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RESEARCH ARTICLE

SWAT-BASED HYDROLOGICAL ASSESSMENT OF THE WAINGANGA RIVER CATCHMENT

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ABSTRACT

The Wainganga River Basin in Maharashtra, a critical component of the Godavari River system, faces increasing hydrological stress due to urbanization, land use changes, and climate variability. To address these challenges, this study employed the Soil and Water Assessment Tool (SWAT) integrated with GIS to assess surface runoff dynamics and evaluate the watershed's response under varied physiographic and climatic conditions. The main objective was to simulate hydrological processes—including surface runoff and streamflow—based on inputs from high-resolution land use/land cover (LULC), soil, topographic, and daily hydro-meteorological datasets. The basin was discretized into 2,468 sub-basins and 10,594 Hydrological Response Units (HRUs). The SWAT model was calibrated using observed streamflow data for the period 2015–2019 and validated for 2020–2024. The model's performance was evaluated using statistical indicators: R^2 was 0.86 for calibration and 0.89 for validation; RMSE values were 6.32 and 8.32 respectively; and Index of Agreement (IA) values were 0.82 (calibration) and 0.56 (validation). These results confirmed the model's accuracy in replicating seasonal runoff patterns and peak flow events. The study concludes that the SWAT-GIS framework is a reliable decision-support tool for watershed management, offering robust predictive capabilities even in data-scarce or topographically complex regions. The findings can inform sustainable water planning, especially in regions undergoing rapid land cover transformation.

KEYWORDS

SWAT model, Wainganga River Basin, hydrological modeling, runoff simulation, GIS, watershed management, HRU analysis.

1. INTRODUCTION

Human activities driven by development and urban expansion have significantly altered land use and land cover (LULC), leading to profound impacts on watershed hydrology (Vaibhav, 2016; Leopold, 1968). Urbanization increases impervious surfaces, reducing infiltration and increasing runoff, thereby worsening flooding and degrading water quality, while also affecting riverine carbon cycling (Fletcher et al., 2013; Liu, 2019). These changes are spatially and temporally variable and are further compounded by climate change, which alters rainfall patterns and intensifies extreme weather events (Miller, 2022; Douville, 2022). Hydrological models are essential tools for predicting watershed behavior under such conditions. The Soil and Water Assessment Tool (SWAT), developed by the USDA, is a widely used, physically-based model for simulating long-term hydrologic processes including runoff, sediment transport, and land management impacts (Kerala et al., 2019). Recent advances such as deep learning-enhanced calibration have further improved SWAT's accuracy (Mudunuru et al., 2021). Integration with Geographic Information Systems (GIS) through ArcSWAT has made model setup, data processing, and result interpretation more efficient (Clark, 1998; Singh et al., 1996; Sui et al., 1999).

Despite widespread use of such models in India, the Wainganga River Basin has seen limited research, particularly using high-resolution datasets for long-term simulation. This study addresses that gap by integrating SWAT with GIS to simulate hydrological responses under diverse land use and climatic conditions. The innovation lies in detailed sub-basin and HRU delineation, and model performance evaluation over a 9-year period. This approach aims to support climate-resilient water management in data-scarce regions. The objective is to assess surface runoff behavior in the Wainganga Basin using LULC, soil, topography, and meteorological inputs. The study includes model calibration (2015–2019) and validation (2020–2024), with a focus on evaluating land use impacts and supporting sustainable watershed management.

2. STUDY AREA

Figure 1 presents the spatial location of the Wainganga River Basin, which covers an approximate area of 51,550.60 km². This basin is a significant sub-basin of the Godavari River system, which drains a vast expanse of nearly 312,800 km² across the Deccan Plateau (Hengade et al., 2019; Patil, 2015; Patil et al., 2023; Nair et al., 2022). The Wainganga River originates in the Seoni district of Madhya Pradesh and flows southward through Maharashtra, eventually merging with the Wardha River to form the Pranhita River — one of the key tributaries of the Godavari River (Patil et al., 2024). Topographically, the Wainganga basin is characterized by a mix

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of elevated plateaus and rolling terrain, creating a dynamic hydrological setting. Geographically, the basin lies between 78°0′ and 80°45′ East longitude and 19°4′ and 21°50′ North latitude (Kudnar, 2020; (CWC) and (NRSC), 2014). This variation in elevation and landform influences the region's hydrology and watershed response. Climatically, the basin experiences a tropical monsoonal climate, with most precipitation occurring during the southwest monsoon season. These climatic and topographical features make the Wainganga basin an ideal site for hydrological studies related to runoff modeling, land use changes, and water resource management.

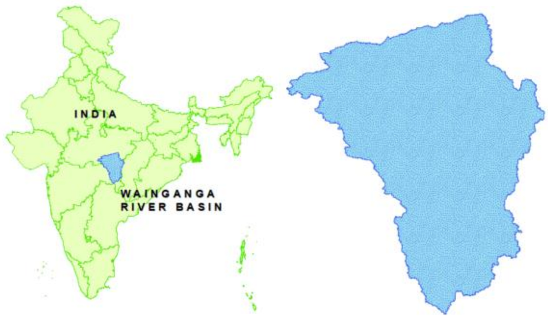

Figure 1: Wainganga basin location

3. Methodology

The methodology begins with a preparation phase involving a detailed literature review to understand hydrological modeling, SWAT applications, and GIS integration. As shown in figure 2 This is followed by data acquisition, which includes gathering remote sensing data such as LULC, soil, and DEM, along with hydro-meteorological parameters like rainfall, temperature, humidity, and wind speed. The next step is pre-processing and input preparation, where GIS processing, land cover classification, and soil grouping are conducted. Using the ArcSWAT interface, the SWAT model is set up for hydrological simulations, including runoff, evapotranspiration, sediment yield (optional), groundwater flow, and water balance calculations. The results are then interpreted and visualized, leading to the final phase of application and decision support, where the model outcomes help assess watershed responses and guide water resource planning and policy-making

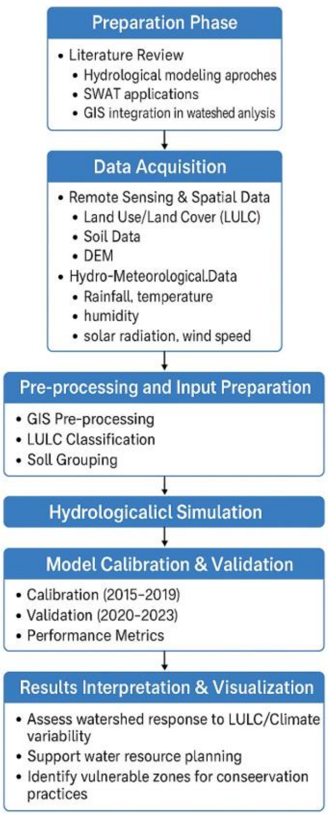

Figure 2: Methodology for SWAT-Based Hydrological Modeling

3.1 Data Collection

The model relies heavily on four key types of input datasets:

- Land Use/Land Cover (LULC) maps,
- Soil properties,
- Topographical data, and
- Hydro-meteorological inputs (e.g., precipitation, temperature, solar radiation, wind speed, and relative humidity) (Waheed et al., 2020; Gassman et al., 2007). These datasets are used to delineate the watershed, define sub-basins and Hydrological Response Units (HRUs), and simulate the movement of water, sediments, and nutrients throughout the catchment area. The spatial data are typically processed and managed through a GIS interface — in this case, ArcSWAT, which operates within the ArcGIS environment and streamlines model setup, input data processing, and output visualization (Wood et al., 1992). This methodological approach enables detailed analysis of watershed behavior under varying land use and climatic scenarios, supporting effective water resource planning and management

3.1.1 Land Use/Land Cover (LULC) Data

Land use and land cover information for the Wainganga River Basin was extracted using publicly available remote sensing data. Specifically, imagery from the IRS-P6 LISS-III sensor with a spatial resolution of 30 meters served as the primary source for LULC classification. Prior to classification, satellite data underwent essential pre-processing steps—including geometric correction, atmospheric correction, and image enhancement—facilitated using ERDAS Imagine 9.2 and ArcGIS 10.1 software tools (Qiao, 2014; Refsgaard et al., 2007). The classification output was used to identify dominant land cover categories such as crops, trees, water bodies, built-up areas, and rangelands, all of which directly affect surface runoff, infiltration, and evapotranspiration within the basin. This processed LULC dataset formed an essential input layer for the SWAT model, influencing hydrological responses across different Hydrological Response Units (HRUs). A spatial representation of the classified LULC map is shown in Figure 3, highlighting the distribution and proportions of land cover types in the Wainganga River Basin. The corresponding legend details the class labels and their fractional coverage.

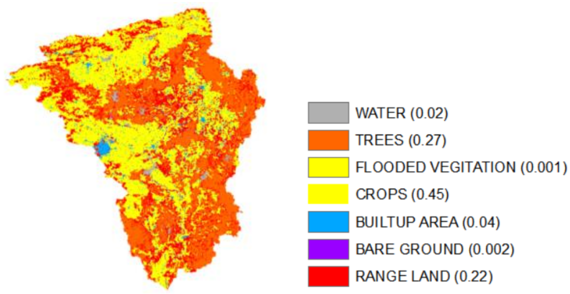

Figure 3: Landuse land cover

3.1.2 Soil Data

Soil characteristics for the Wainganga River Basin were sourced from reliable national and regional databases, specifically the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) and the Maharashtra Remote Sensing Application Centre (MRSAC), Nagpur. These datasets were instrumental in classifying the basin into different soil types, as illustrated in Figure 4, and further grouping them into Hydrological Soil Groups (HSGs) based on their infiltration rates and runoff potential (USDA, 2007). The classification includes soils such as Chromic Vertisols (Black Cotton Soils), PellicVertisols, Ferric Luvisols, Lithosols, and VerticCambisols, each differing in texture, depth, and water retention characteristics. These distinctions are crucial in the SWAT model, as soil parameters directly affect infiltration capacity, percolation, and water availability for plant uptake (Srinivasan et al., 2010; Arnold, 1990).

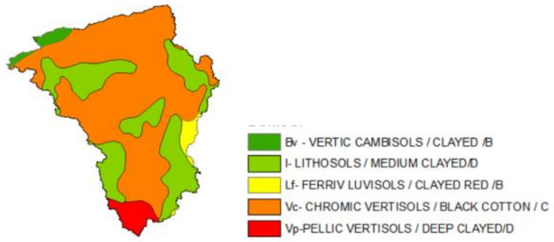

Figure 4: Soil data

Accompanying legend provide a visual overview of the dominant soil types and their spatial distribution within the basin. By integrating this soil data with other spatial layers, the SWAT model can accurately simulate hydrologic responses across different Hydrological Response Units (HRUs).

3.3 Topographical Data

The topographic characteristics of the Wainganga River Basin were analyzed using a Digital Elevation Model (DEM) obtained from the ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) database, which provides a spatial resolution of 30 meters. The DEM served as a critical input layer for hydrological modeling in SWAT, facilitating the extraction of terrain attributes such as elevation, slope, and flow direction. Using this elevation data, the basin was subdivided into sub-watersheds, and stream networks were delineated to simulate the spatial distribution of surface runoff and flow accumulation (Jenson et al., 1988; Grayson et al., 1992). Topographical information not only aids in identifying natural drainage patterns but also plays a crucial role in defining Hydrological Response Units (HRUs), which are essential for accurate watershed simulation.

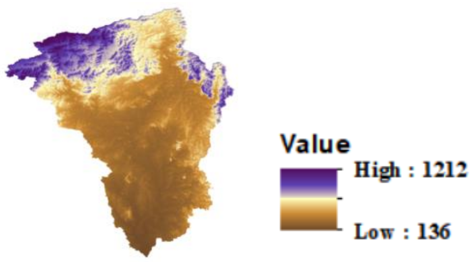

Figure 5: DEM file

Figure 5 presents the elevation distribution across the basin, with elevation ranging from 136 meters to 1212 meters, indicating a significant variation in relief that influences runoff velocity and catchment response.

3.4 Hydro-Meteorological Data

Daily hydro-meteorological records were sourced from the Hydrology Data Users Group (HDUG) located in Nashik, Maharashtra. The dataset comprised critical climatic and hydrological variables such as precipitation, streamflow, maximum and minimum air temperatures, relative humidity, and wind speed. These parameters were instrumental in simulating key hydrological processes including evapotranspiration, surface runoff, and groundwater recharge within the SWAT modeling framework. Figure 5 illustrates the detailed methodological workflow employed in this study. The SWAT model relies on a set of physically-based empirical equations to simulate hydrologic responses. Notably, the SCS Curve Number (CN) method is used for estimating surface runoff (USDA, 1972), while potential evapotranspiration is calculated using the Penman-Monteith equation (Allen et al., 1998). Additionally, sediment yield is modeled through the Modified Universal Soil Loss Equation (MUSLE) (Santhi et al., 2001; Larson et al., 1997). Together, these algorithms provide a robust foundation for representing the water balance and sediment transport at the watershed level.

4. Application Of The SWAT Model To Watershed Simulation

4.1 Input Climate Data

The SWAT model requires comprehensive daily climate data to accurately simulate hydrological processes within a watershed. Key climatic inputs include precipitation (P), maximum and minimum temperatures (Tmax and Tmin), solar radiation, relative humidity, and wind speed. These variables play a critical role in determining the energy and moisture dynamics within the basin. Among their various functions, they are essential for the calculation of evapotranspiration, which significantly influences the water balance by governing soil moisture, surface runoff, and groundwater recharge. Accurate representation of these parameters enables SWAT to simulate key processes such as infiltration, plant water uptake, and streamflow, thereby ensuring realistic modeling of the watershed's hydrological response.

4.2 Water Balance Equation

The SWAT model simulates the hydrological cycle of each Hydrological Response Unit (HRU) using a water balance equation that accounts for the movement and storage of water in the soil profile over time. The equation is expressed as:

$$SWt = SW0 + \sum_{i=0}^{t}(\text{Rday} - \text{Qsurf} - \text{Ea} - \text{Wseep} - \text{Qgw}) \tag{1}$$

Where:

- SWt: Soil water content at time t (mm)
- SW0: Initial soil water content (mm)
- Rday: Daily precipitation (mm)
- Qsurf: Surface runoff (mm)
- Ea: Actual evapotranspiration (mm)
- Wseep: Water percolation below the root zone (mm)
- Qgw: Return flow from the shallow aquifer (mm)

This equation captures the dynamic interactions between precipitation input and various water loss mechanisms, including surface runoff, evapotranspiration, percolation, and baseflow return. By computing these components on a daily time step, SWAT effectively models the temporal variation in soil moisture content, which is fundamental to understanding watershed hydrology and predicting streamflow under different land use and climate conditions.

4.3 Surface Runoff Estimation Using the SCS Curve Number Method

In the SWAT model, surface runoff is estimated using the SCS (Soil Conservation Service) Curve Number (CN) method, a widely accepted empirical approach that relates runoff to land use, soil properties, and antecedent moisture conditions. The runoff equation is given by:

$$Q = \frac{(P-0.2S)^2}{P+0.80S} \quad \text{for} P > 0.2S \tag{2}$$

Where:

- Q: Surface runoff (mm)
- P: Precipitation (mm)
- S: Potential maximum retention after runoff begins (mm), calculated using the curve number
- CN: Curve number, which varies based on land use, soil type, and hydrologic condition

The retention parameter S is determined by:

$$S = \frac{25400}{CN} - 254 \tag{3}$$

This method accounts for the initial abstraction of rainfall due to surface storage, interception, and infiltration before runoff commences. The curve number (CN) is a dimensionless value ranging from 30 to 100, where lower values indicate high infiltration (e.g., forested or sandy areas) and higher values represent low infiltration potential (e.g., urban or clayey soils). By incorporating spatial variability in land use and soil characteristics, this method provides a reliable estimate of runoff generation at the HRU level within a watershed.

4.4 Reference Evapotranspiration Estimation Using the Penman-Monteith Method

In the SWAT model, reference evapotranspiration (ET_0) is commonly estimated using the Penman-Monteith equation, which integrates both energy balance and aerodynamic factors to provide a physically based estimate of water loss from a reference surface. The equation is given as:

$$ET_0=\frac{0.408\,\Delta\,(Rn-G)+\Upsilon\,(\frac{900}{T+273}\upsilon 2\,(es-ea)}{\Delta+\Upsilon\,(1+0.34\,\upsilon 2)} \quad (4)$$

Where:

- ET0: Reference evapotranspiration (mm/day)
- Rn: Net radiation (MJ/m^2/day)
- G: Soil heat flux (MJ/m^2/day)
- T: Mean daily temperature (°C)
- υ2: Wind speed at 2 m (m/s)
- es: Saturation and actual vapor pressures (kPa)
- Δ: Slope of the vapor pressure curve (kPa/°C)
- γ: Psychrometric constant (kPa/°C)

4.5 Groundwater Flow Simulation

In the SWAT model, the contribution of groundwater to streamflow is simulated using an exponential decay function governed by a baseflow recession constant. This approach models the gradual decline of groundwater discharge over time. The equation is expressed as:

$$Q_{gw}= Q_{gw0}.e^{-\alpha gw\,.t} \quad (6)$$

Where:

- Qgw: Groundwater flow at time ttt (mm)
- Qgw0: Initial groundwater flow (mm)
- αgw: Baseflow recession constant (day^{-1})
- t: Time (days)

This equation assumes that groundwater flow decreases exponentially with time, reflecting the natural depletion of subsurface water storage after recharge events. The baseflow recession constant αgw controls the rate of this decline, with smaller values indicating slower drainage and more sustained baseflow. This component is essential for simulating low-flow conditions in stream networks and maintaining water availability during dry periods.

4.6 Sediment Yield Estimation

In SWAT, sediment yield from each Hydrological Response Unit (HRU) is estimated using the Modified Universal Soil Loss Equation (MUSLE). This empirical model calculates soil erosion based on surface runoff characteristics and various erosion-related factors. The equation is expressed as:

Sed=11.8·(Qsurf·qpeak·AHRU)0.56·K·C·P·LS·CFRG (7)

Where:

- Sed: Sediment yield (tons)
- Qsurf: Surface runoff volume (mm)
- qpeak: Peak runoff rate (m^3/s)
- AHRU: Area of the HRU (hectares)
- K: Soil erodibility factor
- C: Cover management factor
- P: Support practice factor
- LS: Topographic factor (slope length and steepness)
- CFRG: Coarse fragment factor

Unlike the original USLE, which uses rainfall energy as the erosive force, MUSLE incorporates runoff volume and peak runoff rate, providing a more dynamic estimation of erosion events on a daily scale. This makes it particularly useful for modeling sediment transport in watersheds under varying hydrological and land use conditions.

5. Model Calibration And Validation In Swat (2015–2023)

Model calibration and validation are essential steps in ensuring that the SWAT model provides accurate and reliable predictions for watershed hydrology.

i. Calibration (2015–2019)

During the calibration period, the SWAT model's parameters are adjusted to align the simulated streamflow with observed data from 2015 to 2019. Calibration is performed using observed streamflow data and tools like SWAT-CUP (SWAT Calibration and Uncertainty Procedures), which systematically adjusts model parameters to minimize the discrepancies between observed and simulated streamflow. Key parameters, such as the curve number (CN2), baseflow recession constant (ALPHA_BF), and groundwater delay time (GW_DELAY), are tuned. Sensitivity analysis is typically conducted beforehand to identify the most influential parameters.

ii. Validation (2020–2023)

After calibration, the model is validated using a separate set of observed streamflow data from 2020 to 2023, without adjusting any parameters. This phase tests the model's ability to predict streamflow under conditions that were not used in calibration, confirming the model's generalization capability.

To assess the performance of both calibration and validation, the following metrics are used:

- Nash-Sutcliffe Efficiency (NSE): Measures how well the model predicts streamflow compared to observed values, with a value closer to 1 indicating a better fit.
- Coefficient of Determination (R^2): Represents the proportion of variance in the observed data explained by the model, with values closer to 1 indicating better model performance.
- Percent Bias (PBIAS): Quantifies the model's systematic bias in simulation, with values near 0 indicating minimal bias between simulated and observed results.

These metrics help evaluate the model's accuracy and reliability, ensuring it can be used for future hydrological predictions.

6. Results And Discussion

The performance of the model in simulating streamflow was evaluated by comparing simulated and observed discharge data over two distinct time periods: calibration 2015–2019 as shown in figure 6 and validation 2020–2024 as shown in figure 7. In the first period, the simulated discharge shows a strong correlation with the observed discharge, effectively capturing the seasonal variation and timing of peak flows across multiple years. The alignment of major discharge events in 2015, 2016, and 2018 indicates that the model performs well in reflecting snowmelt-driven runoff dynamics. However, certain discrepancies are noticeable, particularly during high-flow events where the simulated peaks are either slightly overestimated or underestimated. In the second period (Gtaph 2), the model's performance remains consistent, with the simulated discharge closely tracking the observed discharge. The improved agreement during recent years, especially in 2022 and 2023, suggests enhanced calibration or better-quality input data. The model accurately represents both high and low flow periods, demonstrating its robustness in simulating discharge under varying hydrological conditions. Overall, the close match between observed and simulated values across both timeframes confirms the SRM's reliability in streamflow simulation for mountainous watersheds, making it a valuable tool for hydrological forecasting and water resource management.

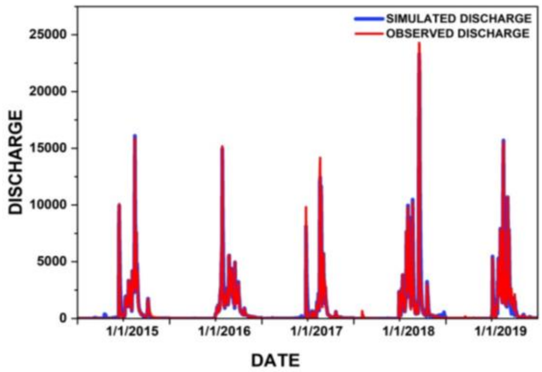

Figure 6: Model Calibration (2015-2019)

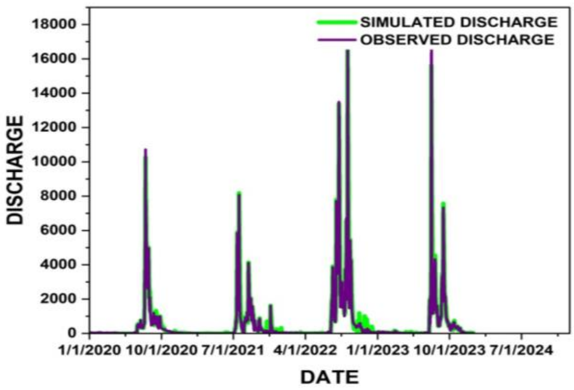

Figure 7: Model Validation (2020-24)

The model's accuracy was assessed using several statistical indices, including the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Nash–Sutcliffe Efficiency (NSE or CE), Mean Bias Error (MBE), and Index of Agreement (IA) for both calibration and validation phases.

Table 1: Statistical parameters of SWAT model for upper sub basin to predict runoff for calibration and validation

SWAT Model	R	RMSE	IA	MBE
Calibration	0.86	6.32	0.82	0.78
Validation	0.89	8.32	0.56	2.54

The results indicated an R^2 value of 0.86 during calibration and 0.89 during validation, reflecting a slightly better correlation in the validation period. The RMSE values were 6.32 (calibration) and 8.32 (validation), while IA values were 0.82 and 0.56, respectively. MBE was lower during calibration (0.78) than validation (2.54), showing lesser bias in the former. Though the correlation coefficient was marginally lower during calibration, other indicators like RMSE, MBE, and IA confirmed satisfactory model performance.

7. Conclusion

This study effectively applied the SWAT model integrated with GIS to evaluate the hydrological behavior of the Wainganga River Basin. The key outcomes and conclusions are summarized below:

- **Model Calibration and Validation:** The model showed strong performance with a Coefficient of Determination (R^2) of 0.86 during the calibration period (2015–2019) and 0.89 during validation (2020–2024). Root Mean Square Error (RMSE) values were 6.32 mm and 8.32 mm respectively, while Index of Agreement (IA) values were 0.82 and 0.56, indicating a good match between observed and simulated streamflows.

- **Runoff Simulation Accuracy:** Seasonal runoff trends, peak flows, and baseflows were accurately simulated across both time periods, reflecting the model's ability to capture the watershed's hydrological response to rainfall and land surface variability.

- **Hydrological Unit Resolution:** The delineation of 2,468 sub-basins and 10,594 Hydrological Response Units (HRUs) enabled spatially detailed hydrological modeling, accounting for variations in land use, soil type, topography, and climatic inputs.

- **Data-Driven Insights:** Integration of high-resolution LULC, soil maps, DEM, and daily meteorological data improved the physical realism of the model and facilitated robust simulation of processes like surface runoff, evapotranspiration, and groundwater flow.

- **Practical Implications:** The findings reinforce the utility of the SWAT-GIS framework as a decision-support system for regional water management, especially in data-scarce and monsoon-dependent basins. The model can inform catchment-level planning, climate change impact assessments, and policy formulation.

The study not only validates SWAT's suitability for large basin hydrological simulation but also showcases its potential to guide sustainable watershed management in ecologically sensitive and development-prone regions like the Wainganga Basin.

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