Received: 6 December 2023 | Accepted: 28 November 2024 | Published online: 22 February 2025

DOI: 10.59797/ijsc.v52.i3.178

ORIGINAL ARTICLE

Indian Journal of Soil Conservation

Vulnerable area identification of a Coastal river basin of India using SWAT model

Uday Mandal[1] | D.R. Sena[2] | Gopal Kumar[2] | Trisha Roy[1,*] | R.K. Singh[1] | M. Madhu[1]

[1]ICAR-Indian Institute of Soil and Water Conservation, Dehradun, Uttarakhand, India.

[2]International Water Management Institute, New Delhi, India.

Corresponding Author :

E-mail: trisha17.24@gmail.com

Handling Editor :

Dr Ashish Pandey

ABSTRACT

The soil and water assessment tool (SWAT) was employed to evaluate hydrological fluxes in the Subarnarekha river basin, a coastal tropical region in India. The study utilized a spatially explicit approach, dividing the area into discrete sub-basins (166 units) and subdividing them into hydrologic response units (HRUs) 1335 units, based on exclusive combinations of slope, land use, and soil combinations. With an area of 26105 km^2 and surface elevations ranging from 0 to 1172 m above mean sea level (amsl), the basin predominantly features less than 8% slope (81.43% area of total basin area). The soil composition varied between loamy, clay loam, and clay. The SWAT model underwent calibration (2000-2007) and validation (2008-2012) using observed monthly average river discharge data from four gauging locations on the Subarnarekha and Budhabalanga hydrologic reaches. The sequential uncertainty fitting 2 (SUFI-2) framework with 22 parameters yielded model efficiencies (NSE) greater than 0.5 for all gauging locations in both periods. Sensitivity analysis identified the curve number (R_CN2.mgt) as the most sensitive parameter among the 22. The runoff and sediment yield data for each sub-basin were normalized to fit into a scale of 0 to 1. An equal weightage of 0.50 was assigned to both the parameter runoff and sediment yield to identify the hotpots area in the Subarnarekha river basin. The basin was divided into five vulnerability categories: slight, low, moderate, high, and extreme, covering 63.27%, 26.40%, 5.58%, 2.21%, and 2.52% of the total basin area, respectively. Sub-basins 38, 40, 126, 148, 142, and 125 exhibited high and extreme vulnerability, respectively. Approximately 10% of the total area fell under moderate to high to extreme vulnerability, emphasizing the need for priority for soil and water conservation measures. The developed methodology can be replicated to delineate vulnerable zones in other river basins to prioritize natural resource management.

Key words:

Arc-GIS
Runoff
Sediment yield
Subarnarekha river basin
SWAT
Vulnerable area

1 | INTRODUCTION

River basins are critical ecosystems that support various forms of life, provide essential water resources for communities, and serve as conduits for sediment transport within the landscape. Thus, a clear concept of the dynamic relationship between the sediment losses and runoff generated from the river basin is of paramount importance for sustainable watershed management, environmental conservation, and disaster risk reduction. The hydrological model, SWAT serves as a powerful modeling tool that enables the comprehensive analysis of runoff and sediment yield, offering valuable insights into the vulnerable areas identification within a river basin (Patil *et al*., 2019; Paddhiary *et al*., 2019; Sahoo *et al.,* 2019).

This study focuses on one of the most important river basin of Odhisa *i.e.* the Subarnarekha river basin. The Subarnarekha is a coastal tropical river originating from the northeastern corner of Peninsular India, and the flood problem of this basin is mainly confined to lower alluvial reaches. Rainfed agriculture is the prime source of livelihood in this flood prone river basin. During monsoon season, the river becomes a menace in its flat alluvial topography, located at the lower reaches close to the sea. In the hierarchy of the sub-basins that contribute more runoff to the mainstream flows, it is essential to identify those vulnerable areas. These areas need prioritization for soil and water conservation measures as best management practices (BMPs). SWAT helps in the efficient identification and categorization of watersheds into critical areas for the prioritization of soil conservation measures (Khalkho *et al*., 2020).

As anthropogenic activities continue to alter land use, vegetation cover, and climate patterns, the need for precise, data-driven assessments of river basin vulnerability becomes increasingly urgent. Identifying areas prone to erosion, flash floods, and sediment transport is a crucial step in developing effective strategies for land and water resource management and mitigating the environmental impacts of sediment deposition in downstream ecosystems. In the present study, the river basin vulnerability has been assessed using the SWAT model which was employed to simulate runoff, estimate sediment yield, and pinpoint areas within the basin that are at the greatest risk. Two important hydrological components, runoff and sediment yield, have been considered to identify the vulnerable area. Equal weight was assigned for both parameters to get vulnerable sub-basins or areas, as outlined by Dash *et al*., 2021. The information garnered from this analysis can serve as the foundation for informed decision-making and sustainable resource management practices. In doing so, we aim to contribute to the preservation and sustainable utilization of river basins, ensuring the unaltered fresh water supply and protection of the downstream environments.

2 | MATERIALS AND METHODS

2.1 | Study Area

The Subarnarekha basin (Fig. 1) is a long sausage-shaped basin located in the north-eastern corner of the Peninsular region (Mandal *et al.,* 2021). Geographically it is bounded by the Chhotanagpur plateau to its north and west. On the south, it shares its boundary with the Baitarani river basin while the Bay of Bengal lies to the southeast. The Kasai valley of Kangsabati river basin lies to the east. The Subernarekha (448.36 km) and Burhabalang (198.62 km) are the two major river systems flowing in the north-south direction which drains into the Bay of Bengal. The Jamira and Panchpara streams in-between the two main rivers are also drained into the Bay of Bengal. The basin also has a coastal navigation canal moving in the west-east direction. It lies between latitude 21°18′37″N to 23°33′N and longitude 85°8′14″E to 87°30′44″E encompassing almost 26105 km^2.

The basin comprises two primary topographical regions: the northern plateau, encompassing Purulia district in West Bengal, and Ranchi and Singhbhum districts in Jharkhand, and the coastal plains. Part of the Mayurbhanj district of Odisha lying in this region, is hilly and has a major land use as forest. The coastal plain includes parts of Balasore district in Odisha and Purba Medinipur and Pashchim Medinipur districts of West Bengal. Based on the

HIGHLIGHTS

- SWAT model successfully employed for evaluating hydrological fluxes of Subarnarekha basin.
- The curve number was the most sensitive parameter.
- 10% Subarnarekha basin area was classified as extremely vulnerable & required immediate soil conservation measures.

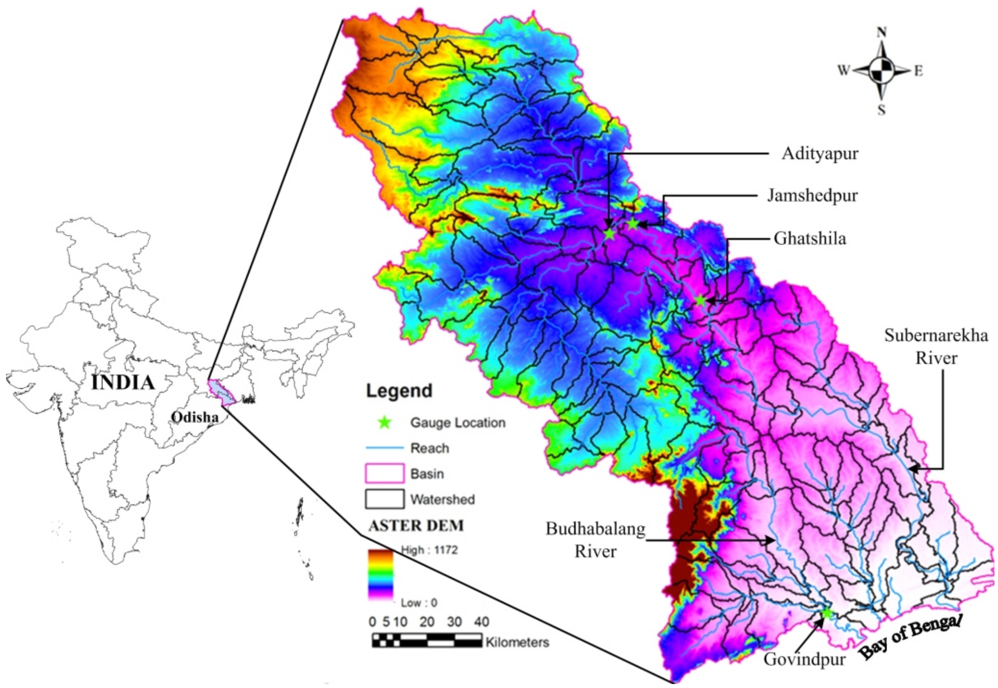

FIGURE 1 Location map of the study area (Subarnarekha river basin) (Mandal *et al.*, 2021)

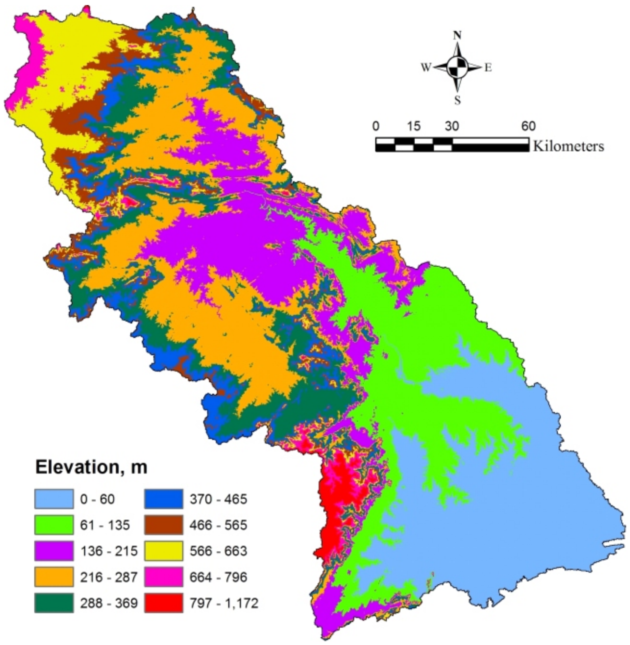

FIGURE 2 Area covered under different elevation zone for the study area, Subarnarekha basin

soil profile depth, moderately shallow to deep (>50 cm) soil covers 86.06 % of the area followed by very shallow (10-25 cm) soil which occupies 12.25% of the area. The general data regarding the soils of the basin comprises sandy clay loam, loam, clay, and silty clay loam. Very severe soil erosion affects only 1.4% of the area (CWC-NRSC, 2014). The slope direction is from northwest to southeast, and almost 81.44% of the area has slopes within 0 to 8%. The altitude of the study area varies between 0 to 1172 m amsl. The area covered under different elevation zones like, 0-60 m (20.71%), 61-135 m (15.90%), 135-215 m (14.02%), 216-287 m (17.64%), 288-369 m (10.35%), 370-465 m (6.22%), 465-565 m (5%), 566-663 m (6.35%), 664-796 m (2.31%), and 797-1172 m (1.50%) of the basin shown in Fig. 2. The area is a hotspot in terms of mineral ore deposits of iron and bauxite and the richest in terms of coal reserves. The south-west monsoon mainly influences the basin, which onset during June preceding a long dry spell and extends upto Oct. Rainfall exhibits significant variation both annual and seasonal. The 34 yrs (1972-2005) average annual rainfall is 1444.53 mm according to the 0.5° grid data and 1385.75 mm for the yrs 1971-2004 according to the 1° grid data (CWC-NRSC, 2014). The rainfall distribution shows higher rainfall as we move from the upper part to the lower part of the basin, and of the total rainfall received, losses due to evapotranspiration account for 57%, while infiltration accounts for 15% (CWC-NRSC, 2014). The region experiences a tropical climate featuring hot summers and mild winters, delineated by three distinct seasons: winter, summer, and monsoon. Mean monthly temperatures fluctuate between 40.5°C (in May) and 9°C (in Dec). The maximum recorded temperature is 47.2°C, and the minimum is 2.8°C. The annual average maximum and minimum temperatures are 32.4 to 18°C, respectively. The predominant portion of the basin falls within the hot sub-humid eco-region characterized by red and lateritic soil zones. The downstream reaches of the basin near the coastal belt fall under a hot sub-humid to semi-arid eco-region with coastal alluvium-derived soils. Groundwater table fluctuation is observed in the range of 0.11 m to 8.20 m (1990 to 2015 data).

2.2 | Hydrological Model, SWAT

SWAT model is one of the most commonly used hydrological models for a wide array of watershed / environmental problems. It is a public domain model supported by the United States Department of Agriculture (USDA) and efficiently simulates physical processes associated with water flow, sediment transport, crop growth, and nutrient cycling (Shi *et al.*, 2013). It has a wide array of applications in watersheds / river basins of varying sizes and earned undisputed popularity among global communities (Schuol and Abbaspour, 2006; Yang *et al*., 2008; Arnold *et al*., 2012; Adhikari *et al*., 2019; Dash *et al*., 2021; Mandal *et al*., 2021). The SWAT can be utilized to assess the vulnerable area identification under present as well as projected climate scenarios of river basins (Dash *et al*., 2021). Moreover, the SWAT-CUP module with SUFI-2 algorithm module has been found to have wide applications for calibration and validation utilizing multi-site observation data (Adhikari *et al*., 2019; Dash *et al*., 2021; Mandal *et al*., 2021).

To reconcile differences between topographic and hydrographic data, streams digitized from the Google Earth interface were utilized to imprint streams derived from the DEM data (ASTER DEM), ensuring alignment between the datasets. A total of 166 sub-watersheds were discretized (Fig. 1). In association with GLC 2000 land-use database with 16 land use classifications (Fig. 3; Table 1), ICAR-National Bureau of Soil Survey and Land Use Planning (NBSS& LUP) soil layer dataset (Fig. 4), and slope classes as per soil water conservation measures (Fig. 5), the basin sub-spaces were further discretised into homogeneous sub-units *i.e.* hydrologic response units (HRUs). A total of 1,335 HRUs were generated by applying threshold values for land use (<15%), soil type (<10%), and slope class (<5%). The agricultural scenarios were introduced in the model by explicitly specifying crop information.

2.3 | Database

Datasets corresponding to weather parameters, topography, soil, and land use/land cover (LU/LC) form the input for SWAT. Global land cover 2000 (Hartley *et al.,* 2006) was utilized as the land use map (1:250,000) as input to the SWAT model. The soil map layer at a scale of 1:250,000, along with its corresponding database, was acquired from the ICAR-NBSS&LUP located in Nagpur, India. The advanced space borne thermal emission and reflection radiometer (ASTER) global digital elevation model (GDEM), featuring a spatial resolution of 30 m, was employed to extract elevation and slope data at the sub-watershed level. Additionally, gridded weather datasets, including daily precipitation (mm), relative humidity (%), wind speed (km hr^{-1}), and maximum and minimum temperatures (°C), were obtained from the global climate forecast system re-analysis dataset (CFSR). These datasets, available at 30 km spatial resolution, covered the period from 2000 to 2012 and were accessed from the website http://globalweather.tamu.edu. Within the study area, weather input for the SWAT model was based on data from 20 grid points.

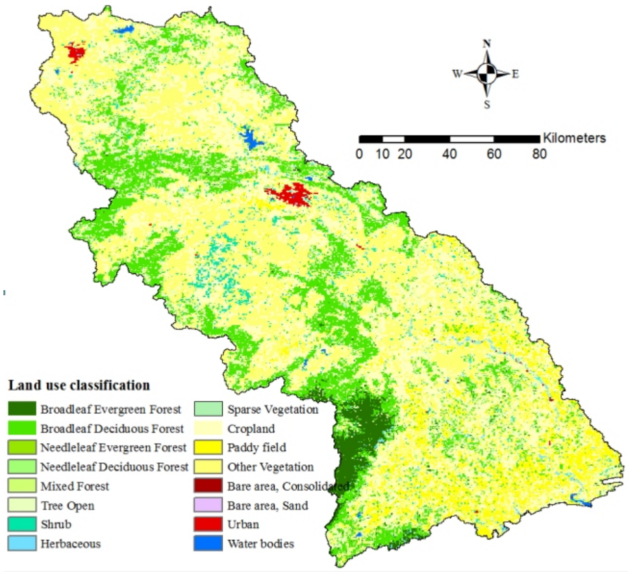

FIGURE 3 Land use classification map of the Subarnarekha river basin

TABLE 1 Land use classes of the Subarnarekha river basin

S.No.	Land use classes	% area cover
1	Paddy field	28.51
2	Cropland	27.02
3	Broadleaf deciduous forest	17.74
4	Tree ppen	12.36
5	Cropland / Other vegetation mosaic	7.68
6	Broadleaf evergreen forest	2.79
7	Shrub	1.96
8	Herbaceous	0.7
9	Urban	0.53
10	Water bodies	0.29
11	Needle leaf evergreen forest	0.22
12	Sparse vegetation	0.13
13	Bare area, consolidated	0.04
14	Needle leaf deciduous forest	0.01
15	Mixed forest	0.01
16	Bare area, sand	0.01

River discharge data at a daily scale from 2000 to 2012 was downloaded from the web distribution portal distributed and maintained jointly by the Central Water Commission (CWC) and the Indian Space Research Organization (ISRO), Govt. of India for the four gauging locations within the Subarnarekha river basin (Fig. 1). The developed SWAT model was calibrated using the observed river discharge rate data and subsequently validated.

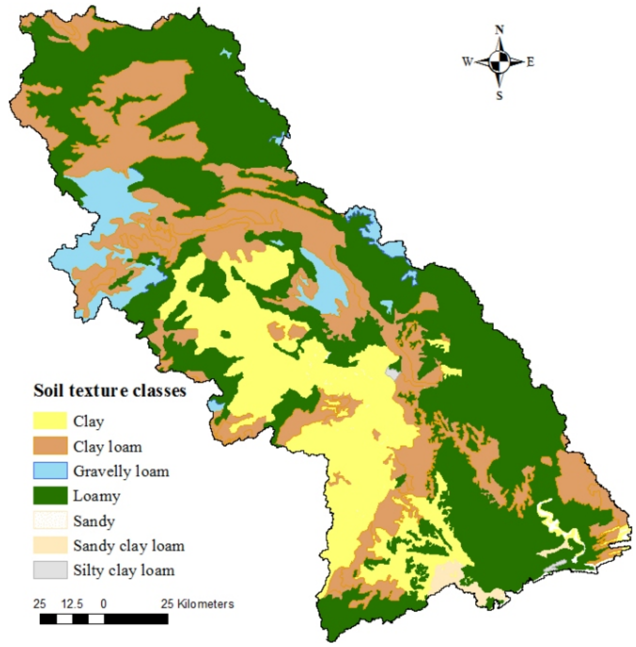

FIGURE 4 Soil texture classes map of the study area

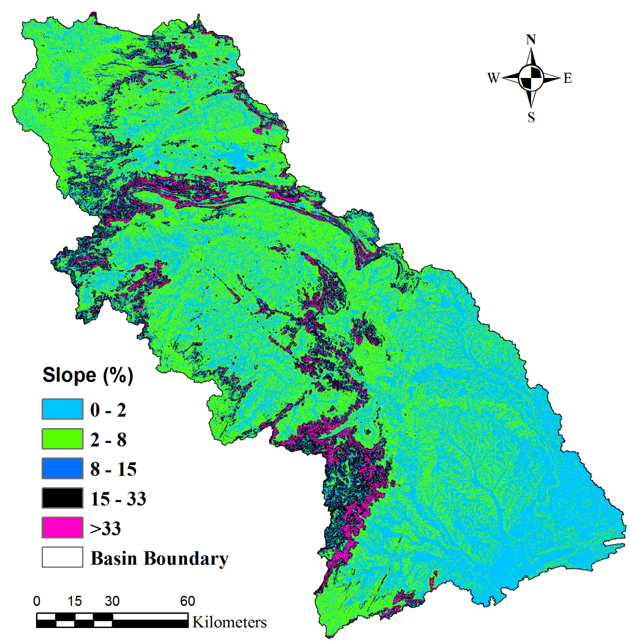

FIGURE 5 Slope classes map of the study area

2.4 | Model Calibration, Validation, and Sensitivity Analysis

SUFI-2 algorithm within the SWAT-CUP auto-calibration tool was utilized for calibration, validation, and sensitivity analysis (Abbaspour *et al*., 2004; Abbaspour *et al*., 2007; Mandal *et al*., 2021). The mean monthly stream flow rates from the four gauging stations, *viz.,* (a) Govindapur, (b) Ghatsila, (c) Adityapur, and (d) Jamshedpur were used for calibrating the model (Fig. 1). The first gauging site is located on the Budhabalanga river stream while the next three stations are positioned along the main river course of Subarnarekha. The flow rate was categorically divided into two groups based on the time period. The model was calibrated with the flow rate dataset received during 2000-2007 while data obtained during 2008-2012 was used for validation. For segregating the daily discharge values from the base flow component, the protocol outlined by Lim *et al.* (2005) was used. Further, the model calibration and validation were done by aggregating these daily discharge values to monthly discharge. Model calibration was done using 22 parameters, which were chosen by method outlined by Mandal *et al*. (2021).

SUFI-2 algorithm (Schuol and Abbaspour, 2006), a multi-site global search procedure was used for calibration. Quantification of the measurement uncertainty is done by the SUFI-2 algorithm by using the following parameters. The first parameter is the "*p*-factor" which is the percentage of measured data bracketed by the 95% prediction uncertainty (PPU) with the aid of latin hypercube sampling (LHS) the 2.5% and 97.5% levels of the cumulative distribution of an output variable is obtained based on which 95 PPU is calculated. The second parameter is the *R*-factor, which is a measure of the mean width of 95 PPU upon the standard deviation of the measurements (Abbaspour *et al*., 2007; Al-Mukhtar *et al*., 2014). The objective of the calibration scheme (SUFI-2) was the concomitant reduction in the *R*-factor and enhancement in the *p*-factor. Three optimization criteria were used to get the optimum solution, *i.e.,* coefficient of determination (R^2), a modified efficiency criterion ϕ (bR^2), and the nash-sutcliffe efficiency (NSE). To identify the global sensitivity of the parameter, a *t*-test was applied with a hypothesis that the higher *t*-value and lower *p*-value indicated higher sensitivity of the parameters to the modeled objective function(s).

2.5 | Model Performance

The performance of any hydrological model like SWAT needs to be tested before application. For evaluating the performance of the model setup, including parameter optimization for further application of the model, the protocol given by Moriasi *et al*. (2007) was followed. The observed and model simulated flow rates were used for evaluation of the model performance. Three statistical indicators, *i.e.* NSE (Nash *et al.,* 1970), coefficient of determination (R^2), and percent bias (PBIAS), were utilized for the same as per the following equations.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O')^2} \quad ...(1)$$

$$R^2 = \left\{ \frac{\left(\sum_{i=1}^{n}(O_i - O')(P_i - P') \right)^2}{\sum_{i=1}^{n}(O_i - O')^2 \sum_{i=1}^{n}(P_i - P')^2} \right\} \quad ...(2)$$

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n}O_i} \times 100 \quad ...(3)$$

Where, n is the number of measured data, P_i and P' are the predicted data at time i and the mean of the predicted data, respectively, while O_i and O' are measured data at time i and the mean of the measured data, respectively. The values of NSE indicator lie between -∞ and 1, while the R^2 values range from -1 to 1. A more positive value towards 1 for both indicators suggests a better model performance and concurrence between the observed and predicted values (Mandal *et al*., 2021). The *PBIAS* values estimate the model bias and a positive value is associated with the underestimation of bias while overestimation is indicated by a negative value (Abbaspour *et al*., 2007; Mandal *et al*., 2021).

2.6 | Identification of Vulnerable Sub-basins

Identifying vulnerable sub-basins within a larger river basin is a critical step in watershed management and environmental conservation. Vulnerable sub-basins are areas at higher risk of experiencing issues related to runoff, erosion, sediment transport, or other hydrological and environmental challenges. The identification of erosion-susceptible areas based on the quantum of runoff and sediment load generated is primarily required for designing efficient soil and water conservation measures. The entire study area was categorized into different zones based on the sediment yield and runoff simulated by the model at each sub-basin level. The different zones formed were assigned a vulnerability index by giving equal weightage to both runoff and sediment load. Following this, all sub-basins were categorized into five vulnerable classes: visually slight, low, moderate, high, and extreme, as shown in Table 2.

3 | RESULTS AND DISCUSSION

3.1 | Model Calibration, Validation, and Sensitivity Analysis

SUFI-2 algorithm inbuilt within the auto-calibration module SWAT-CUP was used for the calibration, validation, sensitivity analysis and uncertainty determination (Abbaspour *et al*., 2004; Abbaspour *et al*., 2007; Mandal *et al*., 2021). The monthly aggregated direct runoff discharge values were used as observed data for both calibration and validation. Optimized parameter values from 1000 parameter combinations (derived from 1000 simulations) obtained from LHS along with lower and upper limits and best fitting value of the parameters set. With the help of sensitivity analysis 22 model parameters were chosen. In various watershed studies worldwide, 13 parameters of the selected 22 have been widely adopted and used (Arnold *et al.*, 2012). In the context of Indian river basins, 10 parameters out of 22 parameters have been predominantly employed in various studies (Mandal *et al*., 2021). It was arguably found that the curve number (R_CN2.mgt) is the most sensitive parameter of all the listed parameters, followed by deep aquifer percolation fraction (V_RCHRG_DP.gw), groundwater re-evaporation coefficient (V_GW_REVAP.gw). This might be attributed to the mild slope in the study area (<8%), the richness of coarser fractions in the soil in the HRUs and the fragmented paddy fields bounded by field bunds.

Table 3 indicates the error statistics obtained through a comparison between the observed and simulated discharge values for both the calibration period (2000-2007) and the validation period (2008-2012). The NSE value exceeding 0.5, as suggested by Moriasi *et al*. (2007), indicates a satisfactory agreement between the monthly simulated flow rates and their observed counterparts at all gauging stations. Notably, the model performance is better during validation, compared to the calibration period, with higher NSE values, except for the Govindpur site. This discrepancy may be attributed to the relatively shorter validation period. It is noteworthy that the NSE and R^2 values show close agreement for each gauging site during both calibration and validation periods. The comparison between the observed (monthly scale) and model simulated stream flow for the four gauging locations are shown in Fig. 5 during calibration and validation periods. From Fig. 5, it was observed that the model underestimated stream flow for all the gauging locations compared to the observed data. The under estimation may be due to the fact that the majority of the basin area (81.40%) has a moderate slope of 0-8%. Additionally, the predominance of fragmented agricultural lands used for rice cultivation bounded by field bunds resulted in a significant reduction of runoff, consequently producing less runoff.

TABLE 2 Criteria for identifying vulnerable area

Vulnerability index	Soil loss classes
<0.25	Slight
0.25-0.50	Low
0.50-0.75	Moderate
0.75-0.90	High
>0.90	Extreme

A PBIAS for all the gauging sites predictions was within ±25% level, further substantiated the "goodness-of-fit" between the simulated and observed discharge data (Moriasi *et al*., 2007; Mandal *et al*., 2021). *R*-factor values are much less than 1, and across all the gauging sites, it shows nominal variation during the calibration and validation period (Table 2), thus, indicating the superior performance of the model (Zhang *et al*., 2014; Uniyal *et al*., 2015; Mandal *et al*., 2021). During the calibration period, the *p*-factor value varies very little (from 0.38 to 0.45) compared to the validation period (0.22 to 0.40), which indicates small parameter uncertainty associated with the monthly stream flow simulation uncertainty (Zhang *et al*., 2014; Uniyal *et al*., 2015). The consistently low *p*-factor values, averaging 0.38 during the calibration period and 0.32 during the validation period, suggest that parameter uncertainty contributes relatively little to the overall uncertainty associated in the simulation process, as reported in various studies (Zhang *et al*., 2014; Yaduvanshi *et al*., 2017). It also suggests that the parameter bounds are smaller for both simulation periods. Overall, these results suggest varying degrees of model performance across the locations and time periods, with some locations showing better model fit and less bias compared to others but overall model performance is highly satisfactory.

3.2 | Stream Flow and Sediment Yield

For conserving most precious natural resources like soil and water by implementing various soil and water conservation measures (agronomical and engineering or bio-engineering measures) or BMPs, the essential prerequisite is identification and prioritization of the hotspot area (sub-basins). In the present study, it is assumed that the soil type, land use pattern as well as agricultural practices remained constant

TABLE 3 Accuracy assessment of the SWAT model during calibration and validation periods

Site	Calibration period (2000-2007)					Validation period (2008-2012)				
	NSE	PBIAS	R^2	*p*-factor	*R*-factor	NSE	PBIAS	R^2	*p*-factor	*R*-factor
Jamshedpur	0.69	3.9	0.71	0.38	0.63	0.78	9.3	0.80	0.35	0.48
Adityapur	0.53	18.1	0.55	0.36	0.44	0.63	-4.8	0.65	0.22	0.45
Ghatsila	0.73	5.8	0.74	0.35	0.59	0.78	21.4	0.83	0.33	0.42
Govindpur	0.76	-2.5	0.78	0.45	0.66	0.59	-4.1	0.62	0.4	0.53

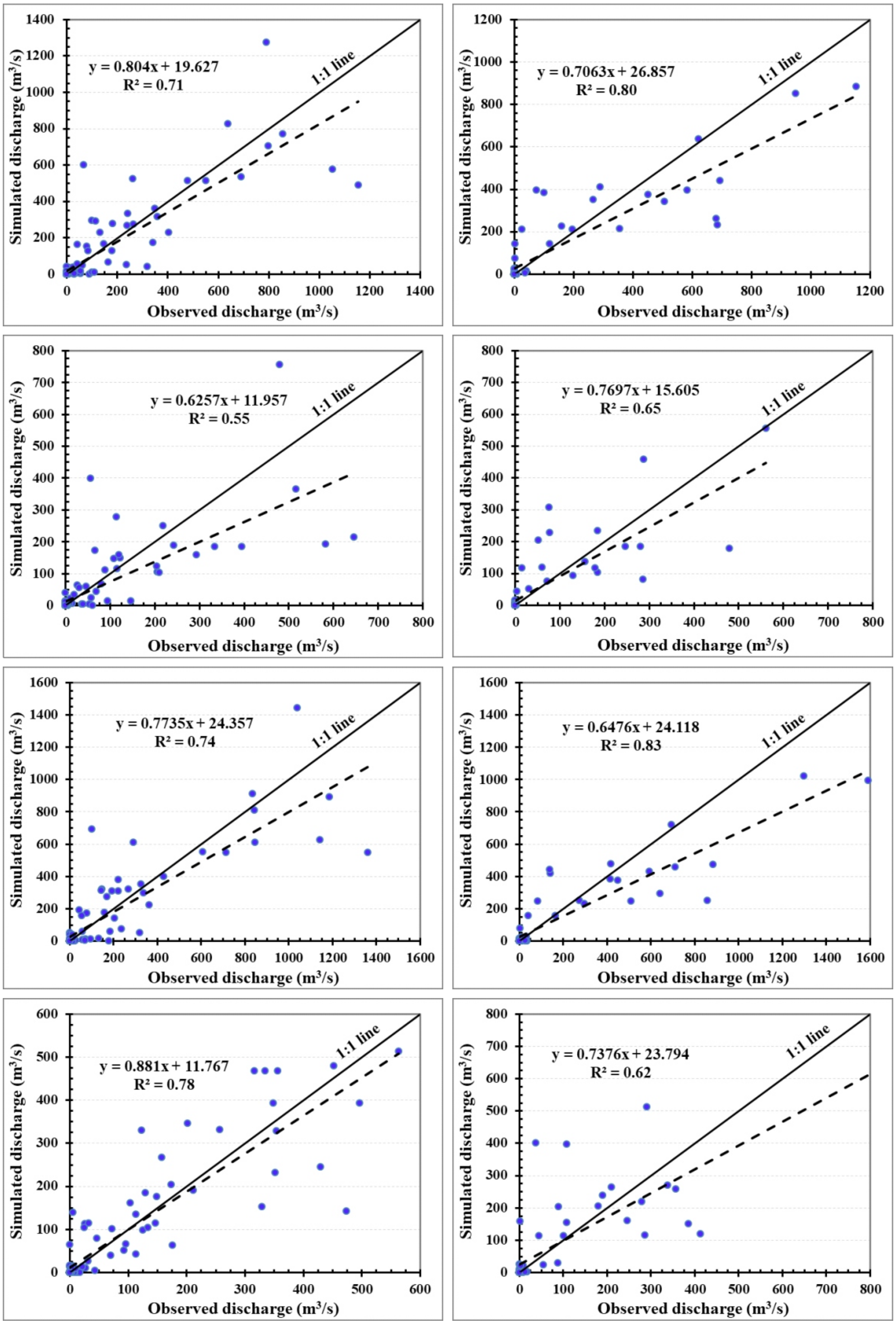

FIGURE 6 Scatter plot of observed and simulated streamflow for the gauging location (a) Jamshedpur, (c) Adityapur, (e) Ghatsila, (g) Govindapur during calibration period (2000-2007) and (b), (d), (f), and (g) during validation period (2008-2012), respectively

during the period of analysis, with any variations attributed solely to changes in climatic input variables.

The long-term average of sediment yield and runoff map of the Subarnarekha river basin is presented in Fig. 7. The sediment yield (t $ha^{-1}y^{-1}$) map was categorized into five classes, *i.e.,* 0-5, 5-10, 10-20, 20-40, and >40 t ha^{-1} y^{-1}. The surface runoff map was also categorized into 5-classes, *i.e.,* 47-100, 100-150, 150-200, 200-300, and >300 mm. The same color code has been utilized for both the map in the line of vulnerability map. Table 4 represents the detailed statistics related to the area under different classes, along with the number of sub-basins under each class. The classification of the sub-basins under each category class is also shown in Fig. 7. From Fig. 7, one interesting observation is that, in most cases, the surface runoff and sediment yield category classes overlap. Notably, the downstream southwest side of the basin mainly experienced high to extreme categories of sediment yield and runoff (Fig. 7). However, the situation was not true for all cases, as observed in the downstream south-eastern part of the basin where sediment yield was less than 10 t $ha^{-1}y^{-1}$ (slight to low category classes). However, runoff classes belonged to the moderate to extreme category.

3.3 | Vulnerable Area Identification

Identification of the vulnerable area is dependent on various parameters. Here, two important parameters (surface runoff and sediment yield) were considered with equal weightage. The weighted sum overlay method was used for generating vulnerable area map of Subarnarekha river basin, shown in Fig. 8. The vulnerable classes were calculated sub-basin-wise. The vulnerability assessment of the sub-basins reveals distinct classes based on their susceptibility to environmental challenges. Among the identified categories, the majority of sub-basins fall into the "Slight" vulnerability class, comprising 89 sub-basins, covering an extensive area of 16,519.02

TABLE 4 Sediment yield and surface runoff statistics for Subarnarekha river basin

Sediment yield (t $ha^{-1}y^{-1}$)	No. of sub-basin	Average sediment yield (t $ha^{-1}y^{-1}$)	Area (km^2)	% area
1-5	14	3.69	2262.35	8.67
5-10	41	7.82	7501.31	28.73
10-20	41	13.97	5717.19	21.90
20-40	41	27.76	5931.08	22.72
>40	29	70.3	4693.53	17.98
Runoff (mm)				
<100 mm	18	77.75	5697.99	21.83
100-150 mm	30	124.95	5932.33	22.72
15-200 mm	46	171.09	7098.48	27.19
200-300 mm	47	240.89	4933.97	18.90
>300 mm	25	375.31	2442.69	9.36

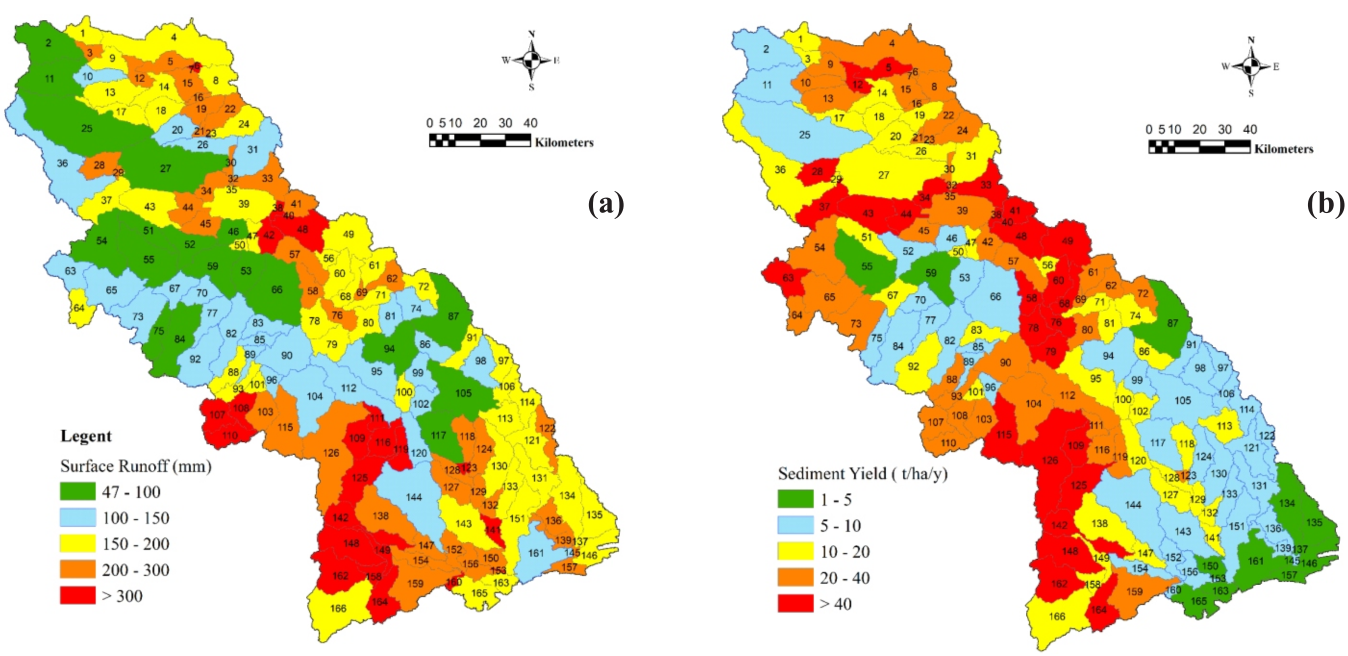

FIGURE 7 Sub-basin wise (a) surface runoff in mm and (b) sediment yield in t $ha^{-1}y^{-1}$ map of Subarnarekha river basin

sq km^{2,} constituting 63.28% of the total area. Following this, the "Low" vulnerability class encompasses 62 sub-basins, with an area of 6,892.24 sq km^2, representing 26.40% of the overall area. Additionally, there are 9 sub-basins in the "Moderate" vulnerability class, covering 1,457.71 sq km^2 (5.58% of the total area). The "High" vulnerability class includes three sub-basins, totalling 578.01 sq km^2 (2.21%). In comparison, both the "Extreme" vulnerability class and another category with three sub-basins each occupy 2.52% of the total area, with areas measuring 658.47 km^2. A total of 4.73% area (sub-basin number 38, 40,126, 125, 142, and 148) is under the high to extreme vulnerable area category. These findings are also supported by the hilly topography (high slope) of the basin and Google Earth images (Fig. 8). This classification provides a comprehensive overview of the distribution of vulnerability classes across the sub-basins in the study area. A similar kind of study was conducted by Dash *et al.,* 2021 for the Brahmani river basin, where 5.38% of the area was under the high to extremely vulnerable category.

4 | CONCLUSIONS

The SWAT model was developed for the Subarnarekha river basin of India. The developed model was successfully calibrated and validated by auto-calibration tool, SWAT-CUP integration with SWAT model using SUFI-2 algorithm, and the calibration and validation results were found satisfactory (NSE>0.5 for all gauging sites). The strong agreement between simulated and observed stream flow throughout the calibration and validation phases validates the suitability of applying SWAT at the river basin scale, affirming its appropriateness for future applications. Uncertainty analysis suggests very little contribution of the parameter uncertainty to the overall output of the calibrated model. The observed and simulated discharge rate is within the 95 PPU band. Curve number (R_CN2.mgt) was found to be the most sensitive parameter during both calibration and validation periods. The vulnerable area identification map was classified into five categories: slight, low, moderate, high, and extreme, and the areas under various categories were 63.27, 26.40, 5.58, 2.21, and 2.52%, respectively. It was found that nearly 10% area of the total basin area belonged to the moderately to extremely vulnerable area class and needs a priority for soil and water conservation measures. The developed methodology may help to identify the vulnerable area of the basin and, based on land use and land cover and slope, BMPs like repairing existing field bunds, proposing field bunds, contour bunds, bench terraces, bio-engineering measures, check-dams for drainage line treatment etc. may be implemented by the various agencies. This strategy will ensure better utilization of the budget effectively to warrant proper management of natural resources for the benefit of the local community.

ACKNOWLEDGEMENTS

The authors sincerely acknowledge the contributions of all reviewers and editors for their instructive comments, which helped us during the writing of this article and improving the quality of the paper. The authors also acknowledge the

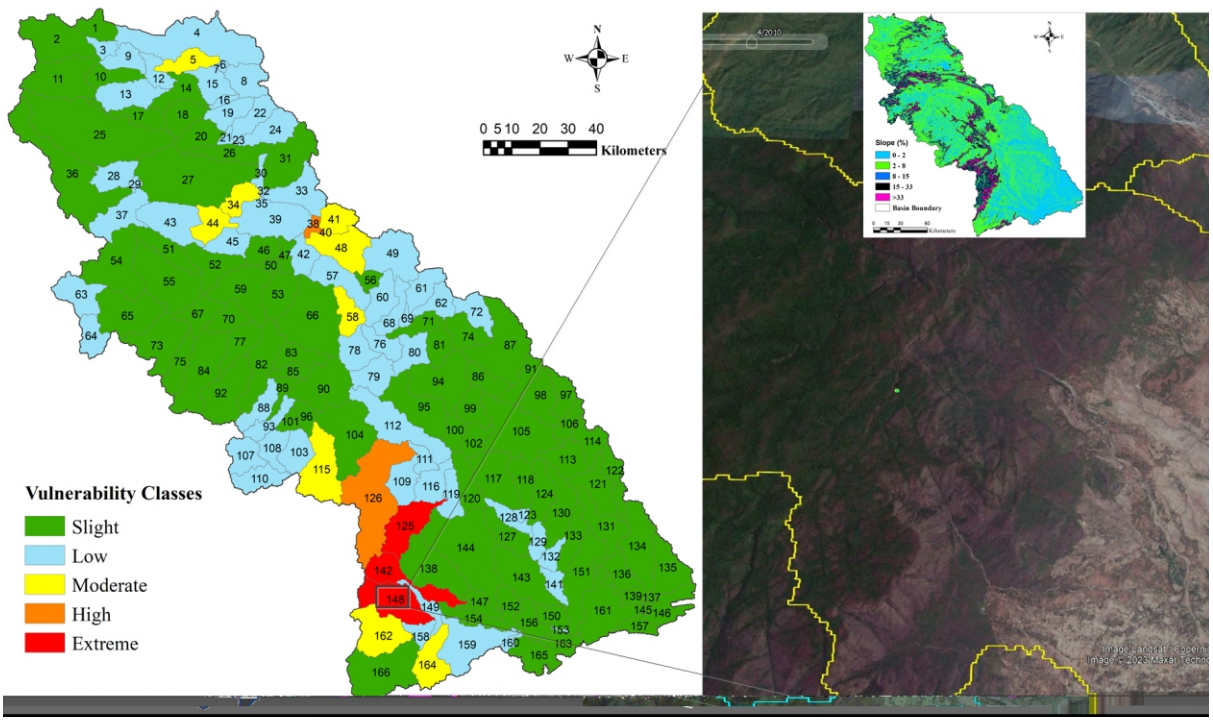

FIGURE 8 Sub-basin wise vulnerability classes and Google Earth image of 2010 for the Subarnarekha river basin

support extended by the Director, ICAR-Indian Institute of Soil and Water Conservation, Dehradun and the Indian Institute Technology, Kharagpur, for conducting this work.

DATA AVAILABILITY STATEMENT

The data generated or analyzed during this study are available from the senior author upon reasonable request.

CONFLICT OF INTEREST

The authors declare there is no conflict.

AUTHOR'S CONTRIBUTION

Conceptualization: U.M., D.R.S. and G.K.; data collection: U.M.; methodology: U.M, D.R.S; resources: M.M. and R.K.S.; investigation: U.M.; validation: U.M. and G.K.; writing-original draft preparation: U.M. and T.R.; writing-review and editing: T.R. and U.M.; visualization: U.M., D.R.S.; supervision: M.M. and R.K.S.; project administration: M.M. and R.K.S. All authors have read and agreed to the published version of the manuscript.

REFERENCES

Abbaspour, K.C., Johanson, C.A. and Van Genuchten, M.T. 2004. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. *Vadose Zone J.*, 3(4): 1340-1352.

Abbaspour, K.C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J. and Srinivasan, R. 2007. Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. *J. Hydrol.,* 333(2-4): 413-430.

Adhikary, P.P., Sena, D.R., Dash, Ch. J., Mandal, U., Nanda, S., Madhu, M., Sahoo, D.C. and Mishra, P.K. 2019. Effect of calibration and validation decisions on streamflow modeling for a heterogeneous and low runoff-producing river basin in India. *J. Hydrol. Eng.,* 24(7): 05019015.

Al-Mukhtar, M., Dunger, V. and Merkel, B. 2014. Assessing the impacts of climate change on hydrology of the upper reach of the spree river: Germany. *Water. Res. Manage.,* 28: 2731-2749.

Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., Griensven, A.V., Liew, M.W.V., Kannan, N. and Jha, M.K. 2012. SWAT: Model use, Calibration, and Validation. *Am. Soc. Agric. Biolog. Eng.,* 55(4): 1491-1508.

CWC-NRSC. 2014. Subarnarekha basin report, Version 2.0, Ministry of water resources, Govt. of India.

Dash, S.S., Sena, D.R., Mandal, U., Kumar, A., Kumar, G., Mishra, P.K. and Rawat, M. 2021. A hydrological modelling based approach for vulnerable area identification in changing climate scenario. *J. Water Clim. Change*, 12(2): 433-452.

Hartley, A., Pekel, J.F., Ledwith, M., Champeaux, J.L., Badts, E.De. and Bartalev, S.A. 2006. GLC 2000 database, European Commision Joint Research Centre.

Khalkho, D., Tripathi, M.P. and Kumar, L. 2020. Identification of critical sub-watersheds in Hamp watershed of upper Mahanadi basin using Arc-SWAT. *Indian J. Soil Cons.,* 48(1): 86-96.

Lim, K.J., Engel, B.A., Tang, Z., Choi, J., Kim, K.S., Muthukrishnan, S. and Tripathy, D. 2005. Web GIS-based hydrograph analysis tool, WHAT. *J. Am. Water Resour. Assoc.,* 41(6): 1407-1416.

Mandal, U., Sena, D.R., Dhar, A., Panda, S.N., Adhikary, P.P. and Mishra, P.K. 2021. Assessment of climate change and its impact on hydrological regimes and biomass yield of a tropical river basin. *Ecol. Indic.,* 126(4): 107646.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Binger, R.L., Harmel, R.D. and Veith, T. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. Am. Soc. Agric. Biol. Eng.,* 50(3): 885-900.

Nash, J.E. and Sutcliffe, J.V. 1970. River flow forecasting through conceptual models part I - A discussion of principles. *J. Hydrol.,* 10(3): 282-290.

Paddhiary, J., Das, M.D., Patra, K.C., Sahoo, B.C. and Panigrahi, B. 2019. Identification of sensitive parameters and uncertainty analysis for simulating streamflow in Jaraikela catchment of Brahmani river basin using SWAT model. *Indian J. Soil Cons.,* 47(2): 111-118.

Patil, M., Kothari, M., Gorantiwar, S.D. and Singh, P.K. 2019. Runoff simulation using the SWAT model and SUFI-2 algorithm in Ghod catchment of upper Bhima river basin. *Indian J. Soil Cons.,* 47(1): 7-13.

Sahoo, P.S., Nema, A.K. and Mishra, P.K. 2019. Rainfall-runoff modeling using SWAT for Ong river basin. *Indian J. Soil Cons.,* 47(2): 126-133.

Schuol, J. and Abbaspour, K.C. 2006. Calibration and uncertainty issues of a hydrological model (SWAT) applied to West Africa. *Adv. Geosci.,* 9: 137-143.

Shi, P., Ma, X., Hou, Y., Li, Q., Zhang, Z., Qu, S. and Fang, X. 2013. Effects of land-use and climate change on hydrological processes in the upstream of Huai river, China. *Water Resour. Manage.,* 27(5): 1263-1278.

Uniyal, B., Jha, M.K. and Verma, A.K. 2015. Parameter identification and uncertainty analysis for simulating streamflow in a river basin of Eastern India. *Hydrol. Proc.,* 29(17): 3744-3766.

Yaduvanshi, A., Sharma, R.K., Kar, S.C. and Sinha, A.K. 2017. Rainfall-runoff simulations of extreme monsoon rainfall events in a tropical river basin of India. *Nat. Hazards,* 1-19.

Yang, J., Reichert, P., Abbaspour, K.C., Xia, J. and Yang, H. 2008. Comparing uncertainty analysis techniques for a SWAT application to the Chaohe basin in China. *J. Hydrol.,* 358: 1-23.

Zhang, X., Xu, Y.P. and Fu, G. 2014. Uncertainties in SWAT extreme flow simulation under climate change. *J. Hydrol.,* 515: 205-222.

How to cite this article: Mandal, U., Sena, D.R., Kumar, G., Roy, T., Singh, R.K., Madhu, M. 2024. Vulnerable area identification of a Coastal river basin of India using SWAT model. *Indian J. Soil Cons.,* 52(3): 239-248.