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Application of SWAT Model for Hydrological Simulation of Rapti River Basin

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Authors' contributions

This work was carried out in collaboration among all authors. Author SK designed the study performed the statistical analysis and managed the literature searches. Authors VS and SS did data collection. All authors read and approved the final manuscript.

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ABSTRACT

This study aimed at application of SWAT model for hydrological simulations of Rapti River Basin (RRB) water systems. The Rapti River originates from Nepal and then it comes in India. SWAT (Soil and Water Assessment Tool) model was used for hydrological simulation of the RRB surface and sub surface water systems. SWAT is a comprehensive, semi-distributed river basin model that requires a large number of input parameters, which complicates model parameterization and calibration. The RRB was discretised into 4 sub-basins and 630 hydrological response units (HRUs) and calibration and validation was carried out at Bagasoti using monthly flow data of 11 years, respectively. We first calibrated the model in SWAT-CUP which is a decision-making framework that incorporates a semi-automated approach (SUFI2) using manual calibration and

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incorporating sensitivity and uncertainty analysis. Parameter sensitivity analysis helps focus the calibration and uncertainty analysis and is used to provide statistics for goodness-of-fit. In this study Calibration has been done between simulated and observed discharge data (1974-1985) for 50 simulations with 6 parameters that is Curve number (CN2 = 0.945), Groundwater delay (GW_DELAY = 50), Baseflow alpha factor (ALPHA_BF = 0.58), Manning's "n" value for the main channel (CH_N2 = 0.15), Effective hydraulic conductivity in main channel alluvium (CH_K2 = 10.20) and Available water capacity of the soil layer (SOL_AWC = 0.28). The results were analysed and compared with the observational data. The model performance evaluation showed acceptable ranges of values (i.e., Nash Sutcliff was 0.75 and R2 was 0.71). After model calibration, in order to predict water balance, the model was validated by using the best parameter.

Keywords: Manual calibration; hydrologic model; SWAT; validation; water balance.

1. INTRODUCTION

Understanding hydrological processes is crucial for managing water movement and its impact on quantity and quality. Basin-focused studies are vital for grasping the mechanisms regulating water flow and predicting their effects on water resources. This knowledge is essential for efficient planning and management, enabling the quantitative assessment of parameters like rainfall and river flow, considering their spatial and temporal variations in river basins [1] these processes are shaped by diverse factors such as weather, topography, geology, land use, and human activities. Water movement on land, both on the surface and beneath, affects unsaturated and saturated zones [2]. A rising surface runoff volume can lead to issues like sedimentation, erosion, and agricultural pollutants, posing significant threats to water resources. Hence, a precise understanding of hydrological behavior is crucial for effective planning and management.

Hydrological models are pivotal for comprehending and forecasting the impact of both natural and human-induced disturbances on water systems. These models integrate mathematical representations of key components in the water cycle, such as rivers, lakes, groundwater, soil, and snow, facilitating the analysis of fluxes in elements like runoff, evapotranspiration, groundwater recharge, and soil moisture. These hydrological models are applicable across a range of scales, from local to global, with their complexity tailored to the specific design scale.

Physically based hydrological models are frequently used to estimate surface runoff, sediment yield, and nutrient losses in watersheds under different management scenarios. Within these models, simulation models replicate processes to explore various scenarios, while optimization models adjust parameters to meet specific objectives. However, a limitation exists in the capability of many water resource models to effectively analyze and display spatial information. A significant number of these models address spatial aspects by simplifying assumptions and parameterization, as highlighted by Walsh [3].

The Soil and Water Assessment Tools (SWAT) model, operating on a daily time step, is designed to predict the impact of management on runoff, sediment, and agricultural chemical yields in large ungauged basins. Over the last two decades, the versatility of the SWAT model has garnered attention for its ability to address a diverse range of watershed problems at desired spatial and temporal scales. Researchers have extensively examined the SWAT model's performance on daily, monthly, or annual bases in predicting runoff and sediment yield. Its simplicity and applicability have been emphasized in numerous studies conducted by researchers such as Srinivasan et al. [4-20].

This study aimed at to calibrate and validate SWAT model for rapti river basin which originates from Nepal and then it comes in India. The Rapti River, a significant left bank tributary of the Ghaghra River, originates south of a notable east-west ridgeline situated midway between the western Dhaulagiri Himalaya and the Mahabharat Range in Nepal, at an elevation of approximately 3048 meters. The Dundwa range, a subrange of the Shiwaliks in Western Nepal, diverts the Rapti about 100 kilometers westward before it resumes its southward course towards the Ganga. Upon traversing Nepal, the river enters Eastern Uttar Pradesh in Chanda Pargana, east of the Kundwa village in Bahraich district. The floodwaters of the Rapti River are regulated by the Rapti Barrage, located upstream of the Bhinga site in Shravasti district, and maintained by the State government. The Rapti River Basin is a part of the middle Ganga plain, receiving contributions from numerous tributaries and affluents that descend steeply into the Rapti from the Shiwalik and its foothills.

2. MATERIALS AND METHODS

2.1 The Study Area

The Rapti Zone is situated between East longitudes 81°35' and 83°52' and North latitudes 26°18' and 28°35' in both Uttar Pradesh and Nepal, covering a total area of 23,237.51 square kilometers. With an elevation of 3,500 meters (11,500 feet), the zone includes the Ghaghara River (located at 26°17'20"N and 83°40'08"E) with a basin size of 23,900 square kilometers (9,200 square miles) and an average discharge of 136 cubic meters per second (4,800 cubic feet per second). The origin of the Rapti River is in the Mahabharat range of the lesser Himalayas, near Rukumkot in Nepal. Starting at an elevation of 3,050 meters within Nepal's Mahabharat range, the Rapti River basin exhibits diverse physiography, encompassing lofty mountains, inner and outer Tarai, and undulating plains. Originating as a small river draining the Chitwan (Inner Terai) valley in Nepal, the Rapti flows westward to converge with the Narayani (Gandaki) River to the north. The Rapti zone, situated in Nepal's Middle Hills between the Karnali and Gandaki Basins, continues its course westward through the Mahabharat range and then southeast across the Indo-Gangetic plains before joining the Sharda (Ghaghara) River. As a significant tributary, the Rapti River plays a vital role in the Ghaghara River system. The river experiences two distinct climatic regions based on altitude differences: the mountainous region has a temperate climate, while the plain region features a subtropical climate. The Himalayan climate is characterized by temperate conditions, with hot summers and cold winters. In the subtropical plain region, a typical monsoon climate prevails, marked by a dry winter season and extremely hot summer.

2.2 SWAT Model Inputs

In addition to topographic, soil, and land use/land cover (LULC) information, SWAT necessitates spatially detailed datasets of climatic data at daily or sub-daily intervals. Key input data for SWAT encompass Digital Elevation Model (DEM), land use/land cover, soil properties, and daily weather data (encompassing precipitation, maximum and minimum air temperatures, relative humidity, wind speed, and solar radiation). The river stream network, land-use maps, and soil maps were all created using the ArcGIS interface of SWAT (ArcSWAT). To capture the extensive spatial variations within the watershed, the model area is divided into sub-basins, which are then further subdivided into bhydrologic response units (HRUs). These HRUs represent distinct combinations of land-use types, soil characteristics, and management practices. In this study, the spatial variability of the watershed is simulated using 4 sub-basins and 630 HRUs within the SWAT model.

2.2.1 Digital Elevation Model (DEM)

The Digital Elevation Model (DEM) holds significance as it serves as a crucial dataset from which all topographic characteristics of the catchment, sub-catchment, and Hydrologic Response Units (HRUs) are derived. These attributes encompass area, slope, slope length, channel length, channel slope, channel width, and channel depth. In this investigation, a 30-meter spatial resolution DEM from the Shuttle Radar Topography Mission (SRTM) was obtained from the USGS website (link: https://lpdaac.usgs.gov/data_access/data_pool) and utilized as an input dataset.It is used as the foundation for delineating the watershed boundaries and stream networks across the three study regions. Additionally, it was utilized to generate the slope map for these watersheds. Fig. 2 shows the elevation of the study area which ranges from 3616 to 60m.

2.2.2 Land use/land cover data (LULC)

The study area-specific, cloud-free digital LANDSAT data was obtained from the Global Land Cover Facility site. The land use/cover map for the study watershed was generated using satellite data captured during the autumn of 2000, 2010, and 2020, sourced from USGS Earth Explorer. The sensor associated with this data provided a spatial resolution of 10 meters. The supervised classification method, which is widely used for land-use classification, was employed. This method involved categorizing each pixel within the image dataset into the land-use class that best matched its characteristics.The classified land use or cover types are agricultural land, wetland, barren land, forest, water bodies, and habitat, were identified. Fig. 3 illustrates the distribution of each land use type within each sub-watershed.

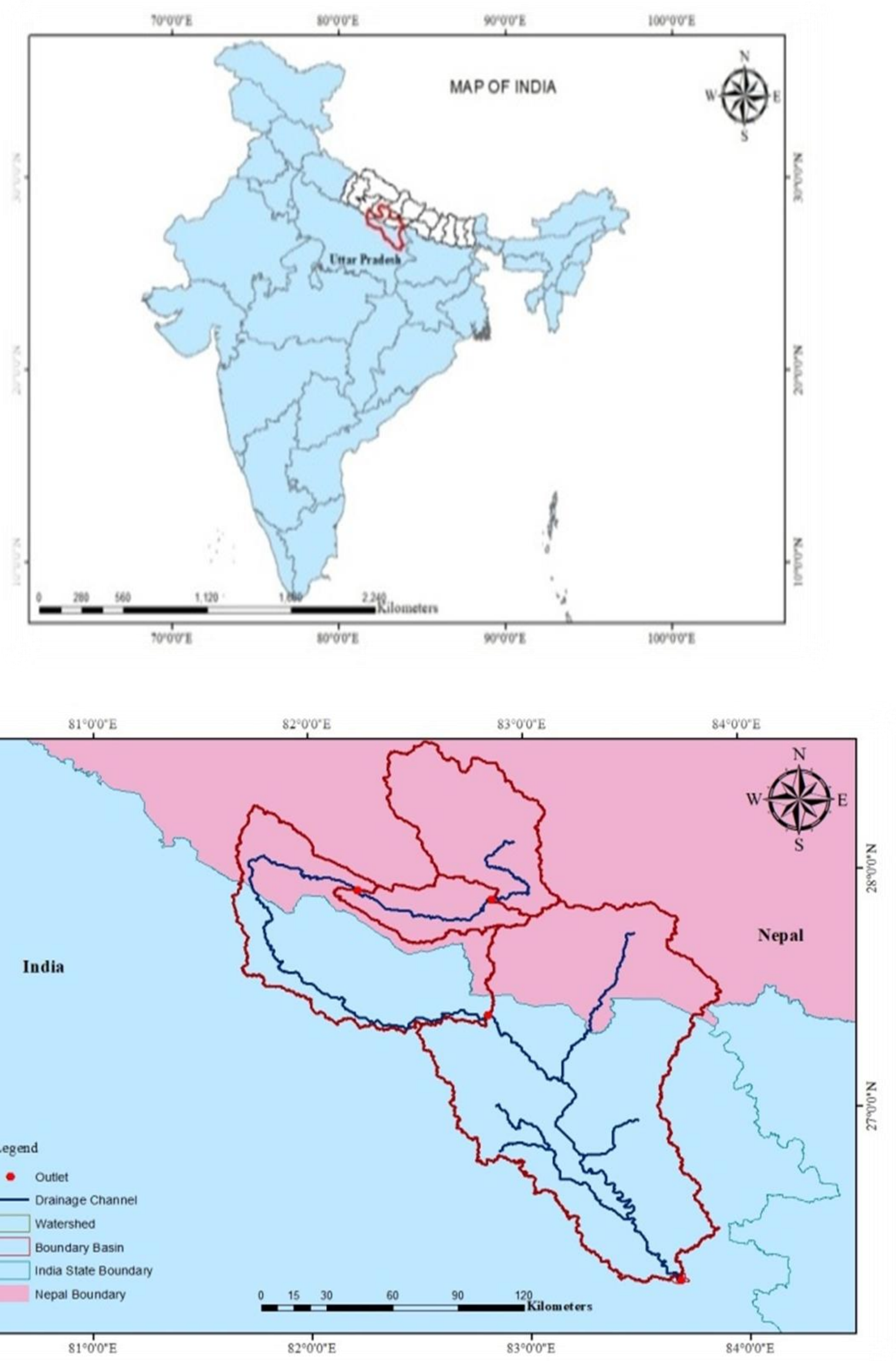

Fig. 1. Location of the study area

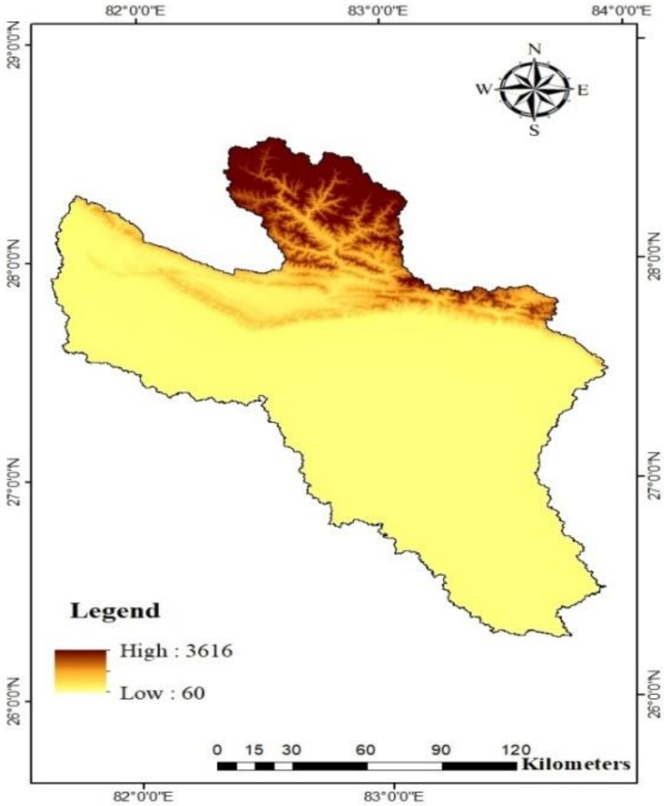

Fig. 2. DEM map of Rapti River Basin

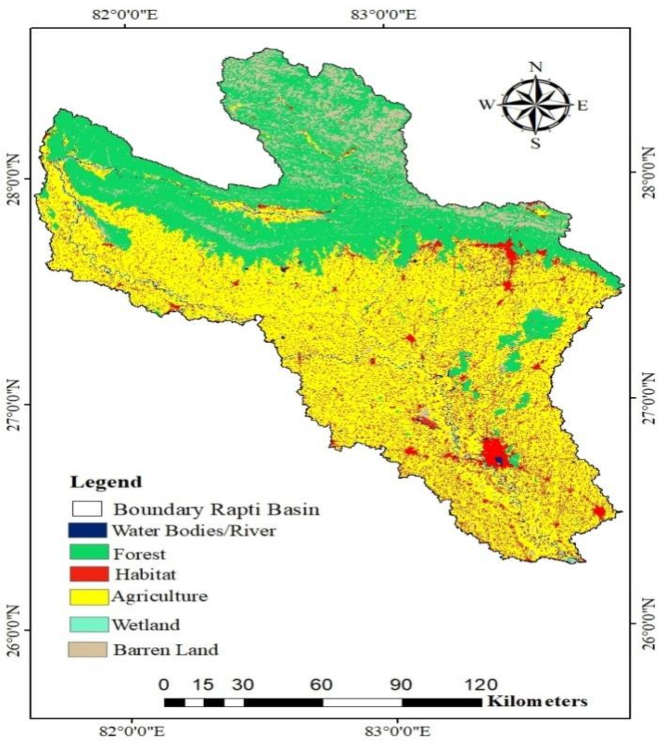

Fig. 3. Land-use map of Rapti River Basin

2.2.3 Soil type and characteristics

The soil map of the basin underwent a detailed process, starting with meticulous outlining, scanning, and subsequent uploading into ArcGIS. Map-to-map registration was conducted using registered topographic maps to ensure accuracy. To facilitate precise identification, individual soils were carefully delineated, and the corresponding polygons were filled with different colors to represent distinct soil types. Fig. 4 visually depicts the spatial distribution of the various soil types within the designated areas.Soils of the basins are classified as Loam and Clay Loam Soil.

2.2.4 Climatic data

The SWAT2012 model necessitates daily data for variables such as precipitation, temperature, relative humidity, solar energy, and wind speed. The SWAT software incorporates a weather generator tool, which proves helpful in filling in missing data during specific time periods within the simulation duration. Moreover, this tool allows the generation of relative humidity, solar energy, and wind speed, provided that a long-term daily precipitation rate and maximum and minimum temperatures are supplied.

2.3 Model Setup and Configuration

This study utilized the Soil and Water Assessment Tool (SWAT) model to estimate all components of the water balance within the study catchment. The initial step in the simulation process was the delineation of the catchment. The GIS interface of SWAT2012 was employed for this purpose, utilizing a 30-meter spatial resolution SRTM DEM (digital elevation model) downloaded from earth explorer, a data distribution center of USGS (accessible at the link:https://lpdaac.usgs.gov/data_access/data_pool/). The procedural details can be found in] Neitsch et al.[21] and [22]. Upon completion of the catchment delineation, the definition of Hydrologic Response Units (HRUs) ensued. The SWAT2012 interface was used for HRU definition, incorporating three essential spatial datasets: slope, land use/land cover, and soil maps. HRUs are essentially lands with similar characteristics in terms of topography, land use/land cover, and soil types. The assumption is that similar HRUs exhibit comparable hydrologic characteristics. This approach allows for the determination of all components of the soil water balance on an HRU basis, as outlined in studies by Neitsch et al. [21-23] Subsequently, the model was supplied with all the necessary climatic variables, including rainfall, minimum and maximum temperature, relative humidity, average wind speed, and solar radiation data. In cases where station data were unavailable, the weather generator tool within the ArcSWAT interface was utilized to fill in the gaps. This tool also allowed for the generation of relative humidity, solar energy, and wind speed based on long-term daily precipitation and maximum and minimum temperature data, as outlined by Neitsch, et al. [21]. The rainfall-runoff process was configured to be estimated using the curve number (CN-method), potential evapotranspiration was determined using the Penman-Monteith equation, and channel water routing was simulated through the Variable Storage Routing method. Upon completion of these processes, the SWAT simulation was initiated, incorporating a three-year warming-up period. Including this warm-up period, the total simulation duration, spanning from 1974 to 1 985, was established. Consequently, a 11 year period of hydrologic variables was simulated for the study catchment, excluding the warm-up periods. The key steps in the simulation process are summarized in Fig. 5.

2.4 Water Balance Equation used by the SWAT Model

The SWAT model is a continuous, process-based, and spatially-distributed model specifically designed to replicate the water balance in a defined geographical area. It takes into account diverse hydrological processes such as rainfall; evapotranspiration, surface and subsurface runoff, and deep aquifer recharge [24-25]. The model functions according to the water balance equation;

$$SW_t = SW + \sum_{t-1}^{t} (R - Q - ET - P - QR)$$

Where,

SW_t= final soil water content (mm),
SW= initial soil water content (mm),
t = time (days),
R = amount of precipitation (mm),
Q = amount of surface runoff (mm),
ET= amount of evapotranspiration (mm),
P = percolation (mm) and
QR = amount of return flow (mm).

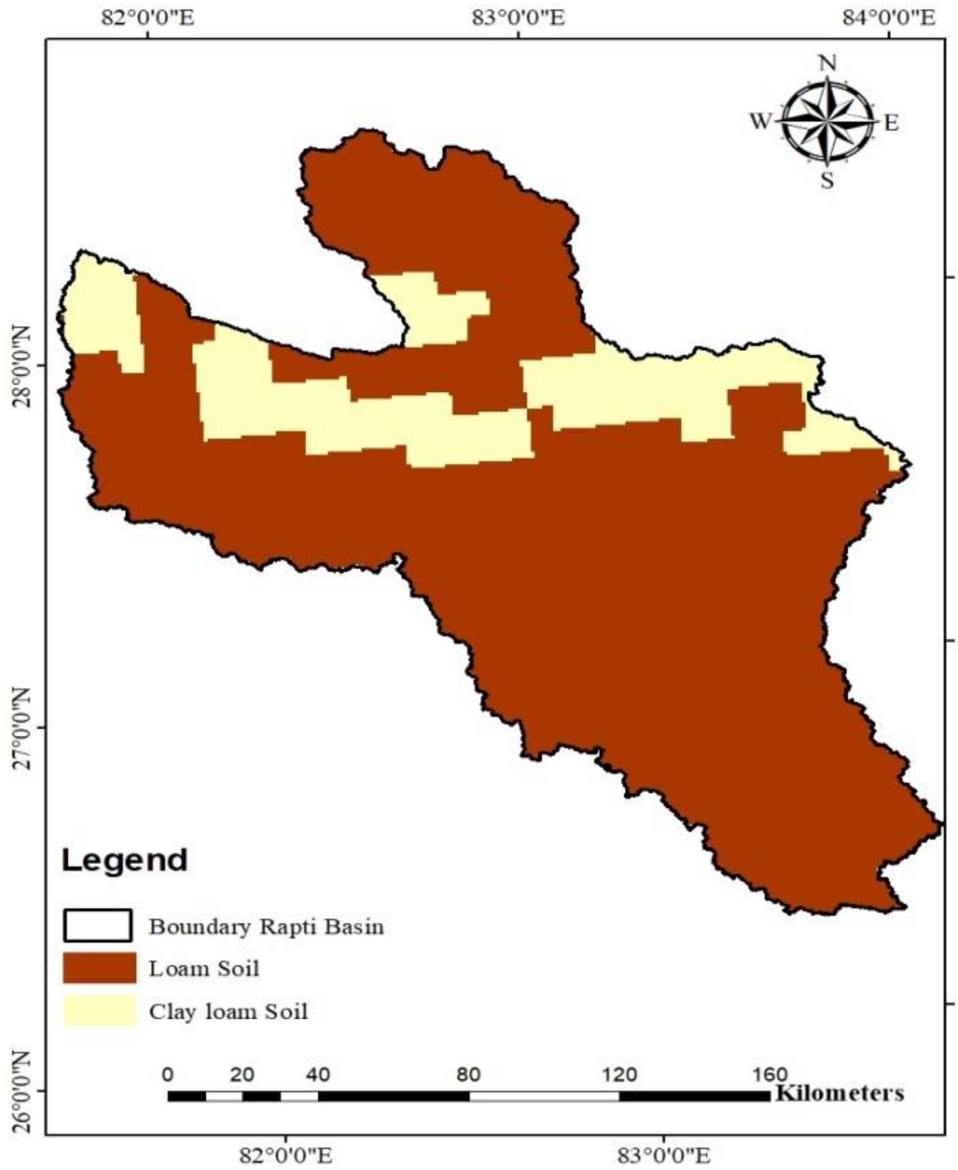

Fig. 4. Soil map of Rapti River Basin

2.5 SWAT-CUP Model

SWAT-CUP is a comprehensive tool that integrates a calibration and uncertainty program with the SWAT hydrological model, providing a range of algorithms including Sequential Uncertainty Fitting (SUFI-2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), and Markov Chain Monte Carlo (MCMC) [26-27]. These algorithms empower users to conduct uncertainty and sensitivity analyses. The process of parameter optimization and calibration, involving an inverse problem, inherently introduces uncertainty as it begins with observed results and subsequently identifies parameter values responsible for producing those results.

In this research, the SUFI-2 [28-32] was utilized for the purposes of calibration, validation, and sensitivity analysis.SUFI-2 is recognized for its efficiency in handling large-scale, time-consuming models [33-35] and for accurately constraining most measured data within a narrow uncertainty band. The algorithm iteratively maps all uncertainties, ensuring that 95% of the measured data falls within the 95% prediction uncertainty (95PPU) of the model.

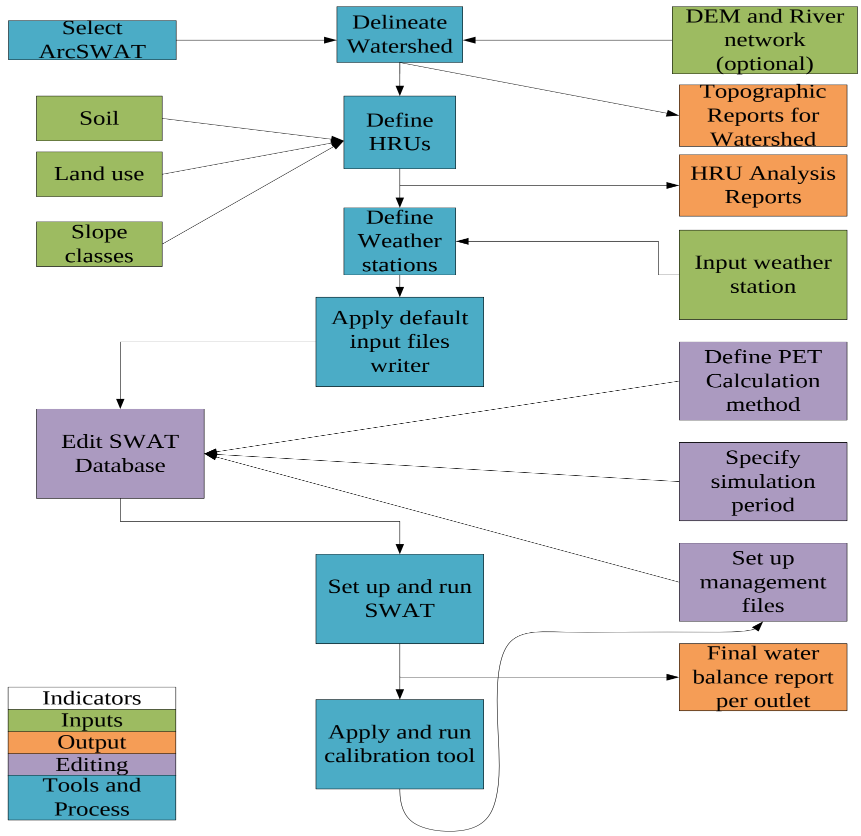

Fig. 5. Framework of the SWAT model

Two pivotal factors, namely the p-factor and r-factor, play a crucial role in assessing the results. The p-factor quantifies simulation uncertainty, while the r-factor gauges the strength of the calibration and uncertainty analyses. The r-factor is calculated as the average thickness of the 95PPU band divided by the standard deviation of the measured data. The goodness of fit is evaluated using the R2 and Nash-Sutcliffe coefficient (NSE) between observed data and the best simulation, where an R-factor of 1 and P-factor of 100% indicate a perfect simulation. The P-factor ranges between 0 and 100%, while the R-factor ranges between 0 and infinity.

The first step involves identifying the most critical factors for the selected watershed, a decision that the user makes based on expertise or through the process of sensitivity analysis. Sensitivity analysis, which examines the influence of adjusting various variables on model output, can take the form of either local (changing parameters one at a time) or global (allowing changes in all parameters) analyses. Both types of analyses provide valuable insights. Subsequently, the calibration process is undertaken to improve the model's fit to local conditions by selecting input parameter values within their uncertainty ranges and comparing the model output to observed data. During calibration, the goal is to fine-tune the model to achieve an optimal match with observed data.

Following calibration, the validation process assesses the model's performance for a specific output variable, such as streamflow or sediment yield, using the parameters determined during calibration. This evaluation involves comparing model predictions to unused observed data. Model validation ensures that the model produces accurate simulations aligned with the project goals [36-38].

3. RESULTS AND DISCUSSION

3.1 Model Calibration

The accuracy of a hydrological model hinges on the precision of its calibration process [39-40] and [41]. In this study, manual calibration was performed for the Rapti river basin, specifically utilizing observed monthly runoff data measured at the outlet during the period 1974–1980. The initial four years of the modeling period, were allocated for model 'warm-up' to enable the model to establish the states of its internal hydrological components realistically.

Manual calibration refers to the process of manually adjusting SWAT model parameters using a trial-and-error method until satisfactory simulation results are obtained.The input parameters employed for model calibration included SCS curve number (CN2), Groundwater delay time (GW_DELAY), Baseflow recession constant (ALPHA_BF), Manning's "n" value for the main channel (CH_N2), Effective hydraulic conductivity in main channel alluvium (CH_K2) and Available water capacity of the soil layer (SOL_AWC) which were listed in Table 1.

Since this study did not account for land-use/land-cover changes, modifications were made to the Curve Number (CN) values to accommodate such changes. The SCS curve number plays a significant role in land use, soil permeability, and antecedent soil moisture conditions. It has been noted that higher CN values reduce infiltration and baseflow, leading to increased spikes in the hydrograph. In this study, a 6% increase was applied to the CN values. A plant's water consumption is determined by its need for evapotranspiration (ET) and the available water in the soil. When the upper soil layers lack sufficient water for potential uptake, the model permits lower layers to make up for the deficit [42].

Water that moves beyond the lowest soil depth through percolation or bypass flow enters the vadose zone before becoming recharge for the shallow aquifer [42]. Groundwater delay time (GW_DELAY) refers to the delay between water leaving the soil profile and entering the shallow aquifer. This delay is influenced by factors like water table depth and hydraulic properties of geological formations in the vadose and groundwater zones. During model calibration, a lower GW_DELAY value was associated with a gradual contribution of groundwater to baseflow, leading to increased surface runoff. The calibrated GW_DELAY value was determined to be 50 days.

The baseflow recession constant (ALPHA_BF) serves as an indicator of how groundwater flow reacts to variations in recharge [43]. ALPHA_BF ranges from 0 to 1. The calibrated value for the alpha factor determining baseflow was 0.58. However, during model calibration, it was noted that as ALPHA_BF increased, runoff, especially during peak flow periods, also increased. Conversely, baseflow significantly decreased during dry period.

Based on Lane [44] recommendations regarding hydraulic conductivity (CH_K2) values for different bed materials, the study area is categorized as Category 4 (Moderate loss rate), characterized by a high content of loam and clay in the bed material. Taking this into account, the calibrated hydraulic conductivity value was set at 10.20 mm/hr.

Manning's n is derived from factors influencing the roughness of channels and floodplains. For natural streams with minimal obstructions like trees, stones, or brush, Manning's n typically ranges from 0.025 to 0.065 [45]. In this study, the calibrated value for n was determined to be 0.15.

SOL_AWC (Available Water Capacity) is a parameter that represents the soil's ability to retain and supply water to plants for their use. It is a critical component in hydrological modeling because it affects how water moves through the soil profile.The SOL_AWC value is typically based on the soil type and depth [46].The calibrated soil available water capacity is 0.28 mm.

3.2 Model Validation

During the validation phase, the model was operated with the input parameters established during the calibration process, and no further adjustments were made. The results were then compared with the remaining observational data. Model validation utilized an independent dataset covering the period from 1981 to 1985, comprising observed discharge data from the gauging site. The findings illustrated that the model estimates closely aligned with the observed runoff. With an NSE value of 0.75 and an R2 value of 0.71, the validation level was deemed well. These results indicate that the model was effectively validated for predicting monthly discharges. Consequently, the SWAT model demonstrates successful performance and can be reliably utilized for the Rapti river basin. Fig. 6, 7 illustrates the best simulated discharge for the validation period.

Table 1. Parameters used for calibration of the SWAT model

Parameter	Parameter Discriptions	Calibration Value		
		Minimum Value	**Maximum Value**	**Adjusted Value**
CN2	SCS runoff curve number	35	98	6% increase
GW_DELAY	Groundwater delay	0	500	50
ALPHA_BF	Base flow alpha factor	0	1	0.58
CH_N2	Manning's "n" value for the main channel	0.01	0.3	0.15
CH_K2	Effective hydraulic conductivity in main channel alluvium	0.01	500	10.20
SOL_AWC	Available water capacity of the soil layer	0	1	0.28

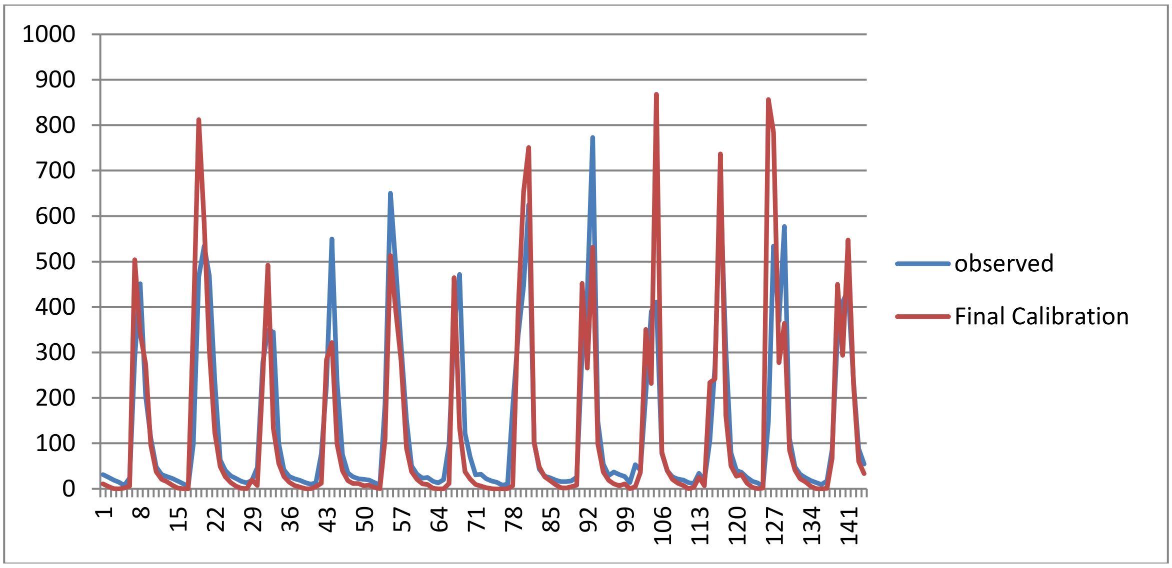

Fig. 6. Observed and simulated discharge at RRB (It is measured between the observed discharge and the simulated discharge after calibration and validation)

As shown in Fig. 6, the peak values of simulated runoff closely align with observed runoff during the initial phase. However, during the intermediate phase, the model tended to underestimate runoff, and in the final phase, the model overestimates runoff.

Fig. 7 displays the observed and simulated monthly runoff during the calibration period, including the 1:1 line for comparison. The simulated runoff values are evenly distributed around the 1:1 line, especially for lower observed runoff value [46]. The distribution of simulated runoff values around the 1:1 line is uniform for lower observed runoff values, as evident in Fig. 7.

However, for higher observed runoff values, the simulated values are slightly below the 1:1 line, indicating an underestimation of high runoff values by the model. The high R-squared value of 0.710 indicates a strong correlation between observed and simulated runoff. R-squared (R2) values range from 0 (no correlation) to 1 (perfect fit), with an ideal PBIAS value being 0.0 indicating accurate model simulation. Positive PBIAS values indicate an underestimation bias by the model, while negative values indicate an overestimation bias [47]. In this study, the PBIAS value was determined to be 12.1, which is considered “good" for calibration according to Van et al. [48]. The RSR (Root Mean Square Error to Standard Deviation Ratio) ranges from 0 (perfect simulation) to higher positive values, with lower RSR values indicating better model simulation performance [49-51]. For this study the value of RSR is 1.05 Overall, these results suggest satisfactory prediction of monthly surface runoff by the SWAT model during the calibration period, making it suitable for further analysis [52-54].

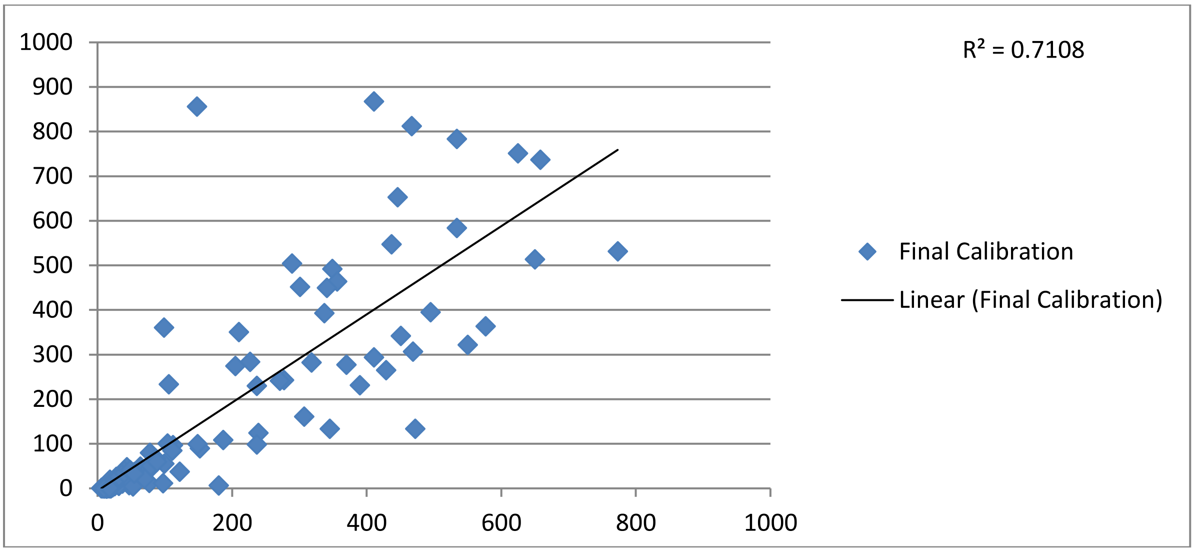

Fig. 7. Comparison between observed and simulated discharge at RRB (It is measured between the observed discharge and the simulated discharge after calibration and validation)

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

In this study, the suitability of the SWAT model for conducting water balance analyses in an agricultural-centric basin was evaluated. The SWAT model was utilized to assess the seasonal water budget of the Rapti River basin spanning India and Nepal.The SWAT model demonstrates proficiency in simulating surface runoff across watersheds of varying sizes, including small, medium, and large ones. In the case of the Rapti River Basin, the SWAT model yielded favorable simulation outcomes for daily runoff data.The findings and conclusions drawn from this study are of significant value for hydrologists and water resource management professionals, offering valuable insights for the effective management and understanding of the Rapti River basin.

Ensuring the accuracy of predictions, particularly in estimating variables like discharge, relies on a thorough calibration of a hydrological model. This study focused on calibrating and validating the Rapti River Basin using the SWAT model. The evaluation of the SWAT model's performance involved a meticulous calibration and validation process. The SUFI-2 technique, chosen for model calibration, proved to be highly convenient and iterative, involving a substantial number of simulations. Within the research area, the curve number emerged as the most responsive parameter affecting the output, with groundwater delay, soil available water capacity, and alpha baseflow following as subsequent influential factors.The results obtained from the SWAT model were highly satisfactory, indicating a successful calibration process. Consequently, the calibrated parameter values derived from this study can be confidently used for subsequent hydrological simulations of the watershed. The study observed a high correlation between observed and simulated discharge on a monthly time scale, validating the accuracy of the SWAT model.

4.2 Recommendations

- This study indicates that utilizing a semi-distributed model like SWAT in the Rapti River Basin can accurately predict river discharge, given the availability of hydrological data spanning a sufficient time period.
- It's crucial to identify the most responsive parameters among a range of model parameters to streamline calibration efforts.
- By emphasizing the importance of long-term hydrological monitoring within the Rapti River basin to validate model projections over extended periods and capture inter-annual variability effectively.
- By investigating the impacts of climate change on hydrological processes, exploring integrated water resource management strategies, or assessing the

resilience of the basin to extreme hydrological events.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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