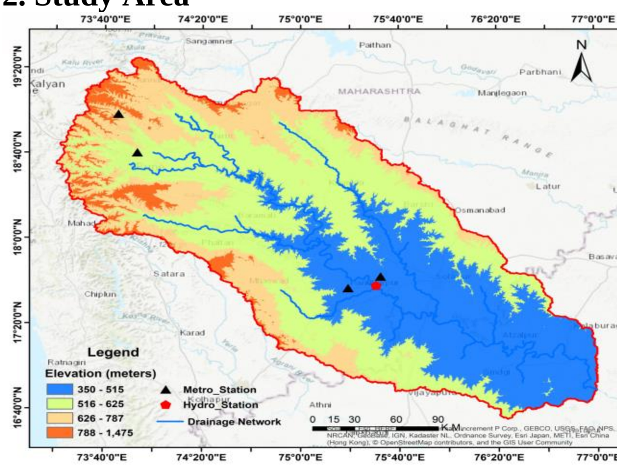

Fig. 1 Bhima Sub-Basin map

The present study is carried out in the Upper Bhima Sub-basin (Fig.1), considered the widest sub-basin among other basins located between 16º0'N and 18º0'N latitude and 73º40'E and 75º0'E longitude. It covers a 3533 Km² area. The region depletes to the Bhima river, a tributary to the Karha, Kukadi and Nira rivers. Every year the Upper Bhima Sub-basin experiences a monsoon from June to September, and the rainfall ranges from 540 mm to 160 mm; 30 to 70 rainy days are recorded annually in a basin. Also, it is observed that 90% of rain occurs during the wet season. The central water commission has monitored the Sediment yield at Takali Gauge in the watershed. Sediment data from 1990-2014 (24 yrs) has been collected for this work.

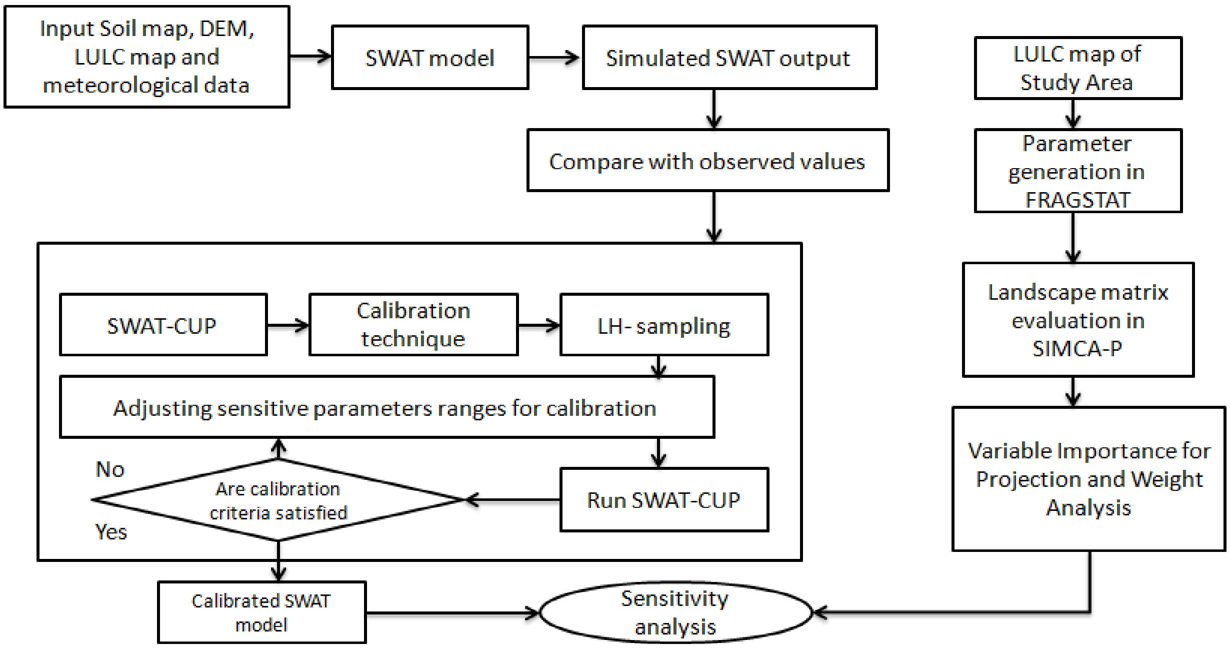

Fig. 2 Methodology flow chart(Desai and Ukarande)

3. Methodology

3.1. Upper Bhima Sub-Basin DEM

The study area digital elevation model (DEM) was accessed from the US Geological Survey Webpage. The elevation representing the 350-1475m range is recorded in the study area. The slope map and flow accumulation map were developed through multi-function elements available in DEM.

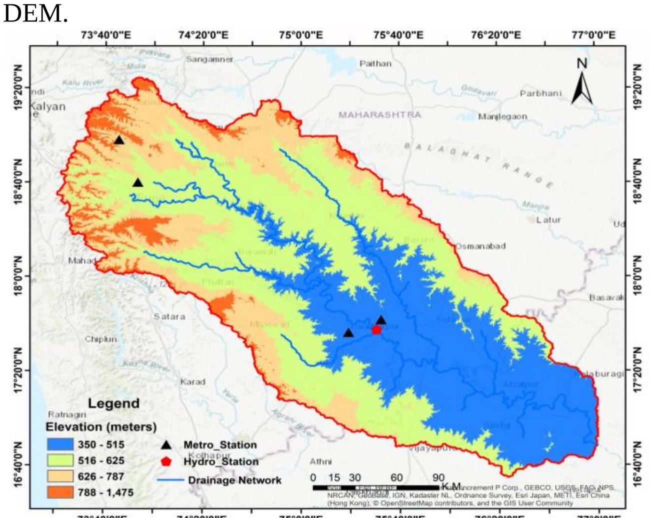

Fig. 3 Digitized view of the study area

3.2. Analysis of SWAT Model

SWAT is ownership gained by a public graphical user interface program assigned a work of watershed modeling. Using the threshold for land use, soil type and total slope watershed are discriticized into Hydrological Response Units (HRUs) which are considered the smallest part of a watershed. The below equation is used during modeling simulation:

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

Where SW_t is Soil water at time 't' (mm), SW_o is the supplement of water to plant (mm), R_{day} is rainfall amount (mm), Q_{surf} is flow from the surface (mm), E_a is the amount of evapotranspiration (mm), W_{seep} is detriment (mm), Q_{gw} is low flow (days).

3.3. Input Data

Daily rainfall, temperature (high/low), sunshine duration and wind speed of 24 years (1990-2014) is applied in this work. The stream network is digitized within a DEM to locate the main outlet of a watershed.

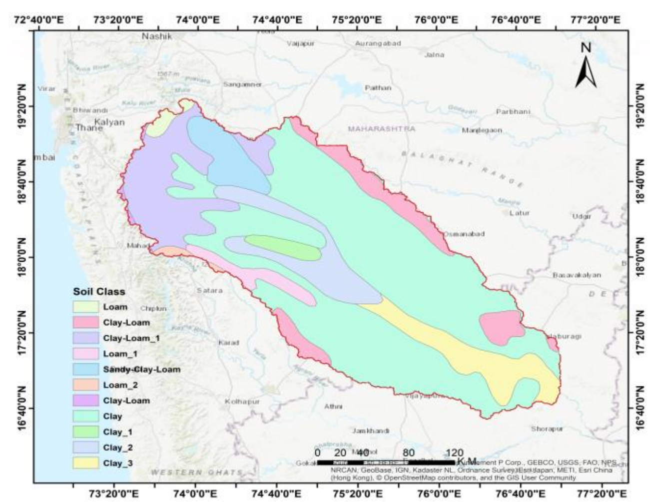

Fig. 4 Soil classification of the study area

The Upper Bhima Sub-Basin soil map is digitized through the ERDAS program before use in the model. The soil record is received from NBSS & LUP, Nagpur. The soil data is also placed in a text file in the GUI of SWAT. After completing the entire process, four types of clay, One type of Sandy-Loam-Clay, two types of Clay-Loam, and three types of Loam, are recognized and displayed over the map.

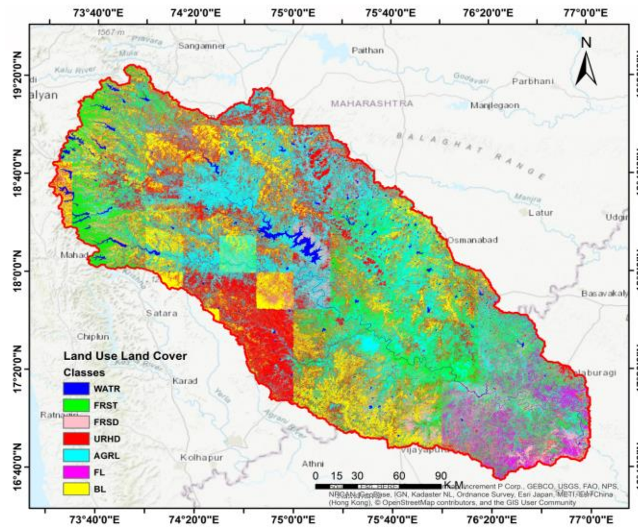

Fig. 5 LULC classification of the study area

The current topographical scenario is projected through a Land Use map. The nomenclature of LULC was also placed in text file format in the GUI of SWAT. After completing the entire process, the study area is combated through barren land, water, range land, forest, pasture and agriculture. Also, most of the watershed is covered in an urban area.

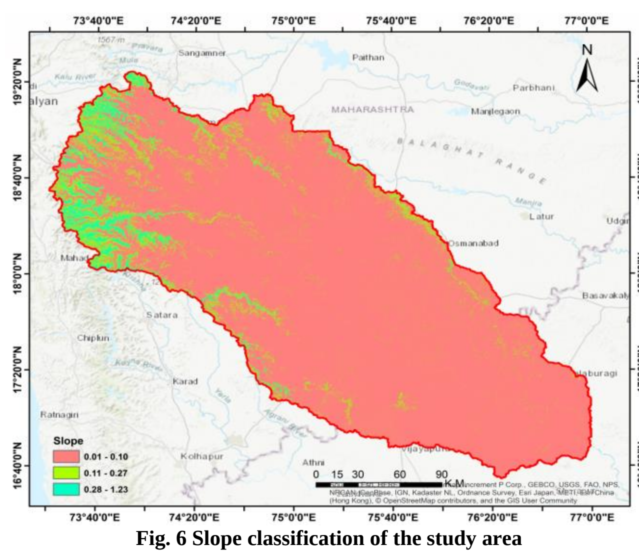

Fig. 6 Slope classification of the study area

Slope Map: The slope tool inbuilt in Arc-GIS Software is used to develop a slop map. A slope from 0.01 to 1.23 is placed through the radio button in the GUI of SWAT.

3.4. Delineation of Basin and HRU definition

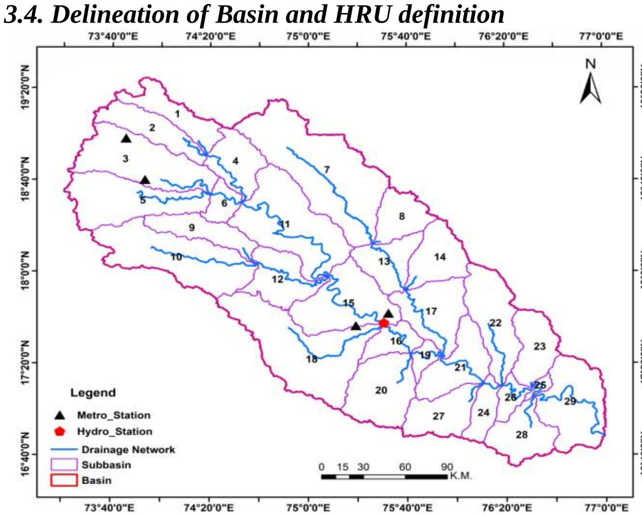

Fig. 7 Delineated Upper Bhima Sub-basin

In the preliminary stage, 29 sub-basin were acquired through delineating DEM, while in the next stage, topographical aspects were overlaid to establish a hydrologic response unit (HRU). HRU classifies soil, slope and land use into the small unit, which allows multiple configurations of these features. 141 HRUs were generated by skipping land use and soil by 5% and slope by 10%. In the final stage, a simulation of soil erosion is carried out by running the SWAT model on a daily and monthly scale by ignoring the early few years as a trial run.

3.5. SWAT-CUP Model Details

The ability of SUFI-2 algorithms, such as providing the largest irrelevant specification unpredictability interval of model parameters, made it to use in this work. SWAT-CUP having a built SUFI-2 algorithm is used in this study. SUFI-2 algorithm helps in resolving uncertainty between actual and simulated parameters. It considers all sources of uncertainties in a watershed, including parameters and driving variables. The distinct characteristics of SUFI-2, i.e., the dry year and wet year, are distributed equally throughout the simulation in the calibration and validation phase. The model's merit is listed based on 3 indices, as below.

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

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

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

Y_i^{obs} is the actual data at ith stage Y_i^{sim} is the predicted data at the ith stage, Y^{mean} is recorded data at an average scale, Y^{pre_mean} is prediction at an average scale.

A period from 1995-2007 is for calibration for model 2014, from which early 3 years are drawn for the warm-up period. Twelve parameters were established through SWAT-CUP via objective function to operate calibration, through iteration near to 500 times. A unique component, i.e. the sensitivity technique integrated with SWAT-CUP, improves the model's performance, which also depends on the quality of model input. Validation of it was administrated to investigate the performance of the model for which five years of data (2007-2014) was used.

A period from 1990-2002 is for calibration for model 2005, from which the early few years are drawn for a warm-up period. Twelve parameters were established through SWAT-CUP via objective function to operate calibration, through iteration near to 500 times. A unique component, i.e. the sensitivity technique integrated with SWAT-CUP, improves the model's performance, which also depends on the quality of model input. Validation of it was administrated to investigate the performance of the model for which five years of data (2007-2014) was used.

Table 1. Details of SWAT-CUP Parameters

Sr.No.	Parameter	Description
1	SPCON.bsn	Max amt of sediment examined.
2	OV_N.hru	Flow with the help of Manning' n.'
3	PRF_BSN.bsn	Peak controlling factor
4	USLE _P.mgt	Practice factor
5	SURLAG.bsn	Surface runoff lag time
6	V_CH_COV2	Channel Erodibility factor
7	CH_EQN.rte	Sediment routing method
8	HRU_SLP.hru	Slope steepness
9	SPEXP.bsn	To avoid sediment re-entrained
10	USLE_K (..).sol	Erodibility factor of soil
11	CH_K1.sub	Hydraulic conductivity
12	CN2	Curve Number of Runoff

3.6. A brief discussion of Partial Least-Square Regression

USGS website is used for downloading high-precision landscape maps of the study area for the years 1985, 1995, 2005 and 2014. Landscape metrics are figured out through the proper arrangement of multiple landscape maps. Multiple landscape metrics have been proposed to examine and carry out landscape patterns or features, and multiple landscape metrics have been proposed; pattern layouts and mapping units are created through these metrics.

15 metrics were recognized to exhibit land use land cover features in this study (Table 2). The researcher uses these metrics to associate the relationship between soil erosion and land cover pattern (Jordan et al., 2005; Nie et al., 2011). With the support of metrics, the PLSR method is employed to check the influence of soil erosion. To determine the matrix, we utilized the program called FRAGSTATS, which is an approved and extensively used tool for landscape metrics quantification (McGarigal et al.). The relationship between two variables is effectively recognized through the PLSR technique.

Compared to other methods, PLSR endeavors to distinguish a unique relationship between two variables integrating each other. The significance of land cover patterns in the distribution of erosion is the fundamental aim of PLSR. This study implements programs like SIMCA-P to run the PLSR procedure.

The design of parameters related to landscape is done in the PLSR model. In the PLSR algorithm, soil erosion act as dependent variable and landscape metrics function as an independent variable. After a few simulations of PLSR models, the addition and exemption of some variables are accomplished to select the PLSR model. A matrix such as Simpson's diversity index (SIDI) displayed a good relation with Aggregation Index (AI). Also, Interspersion and juxtaposition index (IJI) showed good relation with Shannon's diversity Index (SHDI).

Table 3. PLSR analysis landscape metrics correlation

Metrics	*ED*	*LSI*	*PD*	*LPI*	*AREA_MN*	*SHAPE_MN*	*PARA_MN*	*PAFRAC*	*ENN_MN*	*CONTAG*	*IJI*	*COHESION*	*SIDI*	*SHDI*	*AI*
ED	1														
LSI	-0.13	1													
PD	0.74	-0.63	1												
LPI	0.29	-0.97	0.57	1											
AREA_MN	-0.42	0.64	-0.6	-0.77	1										
SHAPE_MN	-0.54	0.72	-0.76	-0.55	0.60	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	0.92	-0.94	0.93	0.93	-0.89	-0.73	0.80	0.88	-0.74	-0.96	1				
COHESION	0.23	0.55	0.15	-0.73	0.42	0.82	0.97	-0.49	0.84	0.88	-1	1			
SIDI	-0.4	-0.67	-0.11	0.75	-0.43	-0.84	-0.96	0.59	-0.86	-0.86	0.99	-0.69	1		
SHDI	0.11	-0.14	0.26	-0.51	0.04	-0.05	-0.12	0.03	0.19	-0.09	0.21	-0.06	0.79	1	
AI	-0.85	0.91	-0.96	-0.44	0.79	0.71	-0.77	-0.85	0.74	0.83	-0.76	0.83	-0.62	-0.53	1

4. Results and Discussion

4.1. Classification of Erosion Zone

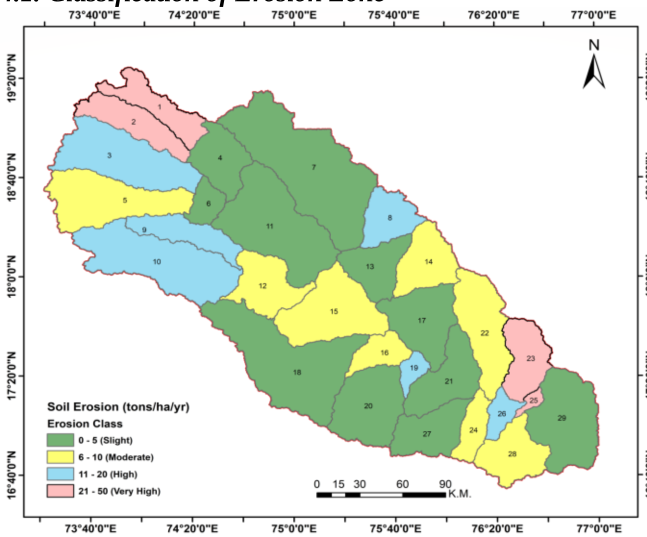

Fig. 8 Classification of Soil erosion zone in the study area

To provide a phase-wise execution, all the sub-watershed are prioritized based on soil erosion rate (Singh et al.), as shown in table no 4.

Table 4. Erosion classification

Sediment loss (tons/ha/yr)	Soil Erosion Class	Percentage of Area
21-40	Very High	8
11-20	High	18
6-10	Moderate	25
0-5	Slight	49

The sub-watershed is rated between Low to Very High Soil Erosion class. Only Four watersheds have shown signs of very high soil erosion, and a larger percentage of the watershed had acquired a slight to moderate erosion class. Three sub-watershed showing a sign of high soil erosion were found on the left bank of the Bhima river. Eventually, all sub-watersheds were ranked likewise by adopting similar.

4.2. Sensitivity Analysis

At a preliminary stage, the value obtained through SWAT output had a disturbance in the 95 PPU graph. To reduce this disturbance, adjustments are done in SWAT-CUP parameters such as (CN2) value is adjusted between 79.32 and 79.67 every month in 2014 and 2005 models, respectively, as well as setting the value of the same parameter at 76.5 and 77.84 for daily basis in 2014 and 2005 model respectively, the main function of this parameter is to increase runoff. (SURLAG) was adjusted between 1.82 and 1.71 monthly in the 2014 and 2005 models, respectively as well as setting the value of the same parameter at 2.49 and 2.91 on a daily basis in the 2014 and 2005 models respectively; the main function of this parameter is to record lag time of runoff towards an outlet. (USLE_P) was fitted at 0.43 and 0.45 monthly in the 2014 and 2005 model, respectively as well as setting the value of the same parameter at 0.37 and 0.34 daily in the 2014 and 2005 model respectively which minimizes the involvement of human endeavor over LULC of the basin (USLE_K) was adjusted with 0.16 and 0.18 value for monthly basis in 2014 and 2005 model respectively, same parameters were fitted with 0.22 and 0.28 values for daily basis in 2014 and 2005 model respectively, the main function of this parameter is to control sediment formation. Mean slope steepness (HRU_SLP) is used to control channel erosion; in work, it was fitted with 0.25 and 0.20 values on a monthly basis in the 2014 and 2005 model, respectively, while the same parameter was fitted with 0.10 for a daily basis in both the 2014 and 2005 model. The (SPCON) who's the main function is to control sediment deposition and is fitted with 0.0003 on a monthly basis in both the 2014 and 2005 models, and the same parameter was fitted with 0.0002 on a daily basis in the 2014 model. The channel erodibiltiy factor (CH_COV2), whose main function is to get linear influence over soil loss, was fitted with 0.11 monthly in the 2014 model. The same parameter was fitted with 0.083 daily in the 2014 model. The (SPEXP) whose function is to represent a non-erosive channel at the outlet of the watershed, was fitted with 1.1 monthly in the 2014 model. (OV_N), which contributes directly to surface runoff generation, was fitted with 9.1 and 7.9 daily in the 2014 and 2005 models, respectively. (PRF_BSN), whose main function is to adjust the effect of peak flow on sediment routing, was fitted with 1.58 and 1.31 daily in the 2014 and 2005 models, respectively. The (CH_K1), which controls the losses at the river bed, is fitted with 27 and 28.33 daily in the 2014 and 2005 models, respectively. The sediment routing method (CH_EQN), which summarizes the channel's physical characteristic, which affects sediment transport, is fitted with 11 and 11.56 for daily basins in 2014 and 2005, respectively. The channel erodibility factor (CH_ERODMO), which controls the bank material, is fitted with 0.25 daily in the 2005 model.

The remark of t-stat and p-value is used to decide the sensitivity of every parameter, and their ranks are allotted as given in table no 1,2,3,4. The remark of less p-value higher the sensitivity is assigned for the parameters ranking system. The parameters such as Curve Number of Runoff (CN2) and Support practice factor (USLE_P) were listed on top of the ranking within the parameters which are part of sensitivity performance criteria in the monthly basis model for the years 2014, and 2005 whereas (SURLAG) and (COV2) stays at the bottom in the sensitivity performance criteria in monthly basis model for the year 2014 and (SPCON) and (SURLAG) stays at the bottom in the sensitivity performance criteria in monthly basis model for the year 2005. The parameters like (OV_N) and support practice factor (USLE_P) were enlisted at the first two places within the parameters engaged with sensitivity performance criteria in the daily basis model for 2014. Parameters like (HRU_SLP) and (OV_N) were at the top two within the parameters which are engaged in the sensitivity performance criteria in the daily basis model for the year 2005, parameters like erodibility factor of soil (USLE_K) and (CH_K1) were enlisted at the bottom in the sensitivity performance criteria in daily basis model for the year 2014 while, (SURLAG) and (PRF_BSN) stays last in the sensitivity performance criteria in daily basis model for the year 2005.

Table 5. Sensitivity Analysis of SWAT parameters (Monthly Basis) (2014)

Parameters	Low Range	High Range	Best. Value	t-stat.	P-value	Rank
V_CN2.mgt	65	80	79.32	6.66	0.00	1
V_USLE_P.mgt	0.3	0.5	0.43	8.40	0.00	2
V_USLE_K.sol	0.1	0.2	0.16	12.11	0.00	3
V_HRU_SLP.hru	0.2	0.3	0.25	32.22	0.00	4
V_SPCON.bsn	0.0001	0.0004	0.0003	0.82	0.24	5
V_SURLAG.bsn	1	3	1.82	2.10	0.32	6
CH_COV2.rte	0.00	0.3	0.11	-2.36	0.41	7

Table 6. Sensitivity Analysis of SWAT parameters (Monthly Basis) (2005)

Parameters	Low Range	High Range	Best Value	t-stat.	P-value	Rank
V_CN2.mgt	65	80	79.67	18.72	0.00	1
V_USLE_P.mgt	0.3	0.5	0.45	4.68	0.00	2
V_USLE_K.sol	0.1	0.2	0.18	16.34	0.00	3
V_HRU_SLP.hru	0.2	0.3	0.20	4.19	0.00	4
V_SPCON.bsn	0.0001	0.0004	0.0003	0.64	0.14	5
V_SURLAG.bsn	1	3	1.71	2.15	0.29	6

Table 7. Sensitivity Analysis of SWAT parameters (Daily Basis) (2014)

Parameters	Low. Range	High. Range	Best Value	t-stat.	P-value	Rank
V_CN2.mgt	65	80	76.5	-2.53	0.126	6
V_USLE_P.mgt	0.3	0.5	0.37	-4.34	0.049	2
V_HRU_SLP.hru	0.1	0.2	0.10	-4.93	0.03	5
V_USLE_K.sol	0.2	0.3	0.22	-1.27	0.33	11
V_SPCON.bsn	0.0001	0.0004	0.0002	0.96	0.43	10
CH_COV2.rte	0.00	0.5	0.083	-2.36	0.14	7
SPEXP.bsn	1	1.2	1.1	1.61	0.24	8
PRF_BSN.bsn	1.1	1.6	1.58	-3.47	0.073	3
V_OV_N.hru	1	10	9.1	5.38	0.032	1
V_CH_K1.sub	20	33	27	0.33	0.76	12
V_CH_EQN.rte	10	20	11	1.52	0.26	9
V_SURLAG.bsn	2.1	3	2.49	3.03	0.093	4

Table 8. Sensitivity Analysis of SWAT parameters (Daily Basis) (2005)

Parameters	Low Range	High Range	Best Value	t-stat.	P-value	Rank
V_CN2.mgt	75	85	77.84	-9.73	0.00	3
V_USLE_P.mgt	0.3	0.5	0.34	-2.28	0.08	6
V_USLE_K (..).sol	0.2	0.3	0.28	-2.43	0.07	5
V_HRU_SLP.hru	0.1	0.2	0.1	-8.93	0.0008	1
V_PRF_BSN.bsn	1.1	2	1.31	0.39	0.71	9
V_CH_K1.sub	20	30	28.33	2.52	0.06	4
V_CH_ERODMO	0.1	0.3	0.25	0.55	0.60	8
V_CH_EQN.rte	10	15	11.16	-0.77	0.47	7
V_OV_N.hru	1	10	7.9	7.87	0.001	2
V_SURLAG.bsn	2.1	3	2.91	-0.25	0.81	10

4.3. Evaluation of Model Calibration

In the beginning, in the 2014 model, calibration was performed using thirteen years of data, i.e. (1995-2007) which involved warm-up for 3 years period, i.e. (1995-1998), in the form of input, the simulated sediment concentration was analyzed in front of sediment concentration obtained at gauge station. The monthly scale and daily scale were upheld during calibration. The monthly scale model of 2014 ran successfully in the range of 95 PPU line, but most of the observed peak values were under-predicted by simulated values. In the daily model of 2014, the predicted value had followed the flow of observed value adequately in large sections, but in some sections over prediction of simulated value concerning observed value was recorded. The scatter plot displays the model's performance to be good for daily scale R^2= 0.62 and monthly scale R^2= 0.67. The analysis standard like NSE= 0.65 for the daily scale and NSE= 0.66 for the monthly scale, PBIAS= 33.9 for the daily scale and PBIAS= 7.6 for the monthly scale, r-factor=0.27 for daily analysis and r-factor=0.4 for monthly analysis, p-factor=0.18 for daily analysis, p-factor=0.56 for monthly analysis had shown positive reflection towards the performance of a model in calibration for both the scale.

In the 2005 model, calibration was performed using twelve years of data, i.e. (1990-2002) which involved 3 years of the warm-up period, i.e. (1990-1992), in the form of input, the simulated sediment concentration was analyzed in front of sediment concentration obtained at the gauge station. The monthly scale and daily scale were upheld during calibration. The monthly scale model of 2005 had run successfully in the range of 95 PPU line, but most of the observed peak values were under-predicted by simulated values. In the daily model of 2005, the predicted value had followed the flow of observed value adequately in a large section. Still, in some sections over, prediction of simulated value to observed value was recorded. The scatter plot performed well for daily analysis R^2= 0.6 and monthly analysis R^2= 0.72. The analysis standard like NSE=0.62 for daily analysis and NSE= 0.7 for monthly scale, PBIAS= 34.1 for daily scale and PBIAS=15.1 for monthly scale, r-factor= 0.43 for daily analysis and r-factor= 0.25 for monthly analysis, p-factor= 0.23 for daily analysis and p-factor=0.14 for monthly analysis had shown positive reflection towards the performance of the model in calibration for all analysis.

4.4. Validation analysis

Implementing 70% of inputs for calibration, the rest of the data is carried forward for validation in the SWAT-CUP model, in which measured and simulated sediment concentration was examined. Model 2014 and 2005 undergo a validation process on both scales. In the validation stage, the observed value was under-predicted by the simulated value in both scales; still, the momentum of the observed value was followed by the value of simulation. The scatter plot displays the model's performance to be good for daily scale R^2= 0.74 and monthly scale R^2= 0.71. The analysis standard like NSE= 0.74 for daily analysis and NSE= 0.68 for monthly analysis, PBIAS= 23.9 for daily scale and PBIAS= 12.7 for monthly scale, r-factor=0.23 for daily analysis and r-factor=0.6 for monthly analysis, p-factor=0.12 for daily analysis, p-factor=0.45 for monthly analysis had shown positive reflection towards the performance of the model in calibration for both the scale.

For model 2005, in the validation phase, the simulated value traced a close path towards the observed value on a monthly scale. However, most of the simulation remains under-predicted for observed value. In contrast, some sections found over-prediction of observed value by simulated value on the daily scale. However, a large percentage of simulation remains under-predicted compared to the observed value on the daily scale. The scatter plot displays the model's performance to be good for daily scale R^2= 0.69 and monthly scale R^2= 0.68. The analysis standard like NSE= 0.61 for daily analysis and NSE= 0.67 for monthly analysis, PBIAS= 39.1 for daily scale and PBIAS= 15.3 for monthly scale, r-factor=0.44 for daily analysis and r-factor=0.34 for monthly analysis, p-factor=0.24 for daily analysis, p-factor=0.13 for monthly analysis had shown positive reflection towards the performance of a model in calibration for both the scale.

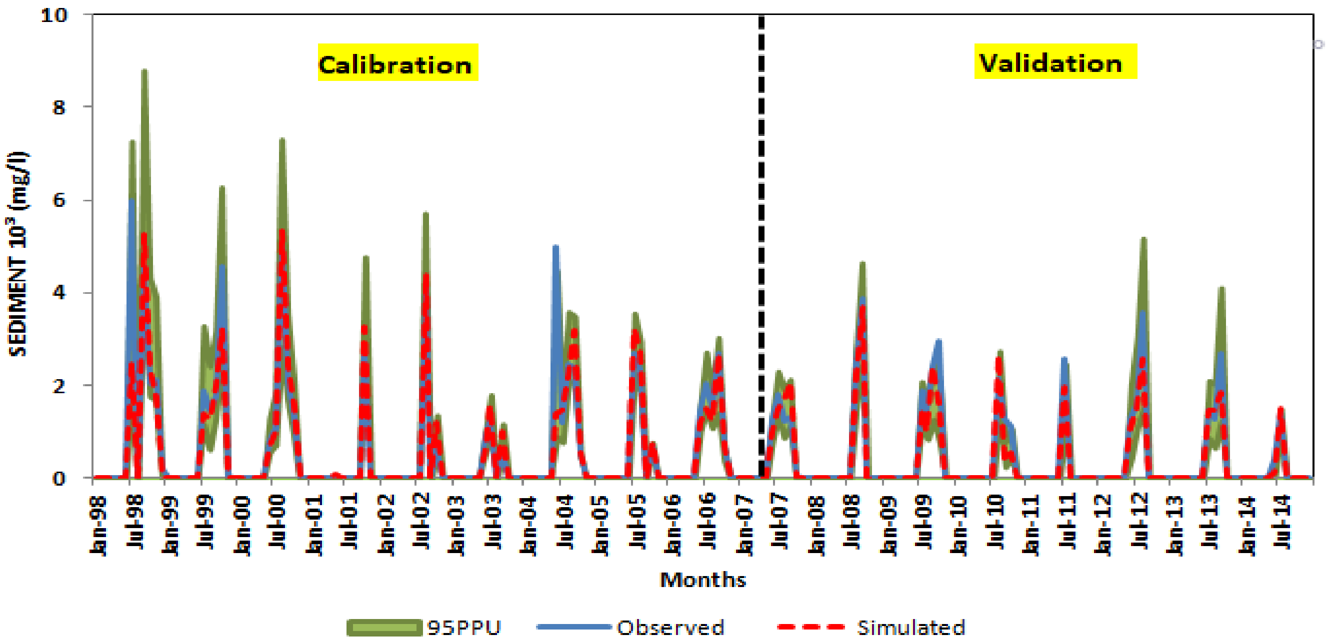

Fig. 9 95 ppu plot of observed vs simulated soil erosion for monthly scale (2014)

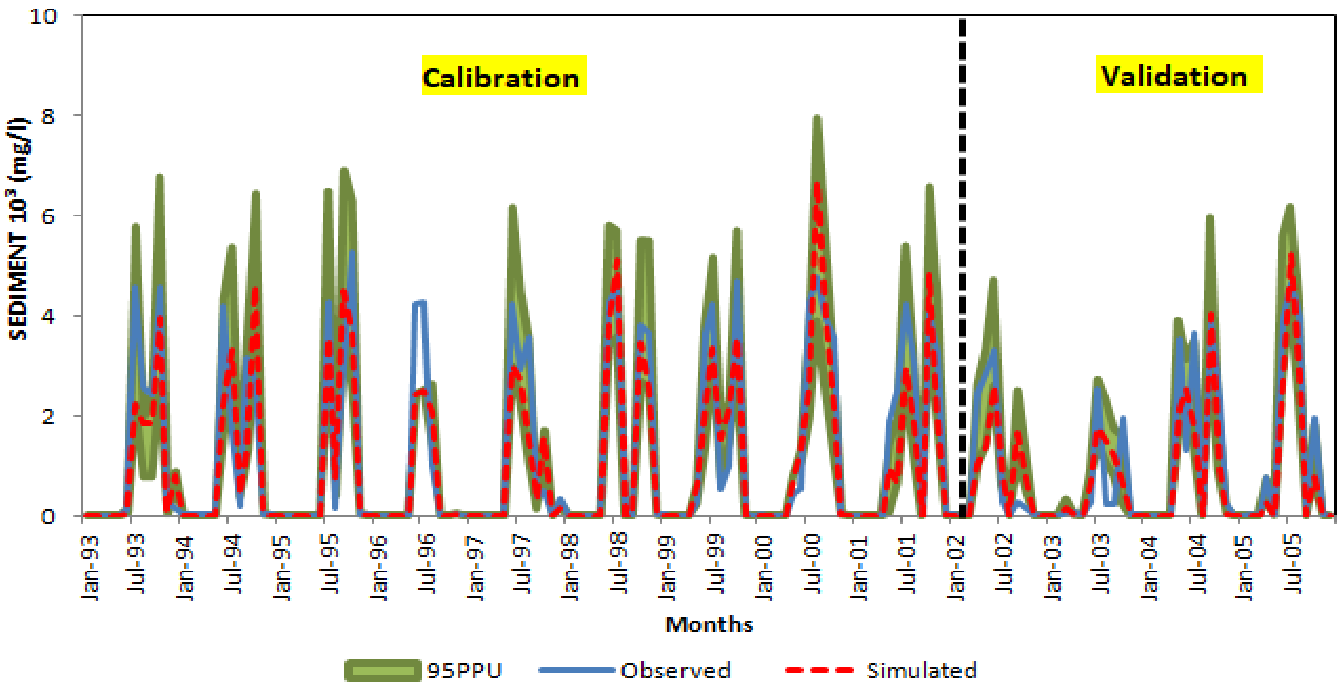

Fig. 10 95 ppu plot of observed vs simulated soil erosion for monthly scale (2005)

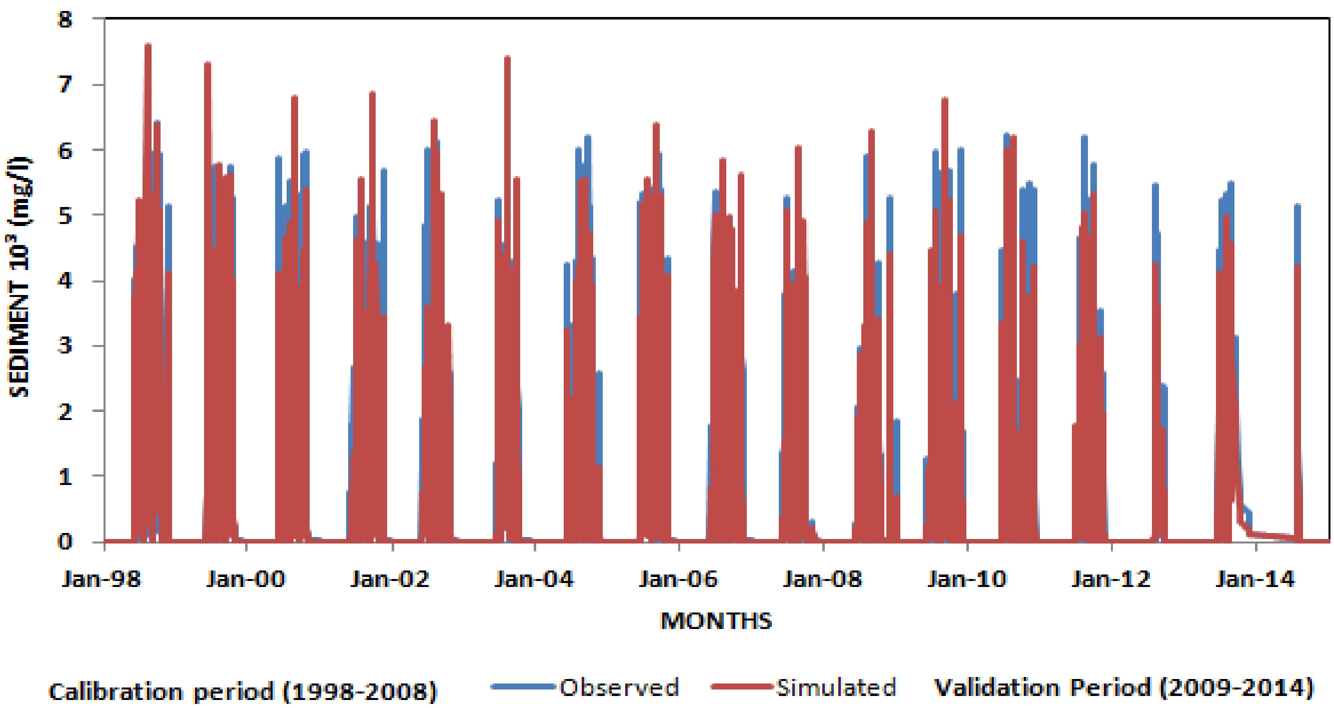

Fig. 11 Daily observed (blue) and simulated (red) soil erosion for the calibration and validation period (2014)

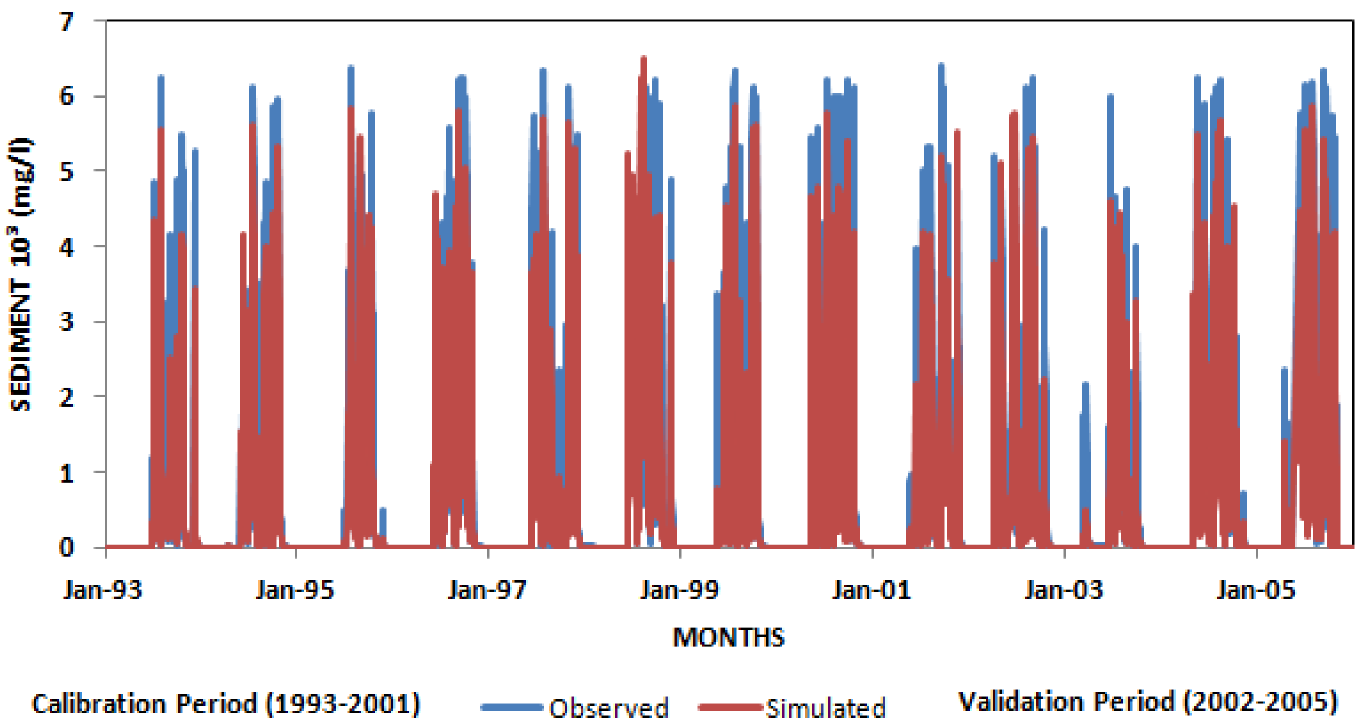

Fig. 12 Daily observed (blue) and Simulated (red) soil erosion for the calibration and validation period (2005)

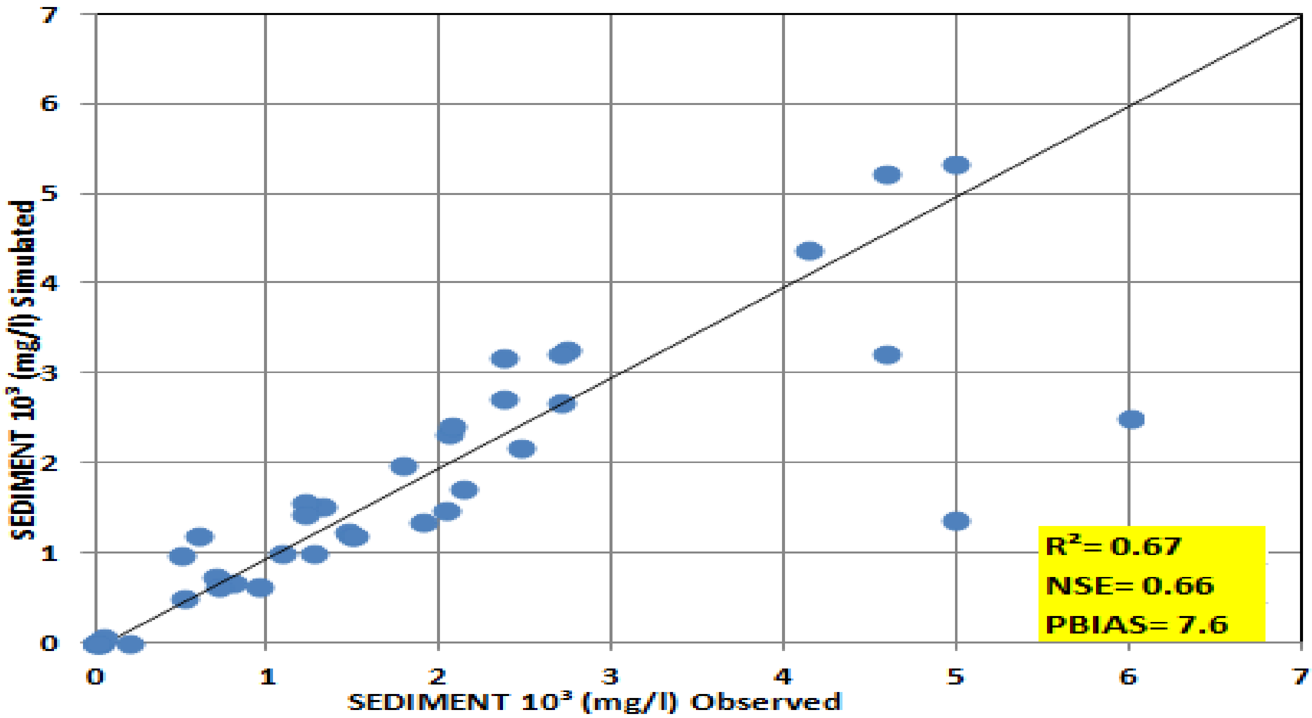

Fig. 13 Comparison of scatter plot between measured and simulated monthly soil erosion for calibration (2014)

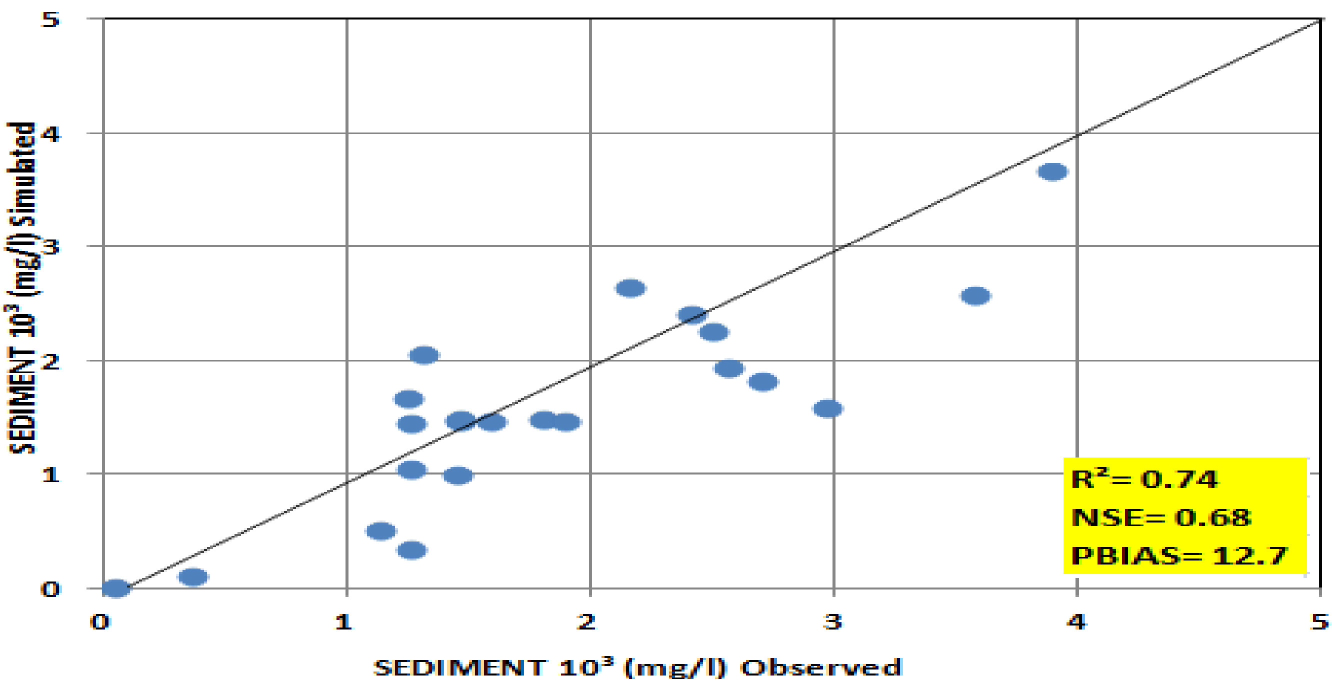

Fig. 14 Comparison of scatter plot between measured and simulation monthly soil erosion for validation (2014)

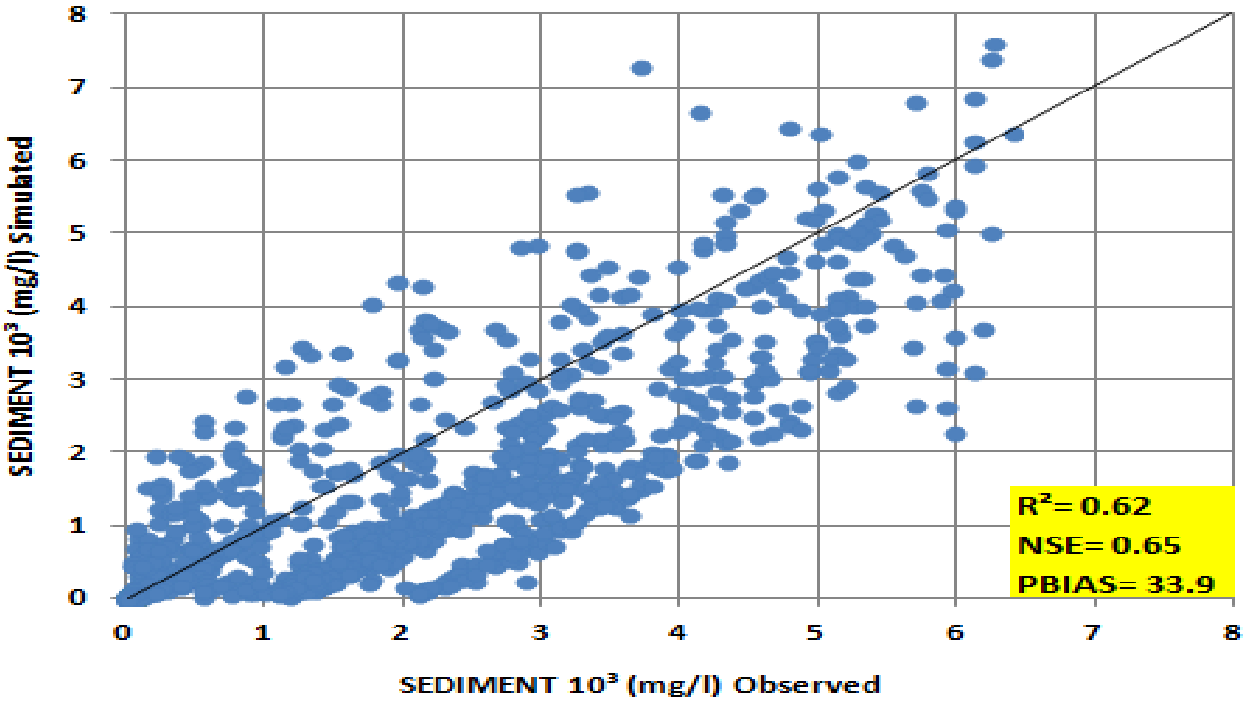

Fig. 15 Scatter Plot comparison between measured and simulation daily soil erosion for calibration (2014)

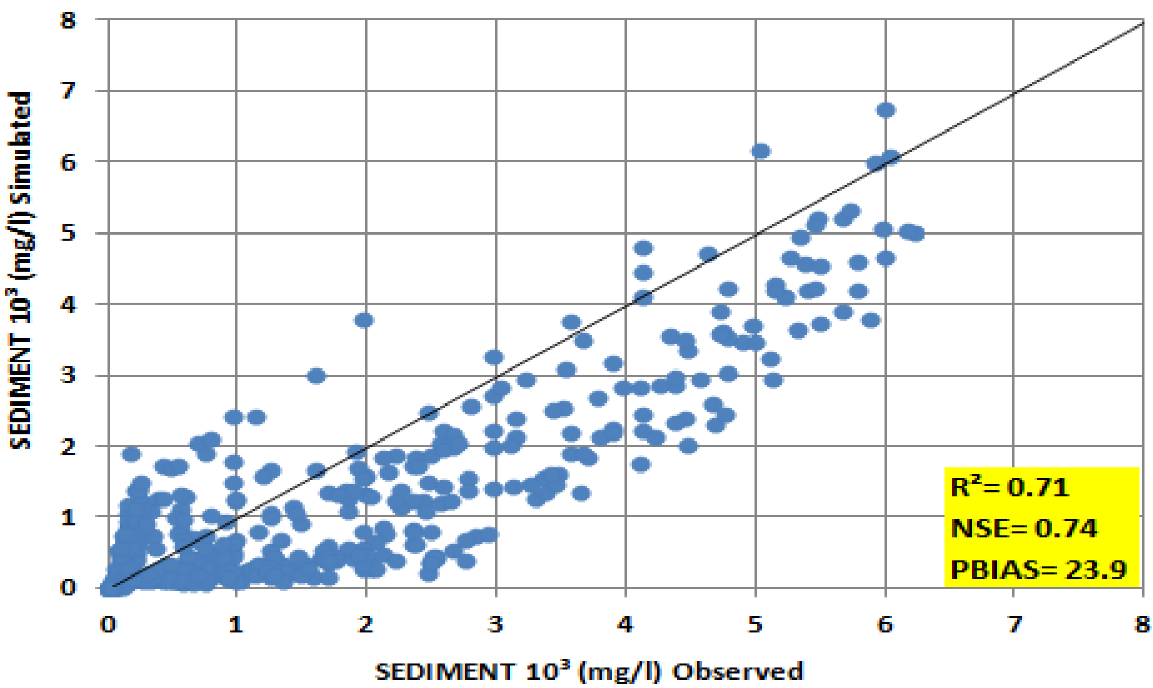

Fig. 16 Scatter Plot comparison between measured and simulation daily soil erosion for validation (2014)

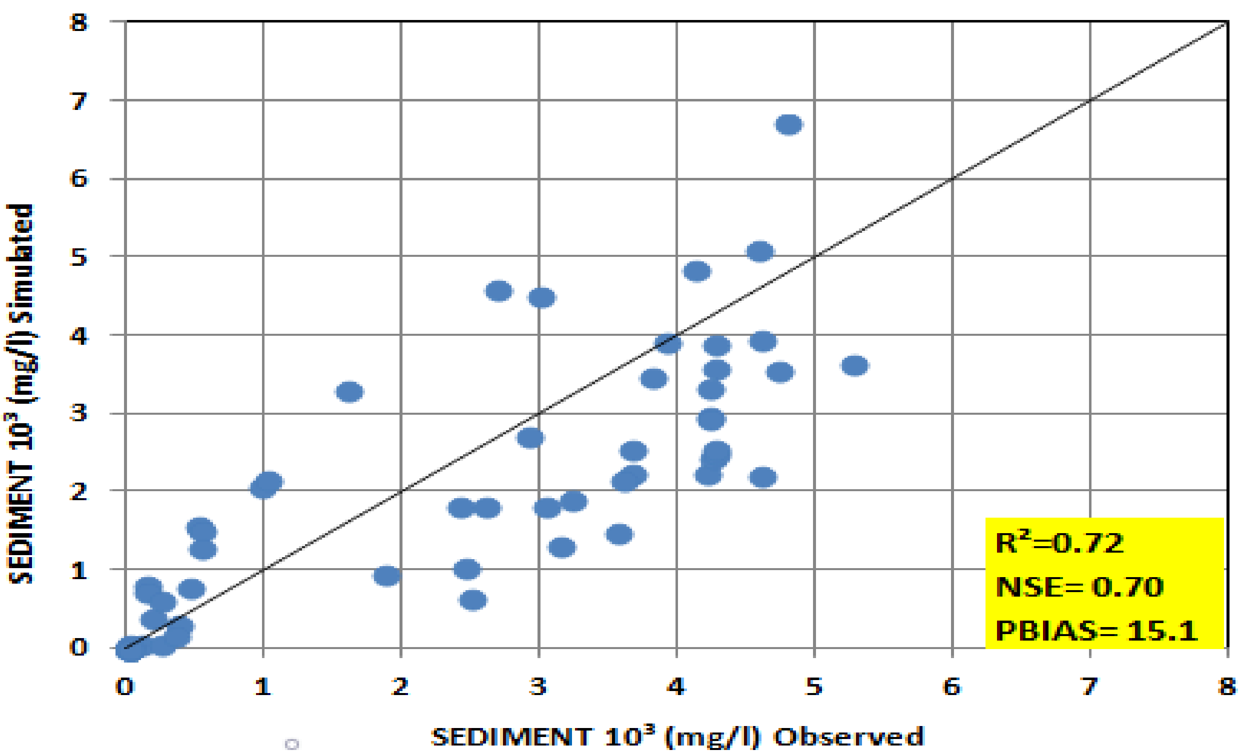

Fig. 17 Scatter Plot comparison between measured and simulation monthly soil erosion for calibration (2005)

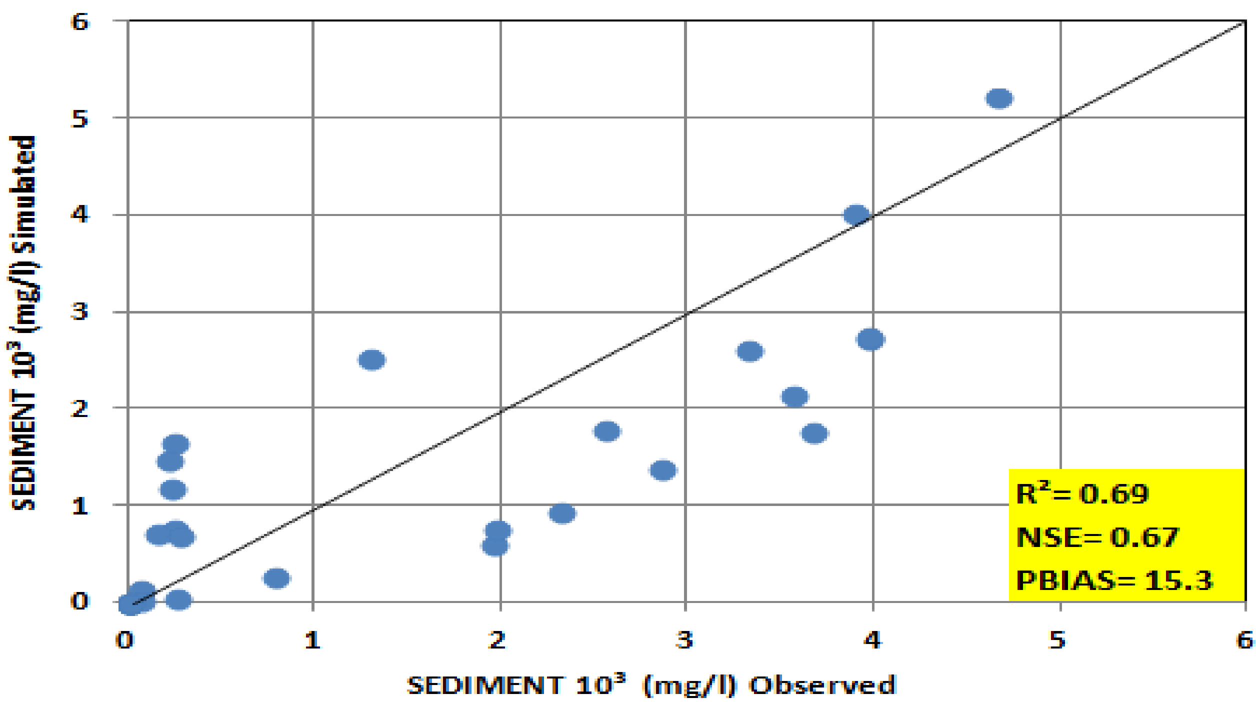

Fig. 18 Comparison of scatter plot between measured and simulation monthly soil erosion for validation (2005)

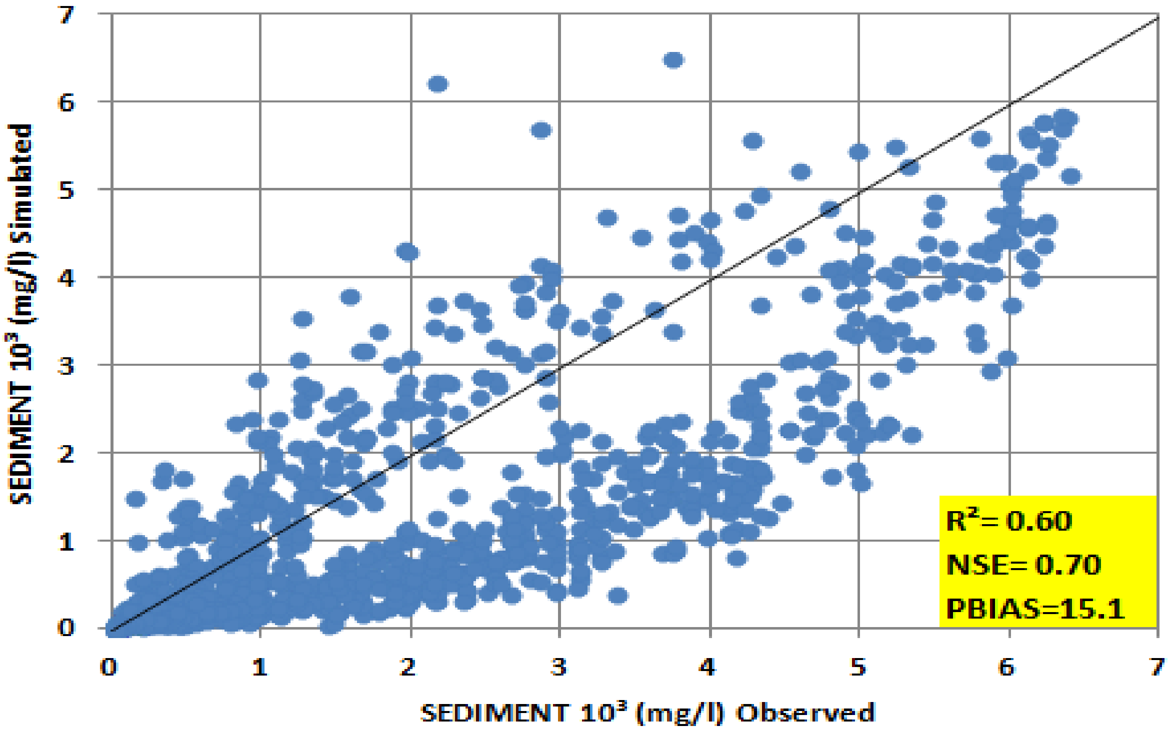

Fig. 19 Scatter Plot comparison between measured and simulation daily soil erosion for calibration (2005)

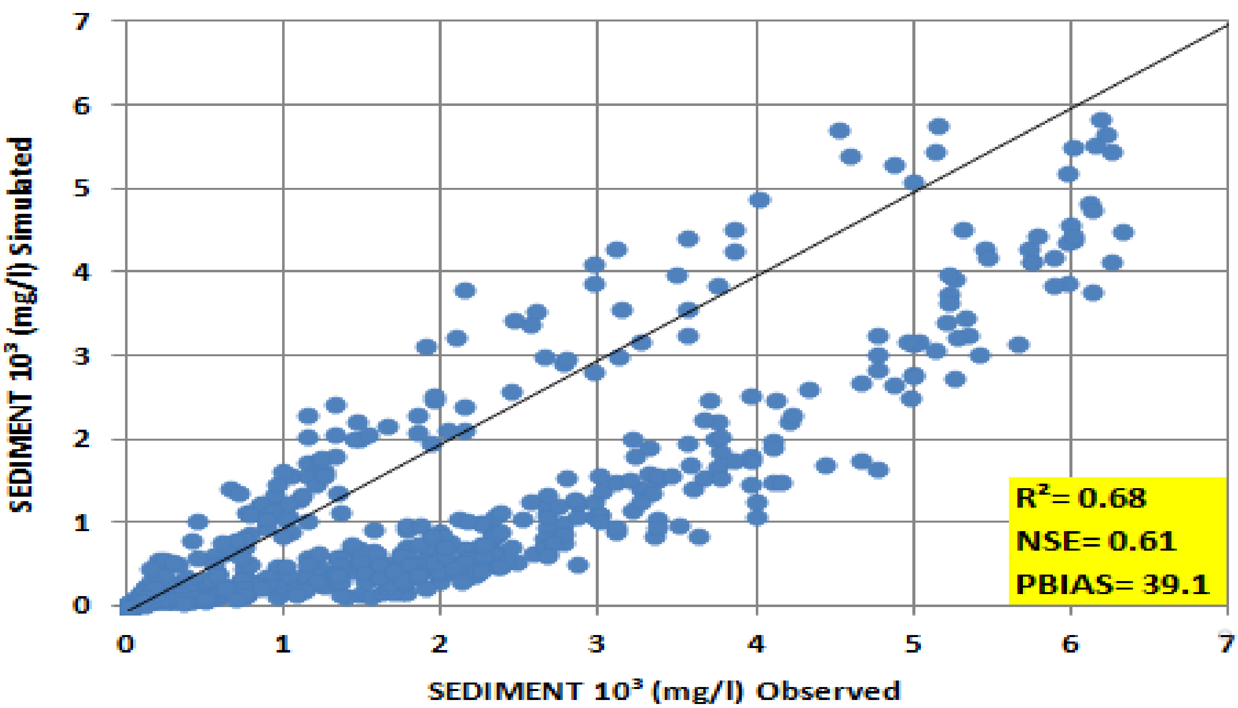

Fig. 20 Scatter Plot comparison between measured and simulation daily soil erosion for validation (2005)

Table 9. Appraisal of statistics performed by the model (2014)

Parameter	Soil Erosion							
	Observed				Simulated			
	Daily		Monthly		Daily		Monthly	
	Calib.	Valid.	Calib.	Valid.	Calib.	Valid.	Calib.	Valid.
Avg (mg/l)	1277.40	1117.35	1846.78	1691.67	868.48	850.76	1706.08	1476.66
SD	1539.06	1529.09	1536.58	953.65	1370.78	1230.01	1357.15	921.81
PBIAS					33.9	23.9	7.6	12.7
r-factor					0.27	0.23	0.40	0.60
p-factor					0.18	0.12	0.56	0.45
NSE					0.65	0.74	0.66	0.68
R^2					0.62	0.71	0.67	0.74

Table 10. Appraisal of statistics performed by the model (2005)

Parameter	Soil Erosion							
	Observed				Simulated			
	Daily		Monthly		Daily		Monthly	
	Calib.	Valid.	Calib.	Valid.	Calib.	Valid.	Calib.	Valid.
Avg (mg/l)	1482.20	1426.25	1865.72	1422.70	1156.50	1104.34	1583.82	1205.15
SD	1679.61	1624.42	1858.34	1584.65	1518.31	1461.46	1635.77	1303.57
PBIAS					34.1	39.1	15.1	15.3
r-factor					0.43	0.44	0.25	0.34
p-factor					0.23	0.24	0.14	0.13
NSE					0.62	0.61	0.70	0.67
R^2					0.60	0.68	0.72	0.69

4.5. Pattern Analysis of Landscape metrics

Initially, for the model 2014, parameters like (SHDI), (SIDI), Area ratio in average form (AREA_MN), (ED), (LSI), and (PD) are placed on negative weight loading as shown in (Fig.5.32). Additionally, a VIP value of less than 1 has been displayed, and these outcomes illustrate that matrix used here is getting the least influence over soil erosion. Parameters like (SHAPE_MN) and Mean Euclidian nearest neighbor distance (ENN) represents negative weight indices but still find VIP value greater than 1. Hence they had a medium impact on soil erosion. Parameters like area ratio in average form (PARA_MN) and Interspersion and Juxtaposition index (IJI) are positioned in positive weight analysis. Also, they have more than 1 VIP value, which greatly impacts soil erosion.

For the model 2005, parameters like (PAFRAC) and (AI) are placed on negative weight loading as shown in Fig. (5.32); additionally, VIP value less than 1 has been displayed; these outcomes illustrate that matrix used here is getting the least influence over soil erosion. Parameters like the Largest patch index (LPI) represent negative weight indices, but they find VIP values more than 1; hence they had a medium impact on soil erosion. Parameters like (SHDI) and (SIDI) are positioned in positive weight analysis. Also, they have a VIP value of more than 1, which provides a high impact on soil erosion.

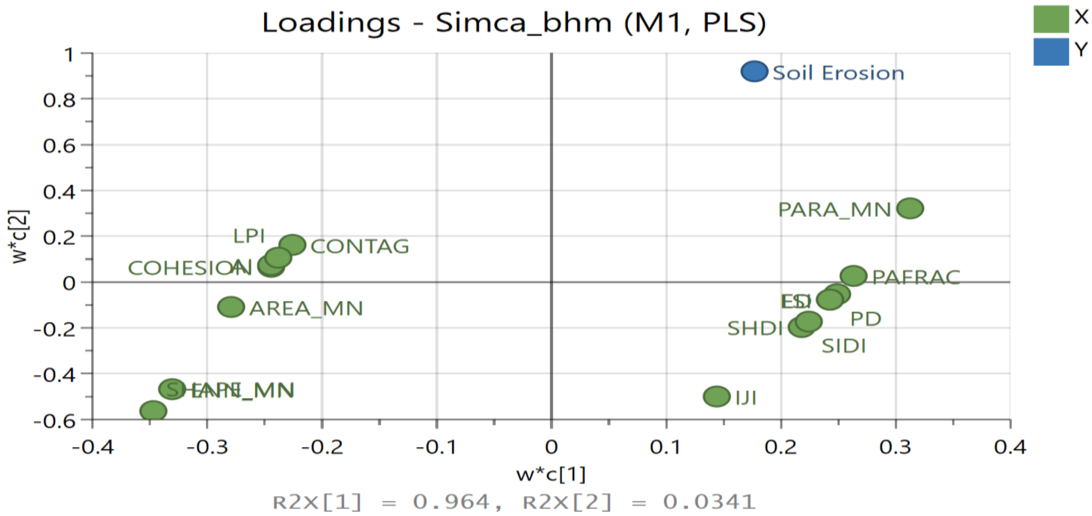

Fig. 21 Loading of landscape matrix for soil erosion (2014)

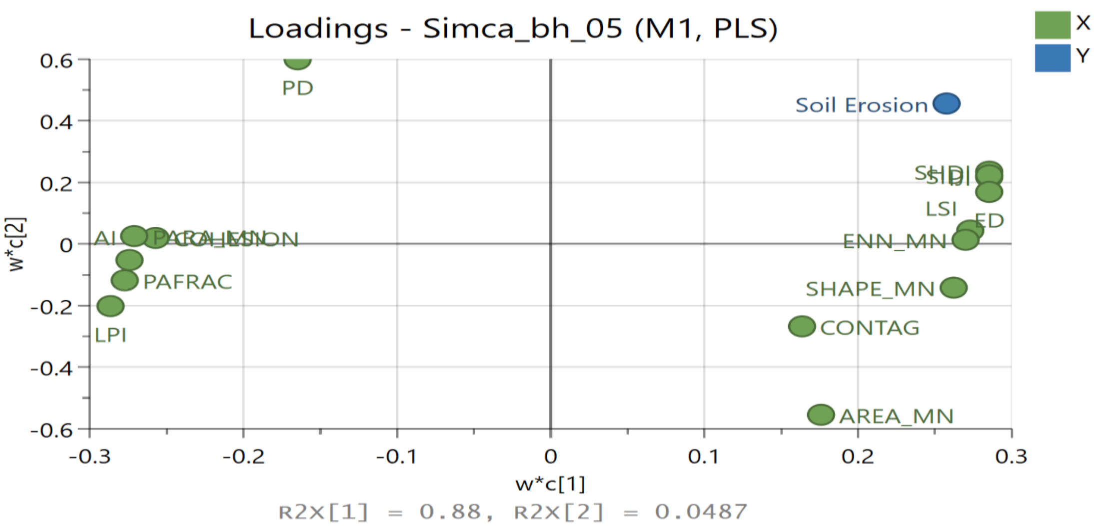

Fig. 22 Parameters of landscape pattern for soil erosion (2005)

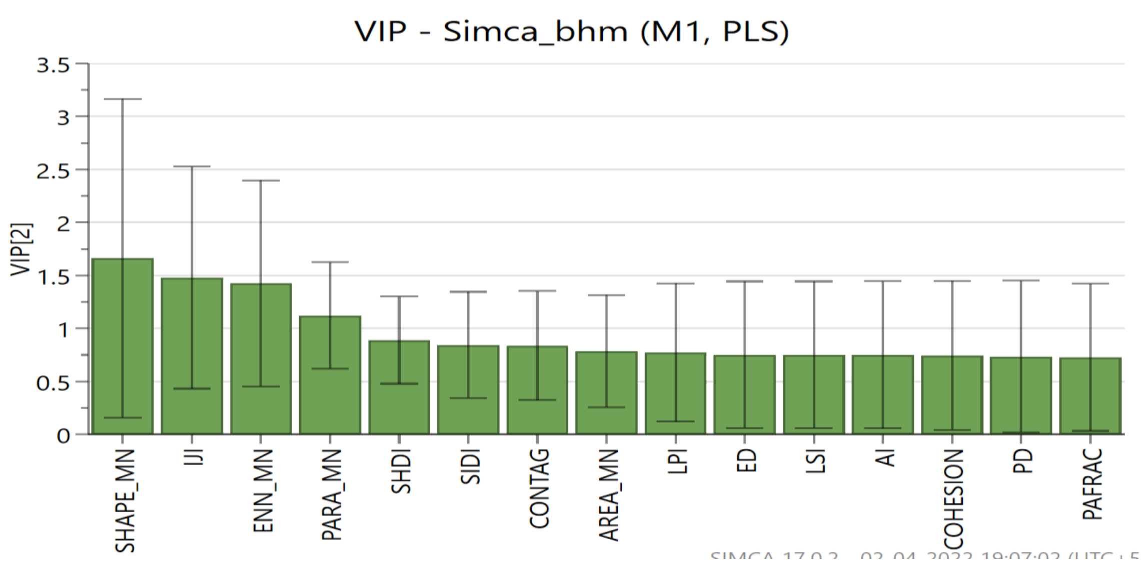

Fig. 23 Graph of VIP vs Parameter (2014)

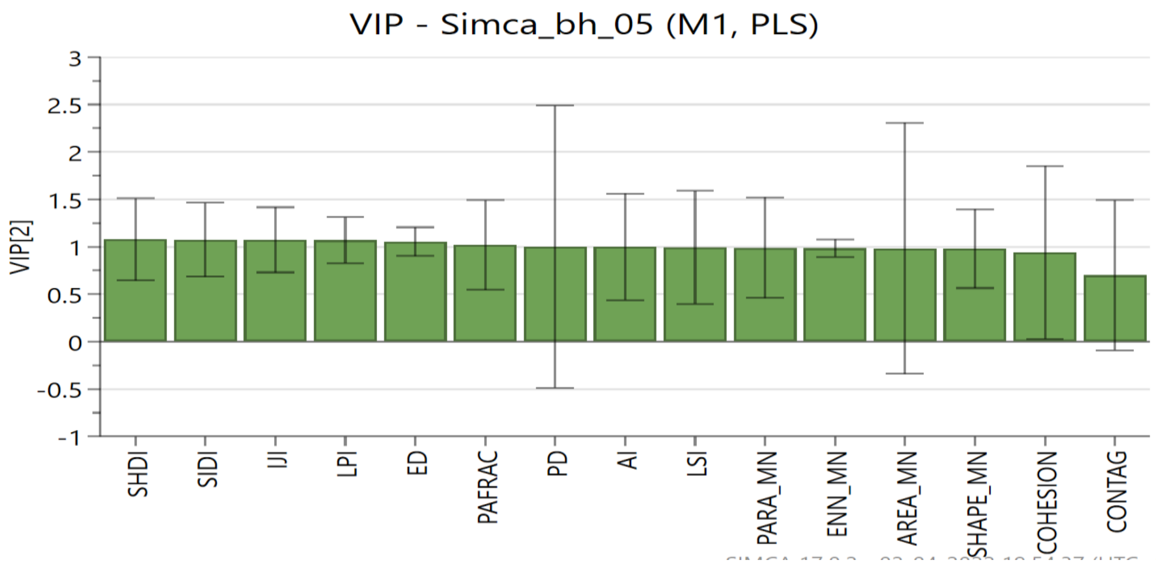

Fig. 24 Variable Importance for Projection (2005)

Table 11. Performance Index of landscape matrix (2014)

Metrics	Dependent Variable		
	VIP	**w' [1]**	**w' [2]**
SHAPE_MN	1.6	-0.32	-0.45
IJI	1.4	0.15	-0.5
ENN_MN	1.3	-0.33	-0.45
PARA_MN	1.2	0.31	0.3

Table 12. Landscape metrics soil erosion results (2005)

Metrics	Dependent Variable		
	VIP	**w' [1]**	**w' [2]**
SHAPE_MN	1.6	-0.32	-0.45
IJI	1.4	0.15	-0.5
ENN_MN	1.3	-0.33	-0.45
PARA_MN	1.2	0.31	0.3

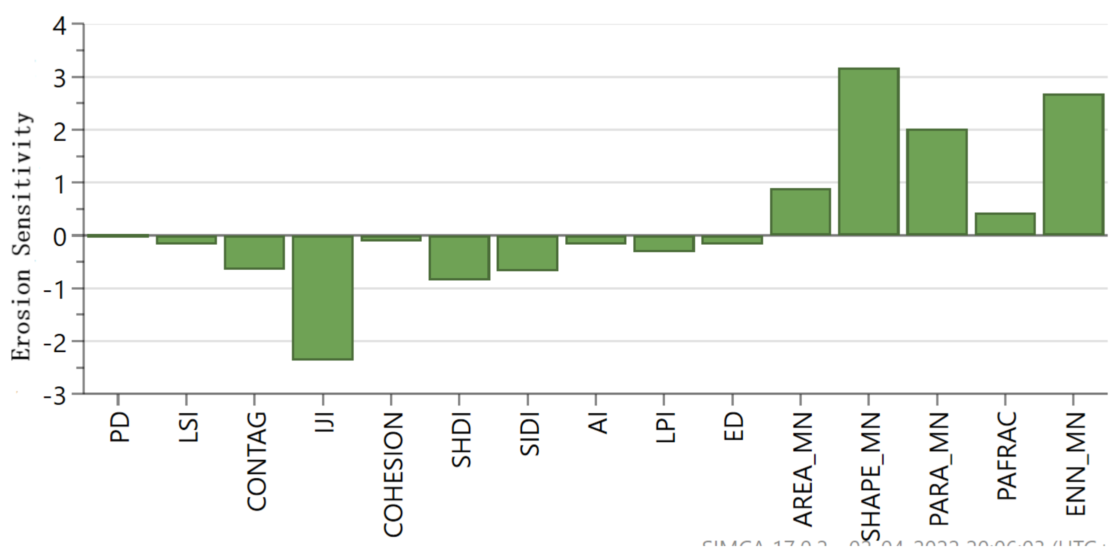

Fig. 25 Soil Erosion Sensitivity of Upper Bhima Sub-Basin (2014)

The fig.(5.36) shows that PD, LSI, SIDI, COHESION, IJI, CONTAG, AI, ED, LPI and SHDI have negative sensitivity towards soil erosion, whereas ENN_MN, PARA_MN, SHAPE_MN, PAFRAC, AREA_MN, and are having positive sensitivity towards soil erosion.

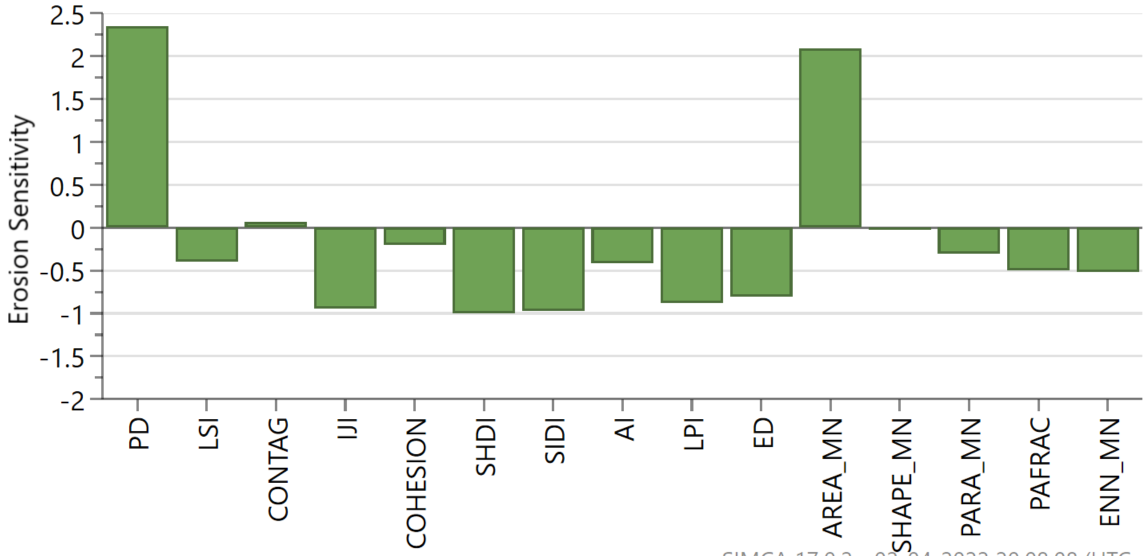

Fig. 26 Soil Erosion Sensitivity of Upper Bhima Sub-Basin (2014)

The above figure shows that LSI, IJI, COHESION, SHDI, SIDI, AI, LPI, ED, SHAPE_MN, PARA_MN, PAFRAC and ENN_MN have negative sensitivity toward soil erosion. In contrast, PD, CONTAG, and AREA_MN have positive sensitivity towards erosion.

5. Discussion

The prime objective of this work was to calibrate and validate soil erosion parameters in the Upper Bhima Sub-basin watershed. The functioning of both models was determined using SA, model calibration and validation. (Van Griensven et al.), Calibrated the SWAT for the discharge and sediment concentration in the Honey Creek basin and concluded that within ten parameters, CN2 along with USLE_P were the most sensitive parameters. (de Medeiros et al.) performed sensitivity analysis in Epitacio Pessoa Dam, it was discovered that CN2, CH_K2, SPCON and EPCON were among the top 4 sensitive parameters. (Gull et al.) calibrated SWAT for the Lolab watershed of Pohru catchment; among four highly sensitive parameters, CN2 was the first, followed by SPCON, CH_EROD and SPEXP. Very close to the above result in this work, 12 parameters were used in the sensitivity analysis as CN2, USLE_P, HRU_SLP, and PRF_BSN are observed to be the most sensitive parameters.

The peak value in July 2004 (calibration) for the model 2014 does not fall under 95 PPU; the same condition was observed for July 1996 (calibration) for the model 2005. Some extreme event cannot be predicted by SWAT; such condition was also observed in the work of (Worqlul et al.). With the help of R^2 and the NSE involving observed and simulated values, their good performance ($R^2>0.6$) uplifted the quality of the model (Bouslihim et al.; Zeckoski et al.; Moriasi et al.). The ability of PBIAS to display poor model performance is used as a supplementary option for showing the effective model performance (Biondi et al.). Time series and scatter plots had equal importance for displaying model performance. This work's scatter plots displayed good collinearity between observed and simulated sediment data.

This research claims that land cover patterns influence soil erosion within the watershed. PD and ED reproduced the magnitude of forest fragmentation. Thus its ineffectiveness was observed in reducing erosion from the agricultural area. In this work, negative sensitivity was featured by COHESION and AI metrics with soil erosion. The model's performance proposed that soil erosion will occur more in distributed land cover patches. SHAPE_MN and PARA_MN displayed positive sensitivity to soil erosion in the 2014 model, which indicates small land use land cover patches increase soil erosion. A similar result was observed in the work of (Boongaling et al.). (Lee et al.) PD, ED and SHDI are positively related to water quality and CONTAG and AI are negatively related to water quality. Also, in the work of (Miller et al.) CONTAG, LPI and COHESION had shown high influence over runoff, and a strong relationship was observed by (Sertel et al.) between PD, NP, LPI and landscape. The above example reveals the use of landscape metrics in other aspects of the watershed where the author had applied similar models in this work. The negative sensitivity of IJI towards soil erosion reflects human domination of land use, such as agricultural land and urban area (Lechner et al.), also found the same result in their study. In our work, SHDI has negative sensitivity to soil erosion, indicating that the watershed has a thick land cover type that prohibits soil erosion. This scenario was repeated in the work of (Lee et al.).

6. Conclusion

The results illustrate that metrics like SOL_AWC, SFTMP, ALPHA_BF & SOL_K had displayed the highest sensitivity towards soil erosion. The algorithm, namely SUFI_2 in-built in SWAT-CUP, develops realistic outputs regarding UA, calibration and validation of the SWAT model. In this work, SWAT-CUP proved to be effective in capturing uncertainty in the modeling and evaluating the impact of watershed aspects. Features of SWAT-CUP to support distributed hydrological modeling, which is an important aspect of watershed management practices, were revealed through this study. The sensitivity investigation was used to select the watershed aspects for calibration; the criteria for selecting the parameter was NSE value should be greater than 0.70 for a daily soil erosion simulation, and similar criteria were followed for the validation period. The results of SWAT-CUP featuring sensitivity and uncertainty analysis reflect the appropriate benefit of the model for soil erosion prediction in the Upper Bhima Basin. The calibration and validation results reflect that the model has closely followed the observed soil erosion. Evaluating soil loss is mandatory to examine the soil erosion consequences; it is also important to implement conservative soil measures in a catchment.

A steady transformation was observed in the landscape from 2005 to 2014, leading to notable changes in the hydraulic function of the watershed. The strong correlation between landscape features and soil erosion was revealed through this study. Land use planners can get good inputs on efforts taken on landscape metrics through this study. It is recommended in the future to expand this study for a better understanding of the complex nature of landscape matrix with soil erosion. The strategies implemented within this work display the contribution of land use changes towards soil erosion; this materialistic information will help stakeholders select the right land use for better water resource management. Through this study, zoning regulation and planning practices need to be carried out to minimize the adverse effects of land use. The investigation of the effect of landscape patterns on soil erosion through PLSR was conducted in this study. In the presence of remote sensing and GIS technology, the land cover aspect can be studied deeply using landscape pattern metrics. PLSR effectively explored land use land cover for sensitivity analysis through the SIMCA-P model. In contrast, climatic and watershed parameters were effectively used by SWAT-CUP for the simulation of soil erosion modeling in the Upper Bhima Sub-Basin.

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