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# A Soil Water Assessment Tool (SWAT) Modeling Approach to Prioritize Soil Conservation Management in River Basin Critical Areas Coupled With Future Climate Scenario Analysis

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**ABSTRACT:** About 44% of the Indian landmass experiences the adverse impact of land degradation. This loss of sediments caused by soil erosion reduces the water quality of local water bodies and decreases agricultural land productivity. Therefore, decision-makers must formulate policies and management practices for sustainable management of basins that are cost-effective and environment friendly. Application of the best management practices (BMPs) to properly manage river basins is difficult and time-consuming. Its implication under various climate change scenarios makes it more complicated but necessary to achieve sustainable development. In this study, the soil and water assessment tool (SWAT) model was employed to prioritize the Tons river basin's critical areas in the central Indian states coupled with future climate scenario analysis (2030–2050) using Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 scenarios. The SWAT model was calibrated and validated for simulation of streamflow and sediment yield for daily and monthly scales using the sequential uncertainty fitting (SUFI-2) technique. The values of coefficient of determination ( $R^2$ ), Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS), and root mean square error (RMSE)-observations standard deviation ratio (RSR) were .71, .70, –8.3, and .54, respectively during the calibration period, whereas for validation the values were .72, .71, –3.9, and .56, respectively. SWAT model underestimated the discharge during calibration and overestimated the discharge during validation. Model simulations for sediment load exhibited a similar trend as streamflow simulation, where higher values are reported during August and September. The average annual sediment yield of the basin for the baseline period was 6.85 Mg ha<sup>-1</sup>, which might increase to 8.66 Mg ha<sup>-1</sup> and 8.79 Mg ha<sup>-1</sup> in the future years 2031–2050 and 2081–2099, respectively. The BMPs such as recharge structure, contour farming, filter strip 3 and 6 m, porous gully plugs, zero tillage, and conservation tillage operations have been considered to evaluate the soil and water conservation measures. Recharge structure appeared to be the most effective measure with a maximum reduction of sediment by 38.98% during the baseline period, and a 37.15% reduction in the future scenario. Sub-watersheds, namely SW-8, SW-10, SW-12, SW-13, SW-14, SW-17, SW-19, SW-21, SW-22, and SW-23, fall under the high category and are thus considered a critical prone area for the implementation and evaluation of BMPs. Compared to the baseline period, the effectiveness of BMPs is slightly decreasing in the 2040s, increasing in the 2070s and decreasing in the 2090s. Recharge structure and filter strip 6 m have been found to nullify the high soil erosion class completely. Overall, SWAT model simulations under the RCP 8.5 scenarios were observed to be reliable and can be adopted to identify critical areas for river basins having similar climatic and geographical conditions.

**KEYWORDS:** BMPs, climate change, hydrological modeling, SWAT, Tons basin

**TYPE:** Advances in Spatial Modeling, Geostatistics, and Machine Learning in Soil Science - Original Research

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## Introduction

River basin management reduces excess streamflow, thereby reducing soil erosion and non-point source pollutants in the form of nutrients from agriculture-dominated areas to ensure sustainable agricultural production (Tripathi et al., 2005; Tuppada et al., 2011). Soil erosion and pollutant loads from agricultural practices are the primary sources of the non-point sources pollutants (Himanshu et al., 2019). In general, best management practices (BMPs) are designed to reduce or prevent sediment movement, nutrient, and pesticide loadings from the agricultural land to surface or groundwater resources (Abbas & Fares, 2009). BMPs are useful, practical, and structural or non-structural methods, and the goal is to optimize crop production and minimize environmental impacts, that is, land degradation. India constitutes 18% of the world's human population, supported by 2.4% of world land area, which led to land

degradation to nearly 44% (Mythili & Goedecke, 2016), which is also a matter of concern. Therefore, suitable BMPs are needed to control land degradation due to soil erosion and other non-point source pollutants from agricultural watersheds. Due to financial and technical constraints, it is challenging to implement the BMPs scenario on a whole watershed; hence, identifying and prioritizing critical sub-watersheds is mandatory (Himanshu et al., 2019; Pandey et al., 2009; Tripathi et al., 2003). From an environmental point of view, abandonment results in an increase in the infiltration rates (Barrena-González et al., 2020(a)) due to vegetation recovery that results in changes in streamflow and landforms (Keesstra, 2007). Soil erosion is also reduced by the effect of the vegetation cover and the recovery of organic matter (Cerdà et al., 2018). Many studies confirmed the positive impacts of soil and water conservation practices on soil physicochemical properties and crop yields.



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Guadie et al. (2020) in Ethiopia, Novara et al. (2019) in Italy, and Keesstra et al. (2012) in the Netherlands found how relevant management is to control soil and water losses.

Human activities like burning fossil fuels and land-use changes help increase greenhouse gas concentrations that lead to climate change. Climate change has shown its impacts on water resource availability and management throughout the world (V. P. Singh et al., 2014). These changes affect the hydrological cycle's critical components such as streamflow, the base flow that alters the transformation and movement characteristics of sediment and other non-point source pollutants. There exist many uncertainties in the assessment of possible impacts of future climate changes on the hydrological cycle. The Intergovernmental Panel on Climate Change (IPCC) affirms that the Earth's climate is warming (Pachauri et al., 2014). However, hindcast modeling likely has less uncertainty and can be used to assess the climate change impact and evaluate the effectiveness of BMPs (Alibuyog et al., 2009; Chaubey et al., 2010; Ghaffari et al., 2010). Both climate and land use land cover (LULC) change will be very dynamic this century (Chen et al., 2018; Farjad et al., 2017; Mishra et al., 2018). However, knowledge about the combined impacts of climate and LULC changes is still limited due to the small amount of comprehensive research (Aboelnour et al., 2019; Bussi et al., 2016; Giri et al., 2019; Luetzenburg et al., 2020; Woldeesenbet et al., 2018). Land cover change due to deforestation also has an adverse impact on the streamflow generation and flood hazard in the basin (Khaleghi, 2017).

The world population is expected to rise by 9.7 billion by 2050 for which to meet the food demand; global agricultural output will need to increase by as much as 70%; hence, to meet greater global demands by ensuring increased crop production, as well as the availability of water for competing demands, improvement in the management of water, sediment, and nutrients under future changes in climatic conditions, are needed.

In contrast, its implication concerning the climate change scenario makes it more complicated. Remote sensing and geographical information system (GIS)-based hydrological modeling simplifies the process and evaluates it for proper decision and policymaking (Dayal et al., 2021; Thakur et al., 2020). Hydrological models are design or handling tools to answer those questions (V. P. Singh & Woolhiser, 2003). Some of the hydrological models used for the effectiveness of BMP are Capacity MIKE-SHE, soil and water assessment tool (SWAT), and Water Erosion Prediction Project (WEPP) models. MIKE\_SHE and SWAT are the comparatively similar hydrological model, but the first one is propriety, whereas the SWAT model is free to use. WEPP model is data-intensive, so it was also not used in this study. SWAT is selected for ease of use, and its capability in simulating the impact of different management scenarios. Among various hydrological models, the SWAT model was used by several researchers to

evaluate hydrological regimes under different agro-climatic regimes (Pandey & Palmate, 2019; Swain et al., 2018). SWAT is a physically based, semi-distributed, and continuous-time model that simulates the water and sediment yield in basins over long periods. Rainfall and temperature are the two most essential climate variables in the SWAT model because they significantly impact various water balance components. Other variables do not have such a significant impact on the hydrology of an area. Apart from climatic variables, soil classes and soil textures also significantly impact the streamflow of a watershed. Sandy soils allow a high water infiltration rate and produce less streamflow, while soils consisting of poorly drained clay soils allow a low infiltration and produce more streamflow (Haan et al., 1994). Soil characteristics have a considerable variability and a significant effect on the hydrological cycle's different components, such as groundwater discharge (GWQ) and soil water content (SW) of the watershed. (Bouslihim et al., 2019). One of the challenging issues in watershed management is the sedimentation process during the high streamflow period and sediment concentration with streamflow. Hosseini and Khaleghi (2020) and Varvani et al. (2019) reported high uncertainty in sediment flow simulation using the SWAT model and attributed this to the climatic and geological factors and the weakness in the model simulation. Farajzadeh and Khaleghi (2020) developed the regional erosion model using GIS and a rainfall simulator. Sediment rating curves (SRCs) have been recognized as the most popular method for estimating sediment in hydrology, and multivariate SRCs have better efficiency than the univariate SRCs (Varvani & Khaleghi, 2019).

BMP techniques are efficient measures to improve basin health and agricultural land productivity with a minimal negative impact on the environment (Uniyal et al., 2020). The practical application of the BMPs for the proper management of the river basin is difficult and time-consuming. For agricultural watersheds, SWAT is especially well suited for assessing the impact of future climate change scenarios on streamflow and accurately evaluating BMPs to assess pollutant load reduction (Boufala et al., 2021; Van Liew et al., 2012). Several researchers worldwide assessed the effectiveness of BMPs using the SWAT model and reported the model's satisfactory performance (Bosch et al., 2013; Himanshu et al., 2019; Jeon et al., 2018; Park et al., 2014; Senent-aparicio & Srinivasan, 2019; Uniyal et al., 2020; Wang et al., 2018). We know that all basins and sub-basins have different characteristics, and their response to anthropogenic and natural changes also varies, so it is important to model a variety of basins to understand complex flow and sediment transportation processes for the evaluation of BMPs. BMP performance varies both spatially and temporally by changing climate scenarios (Woznicki & Pouyan Nejadhashemi, 2014). Very few studies have been conducted focusing on the effectiveness of BMPs under the climate change uncertainties in Indian conditions. This study

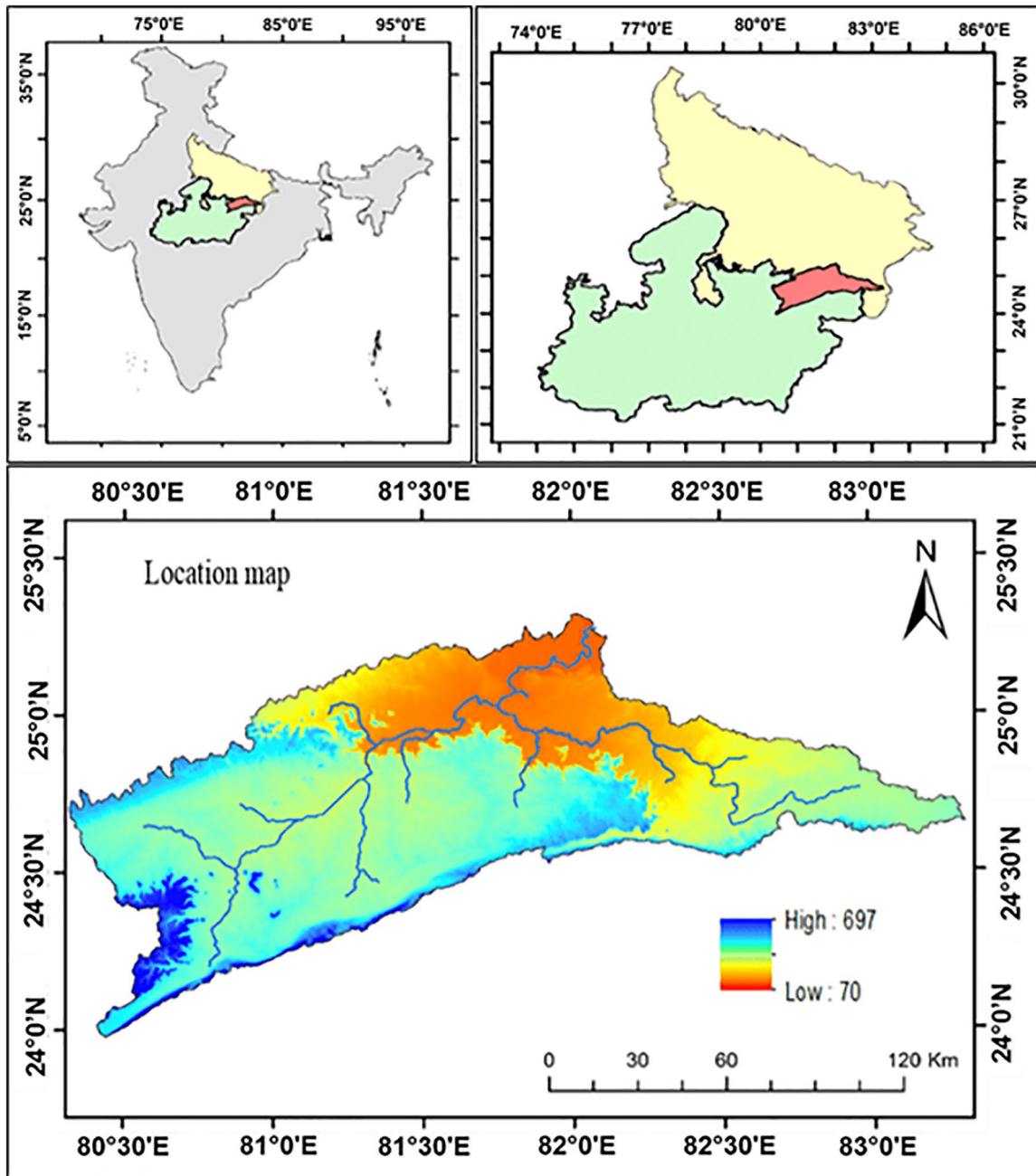


Figure 1. Study area of Tons river basin.

prioritizes critical areas in the river basin and future climate scenario analysis using the SWAT model that aids in river basin planning and management. SWAT model was employed to simulate the water balance components for future scenarios in the 2040s (2031–2050), 2070s (2061–2080), and 2090s (2081–2099) and was compared against the baseline period (1984–1999). Similarly, implementing the seven different BMPs individually for present and future scenarios was performed, and their effectiveness was evaluated based on the percentage reduction in sediment yield. For future climate change projections, precipitation, and temperature data of the Coordinated Regional Downscaling Experiment (CORDEX) South Asia Regional climate model (RCM)-ACCESS 1.0 for

Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios has been used.

### Material and Methods

#### Study area

The Tons river basin is selected as a case study area, and its geographic extent lies between 23° 57'–25° 20' N latitude and 80° 20' E–83° 25' E longitudes (Figure 1). Tons river/Tamsa river originates from Kamore hills in the Satna district of Madhya Pradesh and flows through Madhya Pradesh (M.P.) and Uttar Pradesh (UP) in the central part of India, finally joining River Ganga as its tributary near Sirsa. The Tons river



basin has a great significance to states Madhya Pradesh and Uttar Pradesh in India, concerning water resources aspects and the ecological balances (Kumar et al., 2017). Tons basin is dominated by agricultural land use. The region has a poor agricultural yield, mainly due to the rain-fed agricultural cropping system. In a large part of this region, only one crop is produced due to poor groundwater availability and lack of irrigation facilities (Darshana et al., 2013). This river basin is dominated by agricultural area with a total drainage area of around 17,500 km<sup>2</sup>, out of which 11,974 km<sup>2</sup> lies in M.P., and the rest lies in UP. Total average annual rainfall ranges between 930 and 1,116 mm, while 90% of the rainfall occurs during June to September, and the temperature varies from 46°C in summer to 5°C in the cold season (Duhan et al., 2013). It has undulating topography with land slopes ranging from 0% to 43%, but most areas fall under a gentle plain slope of less than 5%. The Tons river basin is a dominant agricultural watershed with more than 63% coverage of cropland. Agricultural dominant major crops cultivated within the basin are paddy, wheat, soybean, millet, and pulses. The basin's soil type can be classified mainly under sandy clay loam, clay loam, and sandy loam.

#### Data set

Recorded meteorological data for daily precipitation and temperature for the baseline period (1980–1999) were obtained from the Indian Meteorological Department (IMD), Pune. Other meteorological parameters, viz., relative humidity, wind speed, and solar radiation, were downloaded from the SWAT's Global weather database. Daily discharge data measured at the Meja road gauge outlet was collected from the Central Water Commission (CWC) for 1980–1999. A digital soil map prepared by the Food and Agriculture Organization (FAO) soil data ([www.fao.org](http://www.fao.org)) was adopted. Similarly, Decadal Land Use and Land cover classification map for 1995 was prepared using Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) (<https://daac.ornl.gov>). The Earth Explore website (<https://earthexplorer.usgs.gov/>) was used to download Shuttle Radar Topography Mission (SRTM, 30 m spatial resolution) Digital Elevation Model (DEM) data. Furthermore, precipitation and temperature data for future simulations were downloaded from CORDEX South Asia RCM ACCESS 1.0 for both the emission scenarios of RCP 4.5 and RCP 8.5 from the website (<https://cordex.org/>). These data were bias-corrected and adjusted using the Quantile Mapping method through Climate Data Bias Corrector (CDBC) tool.

#### SWAT model set up

The SWAT model envisaged the hydrological cycle's important components in this study. The governing water balance equation (1) is given below

$$SW_t = SW_o + \sum_{i=1}^n (R - Q - ET - W_{seep} - Q_{gw}) \quad (1)$$

where  $SW_t$  is the final soil water content (mm),  $SW_o$  is the initial soil water content (mm),  $t$  is time in days,  $R$  is precipitation (mm),  $Q$  is surface streamflow (mm),  $ET$  is the evapotranspiration (mm),  $w_{seep}$  is percolation (mm), and  $Q_{gw}$  is return flow (mm). The SWAT model used the Natural Resources Conservation Service Curve Number method and Penman–Monteith method to assess surface streamflow and potential evapotranspiration, while the Muskingum method simulates channel routing.

The ArcSWAT interface carried out SWAT model configuration and parameterization. The spatial layers such as DEM, land use land cover, soil, and slope maps are required for parameterization of the SWAT model and are presented in Figure 2. For the SWAT model setup, daily precipitation and temperature data were required. Delineation of the river basin and subsequent analysis of drainage pattern in the basin has been carried out using SRTM DEM. The study basin was divided into 23 sub-watersheds integrated with land use/cover and soil layers that led to 575 hydrological response units (HRUs). HRUs are the basic simulation units based on which the SWAT model simulates the hydrological processes. For initial soil water conditions balance, model simulations were carried out initially for the 4-year warm period of 1980–1983 at a daily time scale. The simulation period (1984–99) was taken as a baseline period based on the availability of measured discharge at the river basin's outlet. Therefore, the SWAT model was calibrated and validated for this period, and this has been taken as a base for comparison of the BMP's. Three future scenarios have been considered in this study, which are the 2040s (2031–2050), 2070s (2061–2080), and 2090s (2081–2099).

#### Sensitivity analysis and calibration

The model sensitive analysis is necessary to identify the most sensitive parameters and reduce the redundancy of parameters during model calibration and simulation. SWAT-Calibration and Uncertainty Programs (SWAT-CUP) are the most popular tools used for sensitivity analysis of the parameters. One alternative of SWAT-CUP is IPEAT (Integrated Parameter Estimation an Uncertainty Analysis Tool) (Yen et al., 2019). IPEAT has not been used in this study because it is recently developed and not much used in previous literature. Some of the algorithms used for uncertainty and calibration are Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), sequential uncertainty fitting (SUFI-2) algorithm, and a Bayesian framework implemented using Markov chain Monte Carlo (MCMC) and Importance Sampling (IS) techniques. Among these, GLUE is convenient and easy to implement, and widely used in hydrology. This

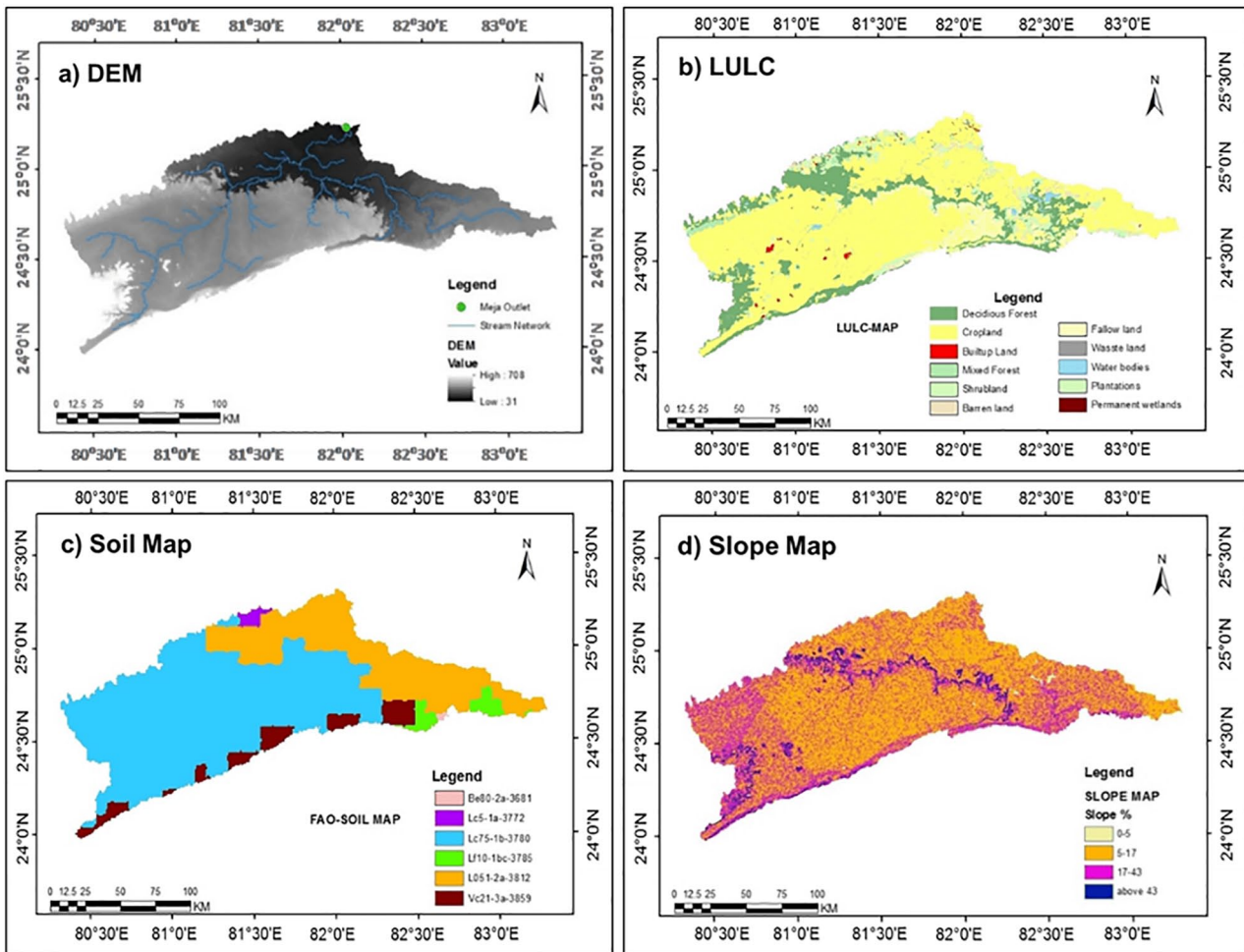
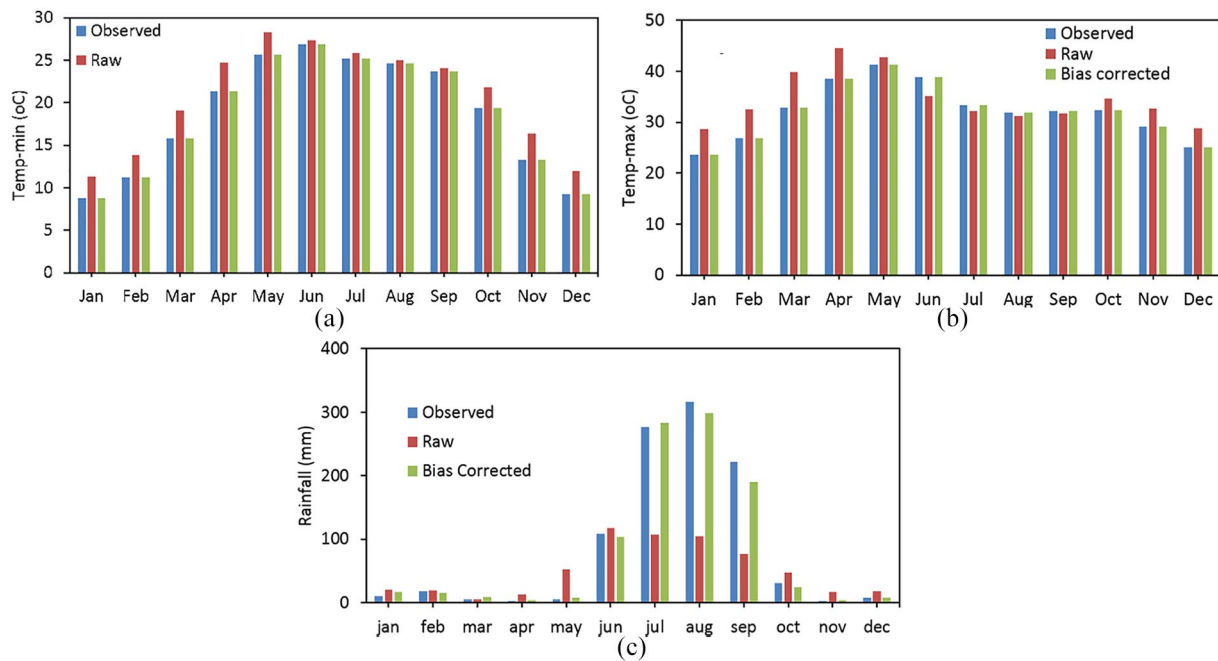


Figure 2. Raster input maps.

approach’s drawback is its prohibitive computational burden imposed by its random sampling strategy (Hossain et al., 2004). In this study, because of the high potential and efficiency of the SUFI-2 program (Abbaspour et al., 2007) for time-consuming large-scale models, it was implemented for sensitivity analysis, model calibration, and validation, and uncertainty analysis in the SWAT-CUP program. SWAT-CUP provides two options for the sensitivity analysis, namely All-At-a Time (AAT), that is, global, and One-At-a-Time (OAT) sensitivity analysis (Abbaspour et al., 2015). Moriasi et al. (2007) provided model evaluation guidelines for hydrological models. Model evaluation techniques were divided into three categories: standard regression, dimensionless, and error-index. Some of the most popular statistics used in literature are slope and  $y$ -intercept, Pearson’s correlation coefficient ( $r$ ), coefficient of determination  $R^2$ , Nash–Sutcliffe efficiency (NSE), persistence model efficiency (PME), prediction efficiency ( $Pe$ ), logarithmic transformation variable ( $e$ ), mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE); percent bias (PBIAS), RMSE-observations standard deviation ratio (RSR), and daily root mean square (DRMS). Based on the literature review on the model application, Moriasi et al. (2007) recommended three quantitative statistics, NSE,

PBIAS, and RSR. The  $t$ -stat provides a measure of sensitivity (large absolute value is more sensitive). The  $p$  value determines the significance of the sensitivity (a value close to 0 has more significance). It is observed that the parameter with the largest  $t$ -statistic value is the most sensitive parameter in SWAT-CUP sensitivity analysis results. There are negative and positive  $t$ -statistic values. The  $p$  value for each term tests the null hypothesis that the coefficient is equal to 0 (no effect). A low  $p$  value ( $<.05$ ) indicates that you can reject the null hypothesis. A larger  $p$  value suggests that the parameter is not very sensitive. Confidence intervals, Bayesian methods, effect sizes are alternatives for  $p$  values and  $t$ -stat (Denis, 2003). Global sensitivity analysis is determined based on  $t$ -stat and  $p$  value. The higher the absolute  $t$ -stat value and the smaller the  $p$  value, the parameters are assumed to be more sensitive (Abbaspour et al., 2015). Based on the sensitive parameters model, it has been calibrated and validated daily for discharge only. The SWAT model was run for the calibration period of (1984–1994) and the validation period of (1995–1999) with a warmup period of (1980–1983). Performance of the SWAT model was carried out by various statistical parameters such as NSE, percentage bias (PBIAS), coefficient of determination ( $R^2$ ), RMSE, and standard deviation ratio (RSR).



**Figure 3.** Comparison of ACCESS 1.0 climate historical data with the observed data: (a) minimum temperature, (b) maximum temperature, and (c) rainfall.

#### *Comparison of ACCESS-1.0 climate data with the observed data*

Downloaded raw data for minimum temperature shows the mild or no change compared to the observed data for the wet months from June to September. Similarly, during those wet months, mild change from July to September, whereas the maximum temperature decreased by  $3.69^{\circ}\text{C}$  in June. There was an increase of  $2.44^{\circ}\text{C}$ – $3.34^{\circ}\text{C}$  for the minimum temperature and a rise of  $1.48^{\circ}\text{C}$ – $7.07^{\circ}\text{C}$  for maximum temperature in the remaining months. All these changes were consistently balanced after the bias correction in both maximum and minimum temperature, as shown in Figure 3. Rainfall being the complex process of formation, observed rainfall was not reasonably captured by neither downloaded raw data nor the bias-corrected rainfall data. Average annual rainfall was under-predicted by  $41.91\text{ mm}$  ( $4.165\%$ ) from the observed average annual rainfall. There was a significant underprediction of rainfall by  $31.97$  and  $17.08\text{ mm}$  in September and August, respectively, during the wet months from June to October.

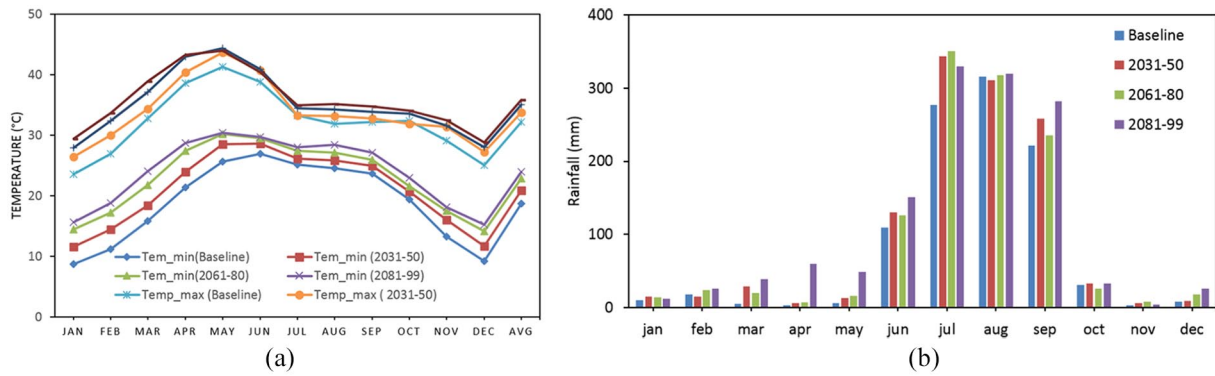
#### *Climate changes compared to baseline*

The projected mean monthly minimum temperature for the future climate scenarios of CORDEX South Asia RCM-ACCESS-1.0 for the periods the 2040s (2031–2050), 2070s (2061–2080), and 2090s (2081–2099) indicate an increase of  $2.13^{\circ}\text{C}$ ,  $4.12^{\circ}\text{C}$ , and  $5.17^{\circ}\text{C}$ , for the respective scenarios. Mean monthly maximum temperature increases by  $1.6^{\circ}\text{C}$ ,  $2.94^{\circ}\text{C}$ , and  $3.6^{\circ}\text{C}$  for those respective scenarios (Figure 4). These increments are found to be similar to the projections of

Narsimlu et al. (2013). Average monthly precipitation for future scenarios compared to the baseline period shows an increasing trend in the rain by  $16.25\%$  in the 2040s and a slightly decreasing trend in the 2070s ( $15.55\%$ ), and then a significant increasing trend by  $32.09\%$  in the 2090s.

#### *Identification of critical prone areas and BMP implementation*

The poor land use management and the lack of appropriate soil conservation measures are among the most critical threats to sustainable agriculture and watershed management worldwide. Rainfall- and streamflow-induced erosion from watersheds and farm fields produce major non-point source pollutants for many significant environmental resources. Riverbank erosion and the associated rise of channel beds can lead to a diminished flow capacity and higher vulnerability to floods. Land degradation caused by the acceleration of agricultural activities, deforestation, and urbanization remove fertile topsoil, resulting in a decrease in agricultural productivity. Predictions of streamflow and sediment yield support decision-makers in developing watershed management plans for better soil and water conservation measures (Setegn et al., 2010). Therefore, in this study, the quantity and rate of streamflow and sediment transport from the land surface into streams and rivers for better river basin management has been modeled. Critical sub-watersheds prone to soil erosion were identified and subsequently prioritized based on the average annual sediment yields modeled for both present (baseline period) and future scenarios as per the criteria suggested by G. Singh et al. (1992). BMPs implemented to those critical sub-watersheds in this study were recharge structure, contour farming, filter strip of  $3\text{ m}$  and  $6\text{ m}$ ,



**Figure 4.** (a) Comparison of the future climate with the baseline for (a) average monthly minimum and maximum temperature and (b) average monthly rainfall.

**Table 1.** BMPs Input Parameters.

S. NO.	BMPs	PARAMETERS INPUT	PRE-BMP	POST BMP VALUES
1	Contour farming	CN2.mgt	Varies	-3
		USLE_P.mgt	1	slope 0%–5% = .55 Slope 5%–17% = .65
2	Porous gully plugs	CH_N1.sub	.014	.05
3	Recharge structures	CH_K1.sub	0	25
		CH_N1.sub	.014	.08
4	Filter strip (3 and 6 m)	FILTERW.mgt	0	3 and 6
5	Conservation tillage	DEPTIL (.till)	150	100
		EFFMIX (.till)	.95	.25
		CN2.mgt	varies	-2
6	Zero tillage	DEPTIL (.till)	150	25
		EFFMIX (.till)	.95	.05
		CN2.mgt	varies	-3

BMP: best management practices.

gully plugs, zero tillage, and conservation tillage operations. The summary of the BMPs and the modeled parameters in ArcSWAT has been presented in Table 1 (Tuppad et al., 2011). The methodology flowchart for the evaluation of BMPs is given in Figure 5.

## Results and Discussion

### Sensitivity analysis

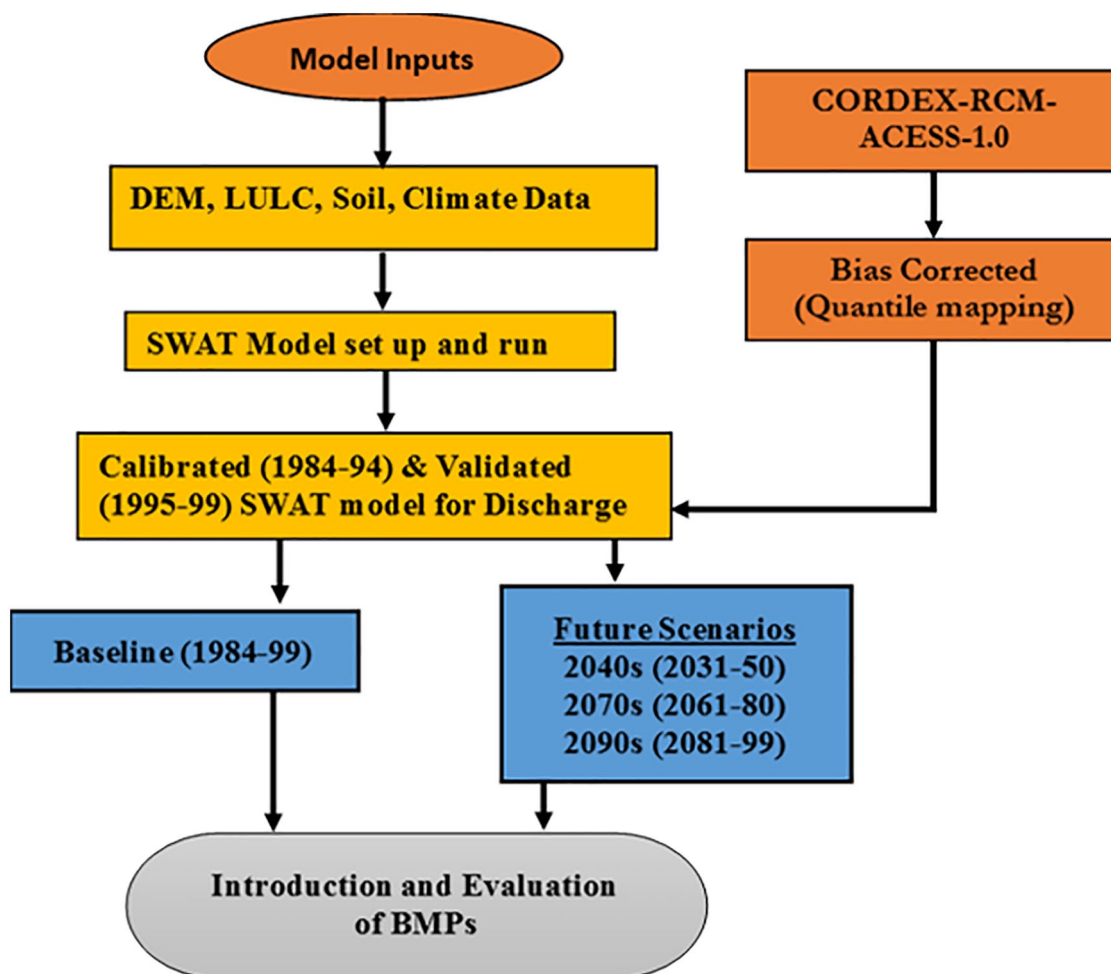
Based on the literature and relevance of parameters in stream-flow and sediment yield modeling, a total of 24 parameters were selected for sensitivity analysis. Finally, after sensitivity analysis, 14 parameters were found to be having a significant impact on modeling results. Other key parameters which have not been included in the study are due to their insignificant impact on discharge and sediment yield. The selected parameters are highly sensitive to discharge and sediment yield.

SWAT-CUP/SUFI-2 algorithm-based global sensitivity analysis with a 1,000-time run recommended by Abbaspour et al. (2015) was carried out with 24 parameters that influence the discharge at the river basin outlet. Global sensitivity analysis identified 14 parameters as sensitive with high absolute *t*-stat and minimum *p* value (Table 2). The list of parameters was similar to those reported by Himanshu et al. (2017) and Suryavanshi et al. (2014) for the Indian river basins.

### Evaluation of SWAT model performance

Initially, optimization of 14 sensitive parameters was carried out using SWAT-CUP 2019 for the calibration period (1984–1994), followed by model validation for 1995–1999. The SWAT model’s performance was evaluated for both calibration and validation periods, daily and monthly scales for the Meja road gauge station (Figure 6). Typically, model simulations are





**Figure 5.** The methodology adopted for evaluation of BMPs.

poorer for shorter time steps than for more extended time steps (e.g., daily versus monthly or yearly) (Engel et al., 2007; Larose et al., 2007). The reason for this could be because the monthly totals tend to smooth the data, which, in turn, results in a better simulation of the streamflow (Spruill et al., 2000). Model performance evaluation criteria are presented in Table 3. The graphical comparison shows that the model usually under-predicted the peak flow during both calibration and validation periods daily while indicated a good response at a monthly scale. NSE values of .77 and .93 during calibration and values of .79 and .93 during validation were obtained at daily and monthly scales, respectively. This result shows that the model's performance during calibration and validation is reasonably good, and the model can simulate the streamflow close to the observed streamflow. Similarly, for calibration of discharge on daily and monthly scales, the obtained values of PBIAS were -8.06 and -7.89, respectively. However, for daily and monthly validation, its value was 6.73 and 6.65 during validation at daily and monthly scales, respectively, indicating that the SWAT model underestimated the discharge during calibration and overestimated the streamflow during validation.

Furthermore, to visually analyze these results on daily and monthly scales, scatter plots of the observed and modeled

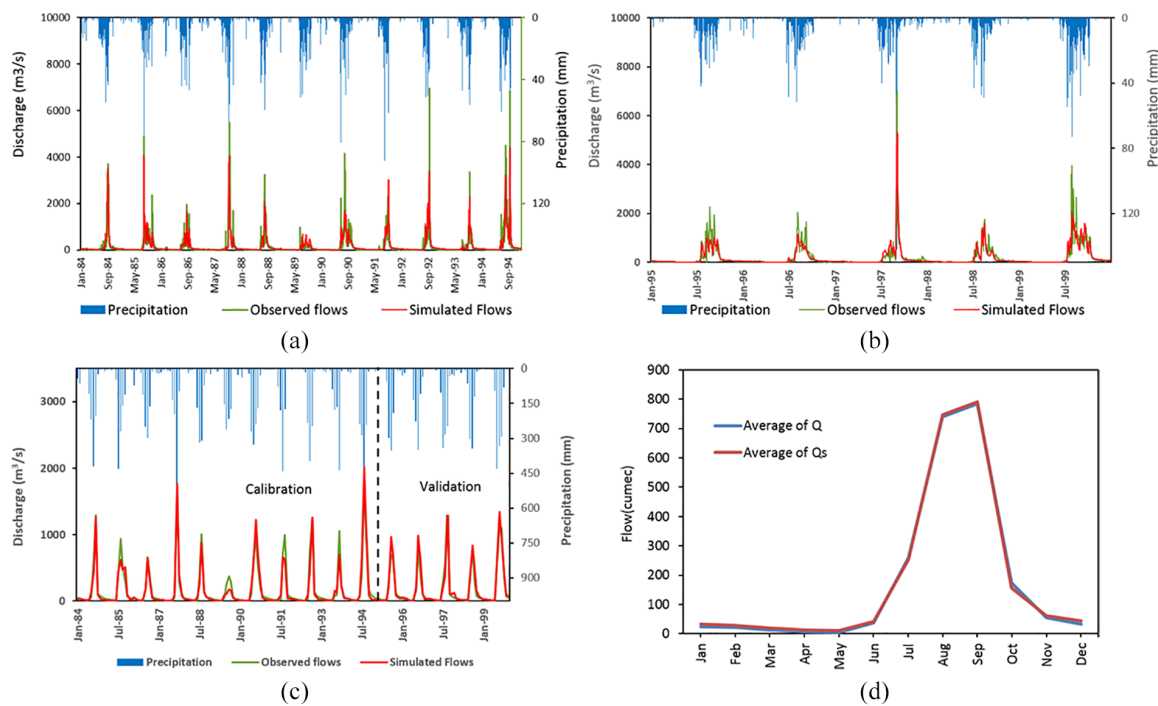
discharge were drawn (Figure 7). Based on the recommendation criteria provided by Moriasi et al. (2007); ( $NSE > .75$ ;  $PBIAS < \pm 10\%$  and  $RSR < .5$ ), the overall SWAT model performance for the study river basin area is found to be very good during both the calibration and validation periods.

#### *SWAT water balance components*

In the study area, hydrological water balance over the entire baseline period (1984–1999) was carried out employing the calibrated and validated SWAT model (Figure 8). It was noticed that evapotranspiration is more predominant in the basin, which accounts for about 59.03% of the average annual rainfall, which is 1,006.7 mm. Approximately 22.22% of rain flows out of the basin as surface streamflow. The average annual water balance chart month-wise presented in Table 4 shows that about 94% of the yearly rainfall occurs within 4 months from June to October, whereas about 90% of the annual streamflow flows out. Evapotranspiration was highest in August with a value of 115.71 mm. Model simulations for sediment load exhibited a similar trend as streamflow simulation, where higher values are reported during August and September. Sub-basin wise distribution of the major water balance components is presented in Figure 9.

**Table 2.** Sensitive Parameters Identified Through Global Sensitivity Analysis.

RANK	SENSITIVE PARAMETERS	SHORT DESCRIPTION	T-STAT	P VALUE	DEFAULT RANGE	FITTED VALUE
1	CN2.mgt	Initial Soil Conservation Service (SCS) streamflow curve number	33.22	0	-.25 to .25	-.08
2	ALPHA_BNK.rte	Base flow alpha factor for bank storage	-18.02	0	0 to 1	.99
3	CH_K2.rte	Effective hydraulic conductivity in main channel	-9.01	0	0 to 500	300
4	GW_REVAP.gw	Ground water revap coefficient	-5.29	0	.02 to .2	.05
5	CH_N2.rte	Manning's <i>n</i> value for the main channel	-5.22	0	0 to .3	.023
6	ESCO.hru	Soil evaporation compensation factor	-2.45	.01	0 to 1	.6
7	EPCO.hru	Plant uptake compensation factor	1.84	.07	0 to 1	.7
8	ALPHA_BF.gw	Base flow alpha factor	-1.32	.19	0 to 1	.25
9	CANMX.hru	Maximum canopy storage	1.11	.27	0 to 100	40
10	OV_N.hru	Manning's <i>n</i> value for overland flow	.90	.15	0 to 23	1.4
11	GW_DELAY.gw	Ground water delay time	.88	.24	0 to 500	.5
12	RCHRG_DP.gw	Deep aquifer percolation factor	-.73	.25	0 to 1	.36
13	SOL_AWC().sol	Available water capacity of soil layer	.65	.24	-.25 to .25	.23
14	SOL_BD.sol	Moist bulk density	.61	.16	1.1 to 1.9	1.4



**Figure 6.** (a) Daily flow comparison (calibration), (b) daily flow comparison (validation), (c) monthly flow comparison (calibration + validation), and (d) average monthly flow comparison.

*Impact on hydrology compared to baseline*

Projected average monthly streamflow for the future years of 2031–2050, 2061–2080, and 2081–2099 for both scenarios of RCP 4.5 and 8.5 are shown in Figure 10. The future flows follow a similar pattern of the observed flow except for future scenarios (2081–2099) and (2061–2080) for RCP 4.5 and may

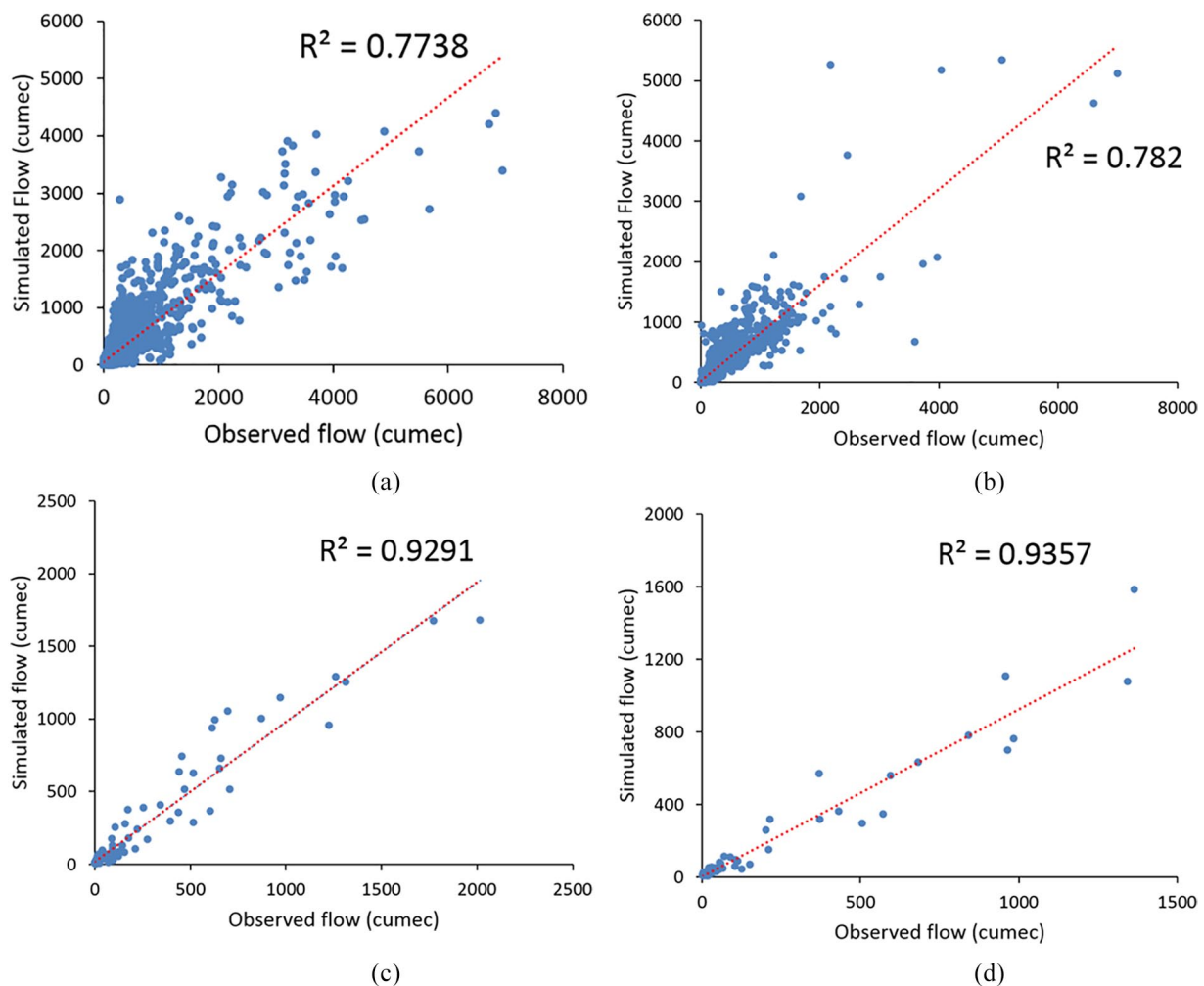
be due to the uncertainty in the climate data prediction. While for RCP 8.5 scenarios, the results have been reliable, so most of the analysis has been carried out under the RCP 8.5 scenarios. The SWAT simulated annual water budget components compared with the baseline period has been presented in Table 5.

This illustrates that the streamflow is also following the pattern traced by the rainfall, that is, the increasing trend at

**Table 3.** SWAT Model Evaluation Statistics.

TOTAL STREAM FLOW					
S. NO.	EVALUATION STATISTICS	DAILY		MONTHLY	
		CALIBRATION	VALIDATION	CALIBRATION	VALIDATION
1	NSE	.77	.79	.93	.93
2	PBAIS	-8.06	6.73	-7.89	6.65
3	R <sup>2</sup>	.77	.78	.93	.94
4	RSR	.48	.46	.27	.26

SWAT: Soil and Water Assessment Tool; NSE: Nash-Sutcliffe efficiency; RSR: RMSE-observations standard deviation ratio; PBAIS: Percent bias.



**Figure 7.** (a, b) Scatter plots of daily observed flow versus simulated flow and (c, d) scatter plots of monthly observed flow versus simulated flow.

the 2040s by 30.23%, slightly decreasing in 2070s by 20.19%, and increase in the 2090s by 57.94% compared to baseline. The maximum of 93.5% increment in end-century was concluded by Narsimlu et al. (2013). Sediment yield from the basin has also been found to be increased by 26.42% in 2031–2050, then only by 10.95% in 2061–2080, and again by 28.32% in 2081–2099. Different from them, evapotranspiration has been found to have an increasing trend in all three future scenarios.

#### *Identification and prioritization of critical areas*

Sediment yield data from a watershed is useful in many ways. It helps us to identify and prioritize the crucial watershed among others in the basin and aids in planning and managing the structural and agricultural BMPs of the basin. So it is a common practice to use average annual sediment yield data in the identification and prioritization of critical watersheds in the basin. The average annual sediment yield of the basin for

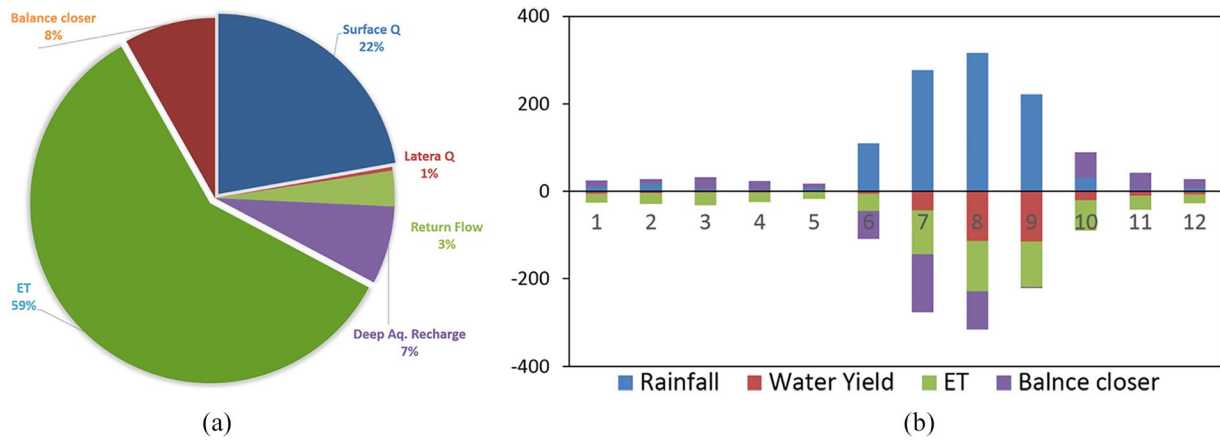


Figure 8. (a) Average annual SWAT water balance and (b) balance chart for the baseline period.

Table 4. Annual Water Budget for Future.

SCENARIO PERIOD	RAINFALL (MM)	STREAMFLOW (MM)	ET (MM)	SED YIELD (T/HA)
Baseline	1,006.49	329.33	594.12	6.85
2040s (2031–2050)	1,170 (16.25%)	428.87 (30.23%)	665.76 (12.06%)	8.66 (26.42%)
2070s (2061–2080)	1,163.04 (15.55%)	395.83 (20.19%)	688.96 (15.96%)	7.6 (10.95%)
2090s (2081–2099)	1,329.48 (32.09%)	520.14 (57.94%)	729.23 (22.74%)	8.79 (28.32%)

ET: evapotranspiration.

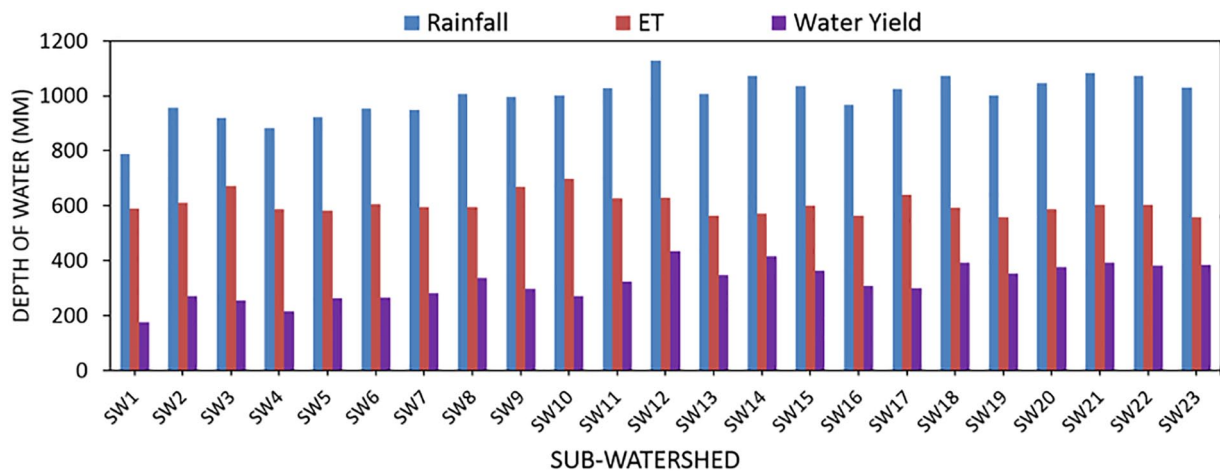


Figure 9. Spatial distribution of the water balance components.

the baseline period was 6.85 ton/ha, which increased to 8.66 and 8.79 t/ha in future scenarios of 2031–2050 and 2081–2099, respectively. For future scenarios, the maximum possible sediment yield that could occur in each sub-basin was analyzed, and the spatial distribution of sediment was plotted, as shown in Figure 11. Based on the sediment yield data, the sub-basin were classified in to different categories of soil erosion classification as recommended by G. Singh et al. (1992), namely slight (0–5 ton/ha/yr), moderate (5–10 ton/ha/yr), and high (10–20 ton/ha/yr) erosion classes. It was adopted to assign the priority levels of I–III (Table 6).

The results clearly show that slight erosion and moderate erosion class may decrease in the future. However, there may be an increase in the high erosion class from 16.07% to 53.61%. It necessitates to take up proper BMPs in the high erosion-prone areas. In an earlier study by Himanshu et al. (2019), high erosion-prone regions were considered to implement and evaluate BMPs. Similarly, all total 10 sub-watersheds, namely SW-8, SW-10, SW-12, SW-13, SW-14, SW-17, SW-19, SW-21, SW-22, and SW-23 falling under high erosion class, are considered as a critical prone area for the implementation and evaluation of BMPs.



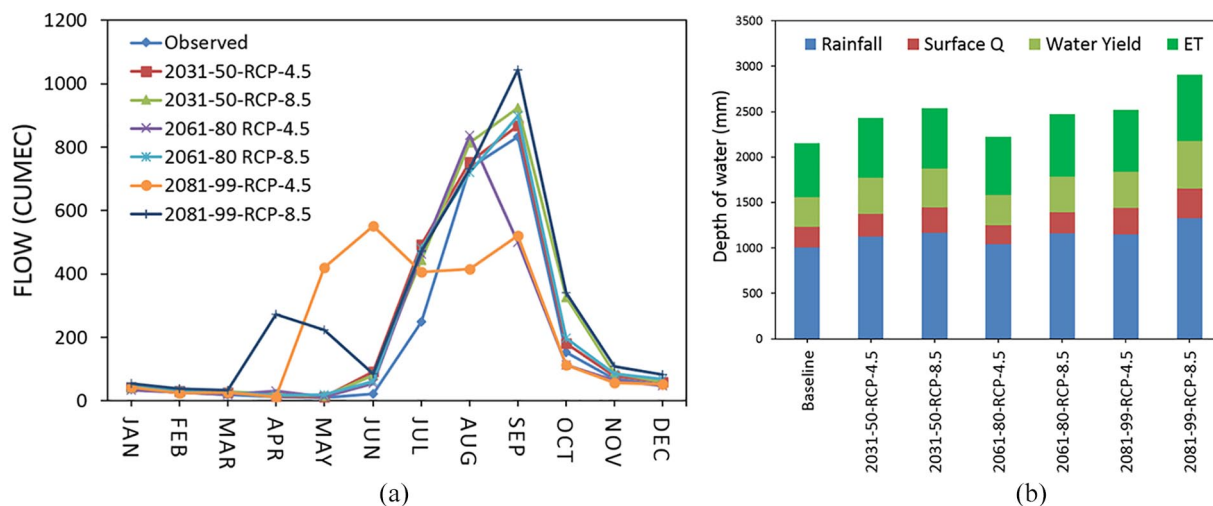


Figure 10. Future hydrology (a) comparison of future streamflow and (b) comparison of future water balance chart.

Table 5. Average Annual Water Balance: Monthly Break Up.

MONTH	RAINFALL (MM)	SURFACE STREAMFLOW (MM)	WATER YIELD (MM)	ET (MM)	SEDIMENT (TON/HA)
January	10.41	.01	5.17	20.36	0
February	17.89	.15	3.62	24.69	0
Mar	4.79	0	2.88	29.16	0
April	2.9	0	2.04	21.9	0
May	5.59	0	1.55	16.31	0
June	108.84	6.36	5.14	39.2	.11
July	276.65	47.28	43.28	101.42	1.19
August	316.17	90.05	112.83	115.71	2.85
September	221.61	75.51	115.54	103.05	2.57
October	31.05	4.18	20.52	68.87	.13
November	3.04	0	9.52	32.78	0
December	7.55	.1	7.24	20.67	0
Annual	1,006.49	223.64	329.33	594.12	6.85

ET: evapotranspiration.

### Evaluation of BMPs

In this study, seven BMPs, namely recharge structure, contour farming, filter strip 3 & 6 m, porous gully plugs, zero tillage, and conservation tillage operation, were evaluated for the soil and water conservation treatment in the Tons river basin. Each of the BMPs was analyzed individually for both the present baseline and future scenarios of the 2040s, 2070s, and 2090s. The percentage reduction on the sediment yield was determined and plotted, as presented in Figure 12. Compared to the baseline period analysis, the effectiveness of BMPs has been found to decrease slightly for future 2040s, increase in 2070s,

and decrease in 2090s. An increasing trend in the 2040s, a declining trend in the 2070s, and a rising trend in the 2090s were observed in the case of sediment yield. Prioritization of the BMPs concerning the percentage reduction basis was carried out initially with recharge structure followed by other BMPs such as filter strip-6 m, contour farming, filter strip-3 m, gully plugs, zero tillage, and conservation tillage operations.

Recharge structure appeared to be the most effective measure with a maximum reduction of sediment by 38.98% during the baseline period and a 37.15% reduction in the future scenario. Specifically, all sub-watersheds except three sub-watersheds (SW-10, SW-21, and SW-22) indicated the highest

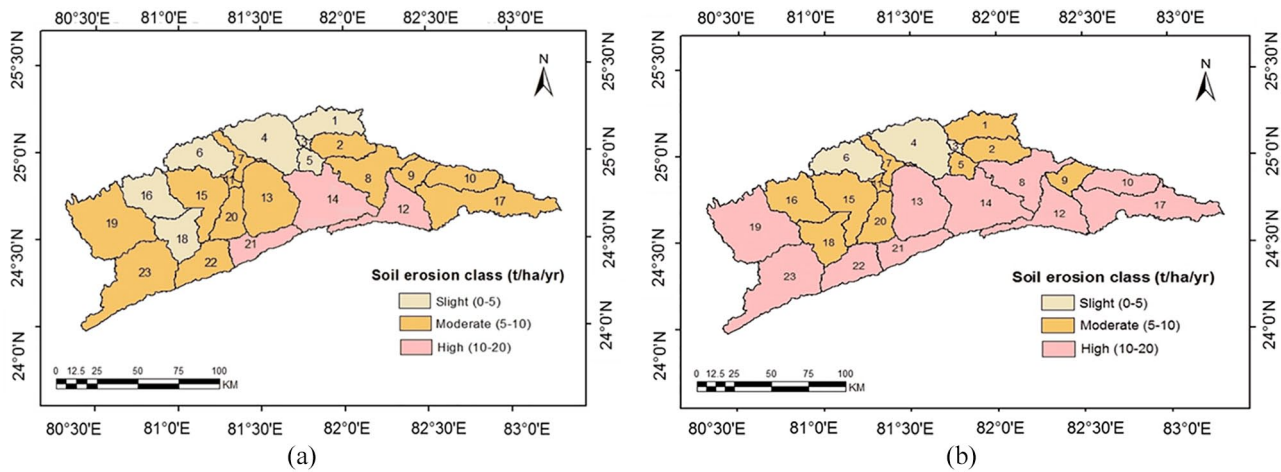


Figure 11. Spatial distribution of the sediment yield (a) baseline period and (b) future period.

Table 6. Categorization of the Sub-Basin as per the Sediment Yield.

SEDIMENT YIELD (TON/HA/YR)	SUB-WATERSHED	AREA %	SOIL EROSION CLASS	PRIORITY CLASS
<b>Baseline</b>				
0–5	1,3,4,5,6,16,18	24.38	Slight	III
5–10	2,7–11,13,15,17,19,20,22,23	59.56	Moderate	II
10–20	12,14,21	16.07	High	I
<b>Future</b>				
0–5	6,4	11.69	Slight	III
5–10	1,2,5,7,9,11,15,16,18,20	34.70	Moderate	II
10–20	8,10,12,13,14,17,19,20,21,22,23	53.61	High	I

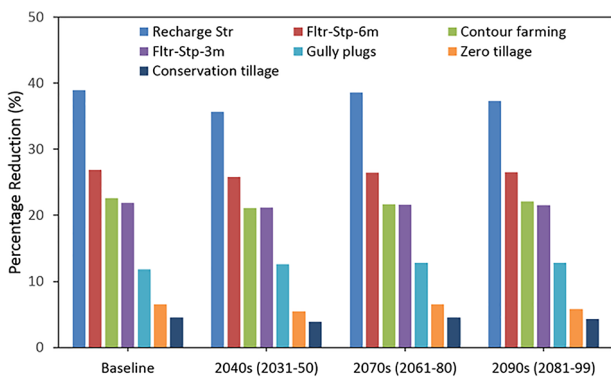


Figure 12. Effectiveness of BMPs in percentage reduction for present and future scenarios.

reduction in the sediment yield when simulations were carried out with this BMP (Figure 13). Percentage reduction vary from 11.00% at SW-21 to 82.59% for SW-19 (Figure 13). The high erosion category in pre-BMP covers 16.07% in baseline conditions and 53.61% in future scenarios, indicating the higher category’s transformation to slight and moderate categories after implementing these management practices (Table 7). This also

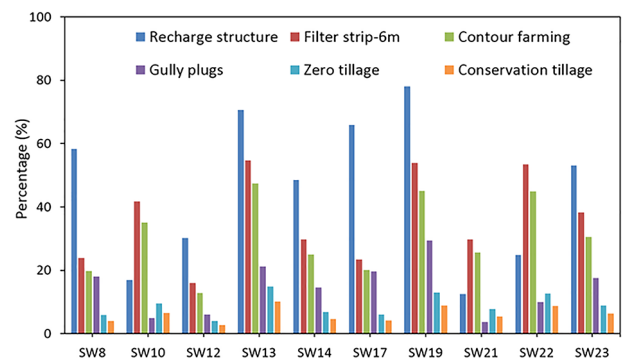


Figure 13. Effectiveness of BMPs in the critical sub-watersheds of Tons river basin.

notifies that the BMP effectiveness in the tributary channel is more dominant.

Implementation of filter strip of 3 and 6 m shows that filter strip of 3 m (21.9%) provides nearly the same amount of sediment reduction of 22.63% as provided by the contour farming. However, a filter strip of 6 m resulted in about 26.54% of sediment reduction in baseline and future scenarios. The baseline period filter strip of 6 m was found to remove the high erosion

**Table 7.** Changes Observed in the Erosion Classes Under Different BMPs in the Percentage of Area Basis.

BASELINE							
EROSION CLASS	PRE-BMP (BASELINE)	RECHARGE STRUCTURE	FILTER STRIP-6 M	CONTOUR FARMING	GULLY PLUGS	ZERO TILLAGE	CONSERVATION TILLAGE
Slight	24.38	65.31	63.57	55.05	41.11	24.38	24.38
Moderate	59.56	34.69	36.43	36.83	46.07	62.80	62.80
High	16.07	.00	.00	8.12	12.83	12.83	12.83
FUTURE							
EROSION CLASS	PER-BMP (FUTURE)	RECHARGE STRUCTURE	FILTER STRIP-6 M	CONTOUR FARMING	GULLY PLUGS	ZERO TILLAGE	CONSERVATION TILLAGE
Slight	11.69	45.88	41.85	41.85	22.08	22.08	22.08
Moderate	34.70	54.12	44.60	39.89	59.67	43.44	43.44

BMP: best management practices.

class, whereas, for the future scenario, it reduced that coverage area by 74.72%. Gully plugs effectiveness was found to be near about 12.0%, and two tillage operations; zero tillage and conservation tillage provides 6.57% and 4.53% reduction in the sediment yield. Change in the extent of three soil erosion classes demonstrated that the moderate class area was found to be increased during future scenarios. The slight erosion class area was increased in the baseline period to balance the high erosion class's decreased area. High erosion class from the coverage of 53.61% in future scenarios was brought to 0%, 13.55%, 18.25%, 18.25%, 34.48% after recharge structure, filter strip of 6 m, contour farming, gully plugs, and two tillage operations, respectively. These percentage reductions are within the percentage reduction of sediment yield as obtained by a different researcher, such as 71% reduction by the implementation of contour farming (López-Ballesteros et al., 2019); up to 37.2% reduction with the recharge structure (Tuppad et al., 2011), 51% reduction by the gully plugs (Park et al., 2014); 5.4%–6.8% reduction in case of conservation tillage and zero tillage, respectively (Himanshu et al., 2019); 25% reduction by the application of filter strip (Parajuli et al., 2008).

Our results can be compared to measurements carried out in other watersheds worldwide, and similar situations are found. In general, the use of vegetation covers such as the one generated when agricultural land abandonment occurs results in a reduction in soil and water delivery. Keesstra (2007) found a reduction in the sedimentation in the Dragonja basin in Slovenia due to the natural afforestation. These are called nature-based solutions, such as later (Keesstra, Nunes, Novara, et al., 2018; Uniyal et al., 2020) disseminated with examples from different regions. The role vegetation plays in agriculture and forest land is definitive at the watershed scale due to its impact on the connectivity of the flows (Keesstra, Nunes, Saco, et al., 2018). This has been intensively studied in vineyards by Rodrigo-Comino et al. (2018b) with traditional topographical measurements and fieldwork assessment and later with lidar

use (Rodrigo-Comino et al., 2018a; Rodrigo-Comino, Lucas-Borja, et al., 2020).

The basin and watershed behavior are determined by the impact of the management at the pedon scale. This is why farmers and forest users should apply the changes. The use of catch crops, straw mulches, chipped pruned branches and other covers such as plants and geotextiles are definitive to achieve the best management of the land to reduce sediments in the river discharge (Barrena-González et al., 2020(b); Cerdà et al., 2020; López-Vicente et al., 2020; Rodrigo-Comino, Terol, et al., 2020).

## Conclusion

Climate change and inefficient management of the basin may lead to an increase in land degradation. So soil conservation is one of the major tasks in sustainable basin management.

In this study, the SWAT model has been applied to evaluate the effectiveness of seven various BMPs for the present (1984–1999) and future 2040s (2031–2050), 2070s (2061–2080), and 2090s (2081–2099) scenarios. The study generated future scenarios using CORDEX South Asia RCM-ACCESS 1.0 for RCP 4.5 and RCP 8.5. SWAT model has been successfully calibrated and validated at daily and monthly time scales for simulation of streamflow and sediment. Evapotranspiration was the predominant water balance component for the baseline period, accounting for 59.03% of precipitation. However, 22.22% of rainfall flows out as surface streamflow.

In future, RCM-derived climate data, the minimum temperature rises from 2.13 °C to 5.17°C, and the increase in maximum temperature was 1.6°C to 3.6°C compared to baseline (1984–1999). Precipitation has an increasing trend in the 2040s, slightly decreasing in the 2070s, and increasing trend by 2090s. Streamflow and sediment followed a similar pattern.

Critical sub-watersheds have been identified, and the implementation and evaluation of BMPs have been performed

individually through the SWAT model. Recharge structure has been identified as the most effective BMP measure with a maximum reduction of sediment by 38.06%, followed by a filter strip of 6 m with 26.54%, and a contour farming with 22.07% considering both present and future. Compared to the baseline period, the effectiveness of BMPs is slightly decreasing in the future 2040s, increasing in the 2070s and decreasing in the 2090s. Recharge structure and filter strip 6 m have been found to nullify the high soil erosion class completely. Adaptation of these management practices will reduce one of the significant components of non-point source pollution, thus maintaining the natural and sustainable environment. These management practices could be applied to the basin, which has similar basin characteristics. A major limitation of this study was the unavailability of the sediment data for the validation of the sediment yield modeling results using SWAT. One of the other limitations of this study is that no consideration has been given to the cost involved in implementing these BMPs. The quality of work could have been improved if the recent data had been available. This study's analysis has carried out assuming constant LULC, whereas there is a rapid change in LULC affecting the basin characteristics. Therefore, it is recommended to consider temporal variation in LULC to develop a more realistic scenario for the evaluation of BMPs. This work's future scope can be the multiple criteria evaluation, including cost as an essential parameter to evaluate BMPs for better management of the basin. Optimization techniques could be applied to select BMPs, which are cost-effective and environment friendly. It is also recommended for the sediment load data collection on suitable locations to improve the efficacy of the BMPs.

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### Author Contributions

A.P. contributed in designing the study, writing, and developing the content of the manuscript. B.K.C. and P.K. contributed to the collecting and analyzing the data, hydrological modeling, and preparation of the manuscript. V.M.C., C.S.J., and A.C. contributed in interpretation and reviewing of the manuscript. All authors read and approved the final content of the manuscript.

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