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Assessing Hydrological Processes and Water Balance in the Pennar River Basin Using SWAT Model

Partha Pratim Adhikary[1,*], Ch. Jyotiprava Dash[1], Uday Mandal[2], and M. Madhu[1,2]

[1]*ICAR – Indian Institute of Soil and Water Conservation, Research Centre, Koraput, Odisha*
[2]*ICAR - Indian Institute of Soil and Water Conservation, Dehradun, Uttarakhand*

Abstract : Intense human activity and climate change are gradually reducing the water yield from the Pennar River basin, a crucial river basin in southern India. Sustainable water use necessitates a thorough understanding of hydrological processes. This study evaluated the performance of the Soil Water Assessment Tool (SWAT), a semi-distributed river basin model, and the SWAT-Calibration and Uncertainty Program (SWAT-CUP) using the Sequential Uncertainty Fitting (SUFI-2) approach for calibration, sensitivity, and uncertainty analysis. The objectives were to: 1) test SWAT's ability to simulate runoff, 2) conduct sensitivity and uncertainty analyses to evaluate model fit, and 3) assess the water balance components of the Pennar basin using SWAT. The Pennar River basin spans latitudes 13º18´-15º49´ N and longitudes 77º1´-80º10´ E, covering approximately 53,949 km², with elevations ranging from 1 to 1,429 meters above mean sea level. Results demonstrated that SWAT effectively simulated hydrologic runoff with good statistical performance (R^2 = 0.89-0.90, NSE = 0.72-0.88, RSR = 0.35-0.52, PBIAS = -31.3% to -1.3%). The model indicated that surface runoff constitutes only 14% of the total precipitation, highlighting the basin's low runoff potential and the urgent need for water conservation. These findings suggest that SWAT is a useful tool for further applications, such as assessing climate change impacts and implementing best management practices (BMPs) to address future water scarcity.

Key words: *Hydrological modelling, SWAT model, Pennar basin, Water balance, Calibration and Validation*

1.0. Introduction

Understanding the hydrological processes of a river basin is crucial for several reasons. It enables effective water resource management by understanding the water cycle, essential for planning and allocating water for various uses while preventing over-extraction (Adhikary *et al.*, 2019). This knowledge is key to predicting and mitigating natural disasters such as floods and droughts, allowing for the development of early warning systems as protective measures. It also supports ecosystem health by maintaining aquatic habitats and biodiversity. For agriculture, understanding hydrology optimizes irrigation practices, enhancing crop yields and conserving water. In urban planning, it aids in designing effective drainage systems to reduce flooding risks. As climate change alters precipitation patterns, understanding hydrology is vital for developing adaptive strategies (Mandal *et al.*, 2021). Additionally, it helps control pollution by identifying sources and transport mechanisms. Finally, informed policy-making relies on scientific hydrological knowledge to create effective water management strategies (Das *et al.*, 2022). Overall,

[*]**Corresponding author**: (Email: Partha.Adhikary@icar.gov.in)

understanding these processes is foundational for sustainable resource management, disaster mitigation, ecosystem protection, and adaptive planning. Thus, accurate quantification of basin runoff is essential for effective planning and protection of water resources. In this context, hydrological models like the Soil and Water Assessment Tools (SWAT) play a significant role.

SWAT is a continuous-time, physically based, spatially distributed model used to simulate water flow, sediment, and agricultural chemical yields at the river basin or watershed scale. It directly models physical processes associated with water flow, sediment transport, crop growth, and nutrient cycling (Shi *et al.*, 2011). SWAT has gained popularity globally for its application across watersheds and river basins of varying sizes, showing promising results in simulating land use change effects, best management practices, and more recently, assessing the impact of climate change on hydrological responses (Adhikary *et al.*, 2019; Mandal *et al.*, 2021).To enhance its capability for realistic watershed simulation, SWAT employs the SWAT-CUP calibration module, which includes calibration, validation, and sensitivity analyses using multi-site observation data (Abbaspour et al., 2004 ; Abbaspour *et al.*, 2007; Schuol and Abbaspour, 2006; Faramarzi *et al.*, 2013; Narsimlu *et al.*, 2013). This module has further expanded the application of SWAT worldwide. Studies utilizing SWAT, such as Gosain *et al.* (2011), have used coarse-resolution datasets to simulate hydrology and assess the impact of climate change on the hydro-climatology of major river basins in India. These studies have identified hot spots requiring immediate attention to mitigate extreme flood and drought situations arising from climate change. However, detailed analysis of the impact of climate change on hydrological behaviour in critical river basins, such as the Pennar basin in southern India, has been limited.

The Pennar basin, predominantly located in a semi-arid region, spans largely through the states of Karnataka and Andhra Pradesh. It is divided into two main sub-basins: the Pennar Upper sub-basin, which makes up 66.85% of the total area, and the Pennar lower sub-basin, accounting for 33.15%. The basin experiences a significant variation in annual rainfall, ranging from approximately 400 mm in the Anantapuramu area to about 1200 mm near Sri Potti Sriramulu, Nellore. Geographically, the Pennar basin falls into two distinct Agro-Climatic Zones: the Southern Plateau and Hills Region, and the East Coast Plains and Hills Region. In terms of land use and land classification (LULC), agricultural land is the most extensive, covering 58.64 % of the basin, highlighting the importance of agriculture in this region. Forests cover 20.37% of the basin, while water bodies make up 4.97%. The basin's soils are diverse, including red soil, black soil, sandy soil, and mixed soil. Elevation within the basin varies, with 26.70% of the area lying between 500-750 meters above sea level. The Pennar basin also features numerous surface water bodies, such as lakes, ponds, reservoirs, and tanks. Notably, tanks are the predominant type of water body, constituting about 93.04 % of the total water bodies in the basin.

Although recent studies, such as that by Adhikary et al. (2019), have conducted hydrological studies in the Pennar basin using SWAT, their focus has been primarily on calibration and validation of stream flow under different calibration approaches. Thus, there remains a gap in the detail understanding the hydrological behaviour of the Pennar basin, which warrants further investigation. Keeping these things in mind the objectives of this study are (1) to calibrate and validate the stream flow of the Pennar basin and its five main sub-basins using a distributed approach with the SWAT model, (2) to analyze the sensitivity of various hydrologic parameters in simulating the basin's stream flow, and (3) to assess the water balance components of the Pennar basin through the SWAT model.

2.0. Materials and Methods

2.1. Study area

The Pennar River basin, located in southern India between latitudes 13°18′-15°49′ N and longitudes 77°1′-80°10′ E, covers an area of 53,949 km^2. Originating in Karnataka's Chikkaballapur district, the Pennar River flows northward and eastward through Karnataka and undivided Andhra Pradesh before reaching the Bay of Bengal (Fig. 1). The basin, shaped like a fan, lies in the rain shadow of the Eastern Ghats, receiving an annual average rainfall of 813.3 mm and experiencing an average temperature of 21.2˚C. Its elevation ranges from 1 to 1429 meters above sea level, indicating diverse topography. Rainfall is mostly concentrated from June to October, leading to seasonal stream flows.

Soils in the basin are mainly coarse-textured, including sandy and mixed types, with red and black soils prevalent. Agriculture dominates land use, occupying 59% of the basin, with 73% of this land dedicated to winter crops. Paddy is primarily grown in the irrigated coastal areas of Sri Potti Sriramulu (Nellore) and YSR (Cuddapah) districts, while jowar (sorghum) and oilseeds are common in the semi-arid regions. Significant deforestation has reduced forest cover to 20%, mostly consisting of tropical dry forests. The basin spans 10 districts in Karnataka and Andhra Pradesh, including approximately 146 drought-prone blocks as identified by the 2002 Drought Prone Area Programme (DPAP).

Effective management of water resources, soil and water conservation, adaptive agricultural practices, improved irrigation infrastructure, and reforestation are crucial to address the challenges of seasonal rainfall, variable stream flow, coarse soils, deforestation, and drought in the Pennar River basin. Understanding these factors is vital for sustainable development, resource management, and climate change adaptation in the region.

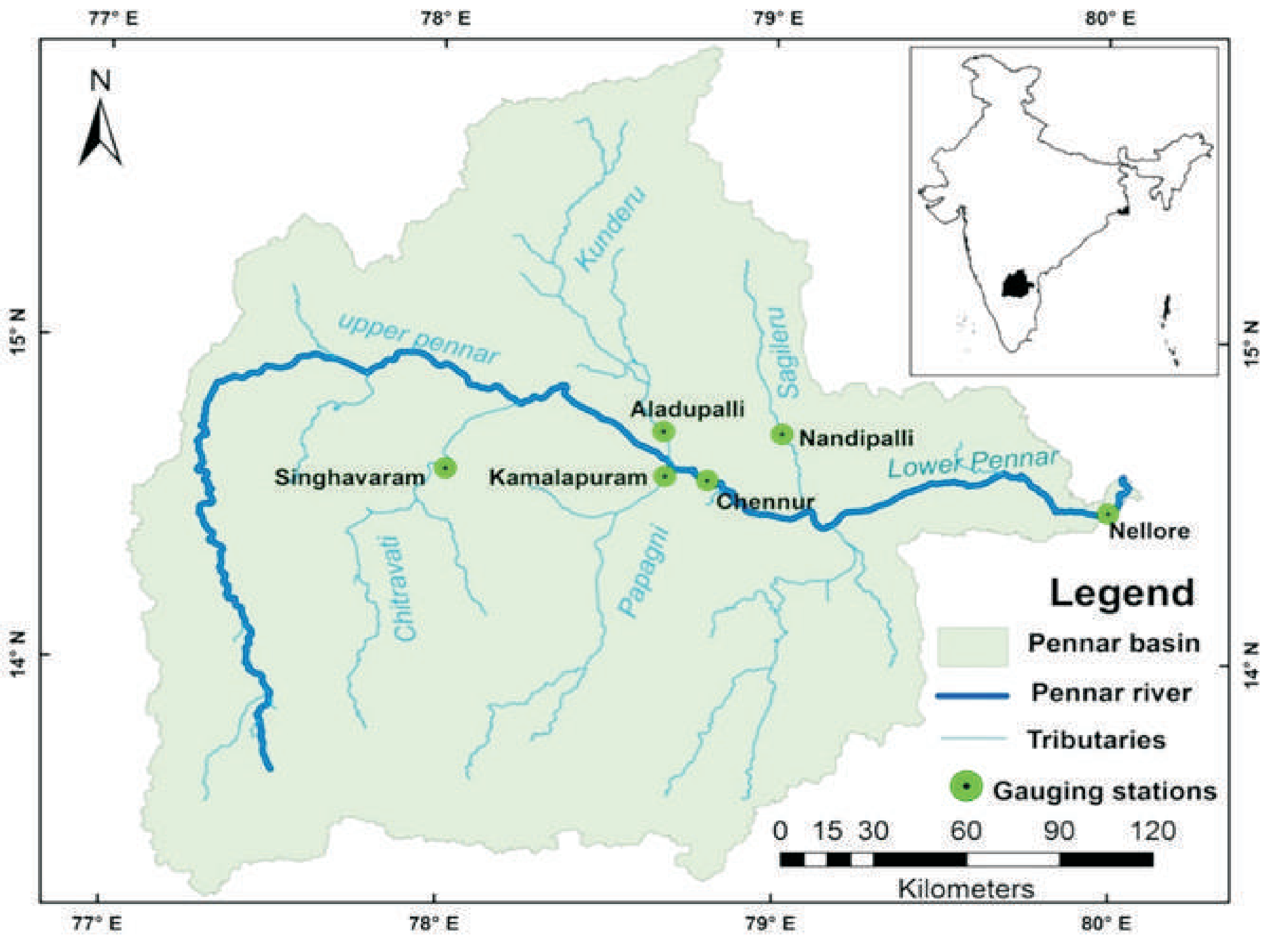

Fig. 1. Map showing the location of the Pennar basin in India and its drainage network

2.2. SWAT model

ArcSWAT, the ArcGIS 10.1 interface of SWAT 2012.10.1.18, was used to simulate runoff in the Pennar basin. SWAT (Soil and Water Assessment Tool) is a continuous, physically-based, semi-distributed hydrologic model designed to assess the effects of land use, management practices, and climate on water, sediment, and agricultural chemical yields in ungauged watersheds. It integrates major components like hydrology, weather, soil, and land use to simulate the hydrologic cycle, including evapotranspiration, infiltration, percolation, surface runoff, lateral flow, return flow, and groundwater recharge (Neitsch et al., 2011).

The Pennar basin's diverse area is divided into sub-basins and further into Hydrologic Response Units (HRUs) with unique soil, land use, and slope combinations. SWAT employs the Curve Number (CN) method for runoff estimation (USDA-SCS, 1972) and the Penman-Monteith method for evapotranspiration calculation (Penman, 1956; Monteith, 1965). Groundwater return flow is calculated using a groundwater balance equation, accounting for contributions from shallow and deep aquifers. Rainfall-induced erosion is estimated using the Modified Universal Soil Loss Equation (Williams, 1975).

Hydrologic simulation in SWAT involves two phases: the land phase, which manages water movement on land using the water balance equation, and the routing phase, which routes water through the channel network using the Muskingum method. This approach allows for a comprehensive analysis of the hydrologic processes within the Pennar basin, enabling effective management and planning of water resources.

2.3. SWAT-CUP

The SWAT model was evaluated using SWAT-CUP 2012.5.1.3 (SWAT Calibration and Uncertainty Program), incorporating algorithms like Sequential Uncertainty Fitting (SUFI-2) (Abbaspour et al., 2007). SUFI-2 addresses uncertainties in deriving variables, model conceptualization, parameterization, and measured data, quantified as a 95% prediction uncertainty (95PPU) band at the 2.5% and 97.5% levels of the cumulative output distribution. A 'Latin hypercube' sampling technique (McKay et al., 1979) was used to draw independent parameter sets.

Calibration and uncertainty analysis are assessed using the p-factor and r-factor. The p-factor indicates the percentage of measured data within the 95PPU, while the r-factor is the average thickness of the 95PPU band relative to the standard deviation of measured data. Ideally, a p-factor of 1 (100%) and an r-factor near zero signify perfect agreement between simulated and observed values (Abbaspour et al., 2007; Abbaspour, 2011). Model performance was further evaluated using the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), Root Mean Square Error to Standard Deviation Ratio (RSR), and Percentage of Bias (PBIAS) (Moriasi et al., 2007).

2.4. Model Input

2.4.1. Elevation

The ASTER DEM with a 30-meter resolution from the Global Land Cover Facility (GLCF) (http://www.landcover.org/) was used to calculate sub-basin parameters like slope and stream network (Fig. 2). The ArcSWAT interface delineated a stream network closely matching observed data from remote sensing. The DEM was projected to UTM zone 44 before modeling.

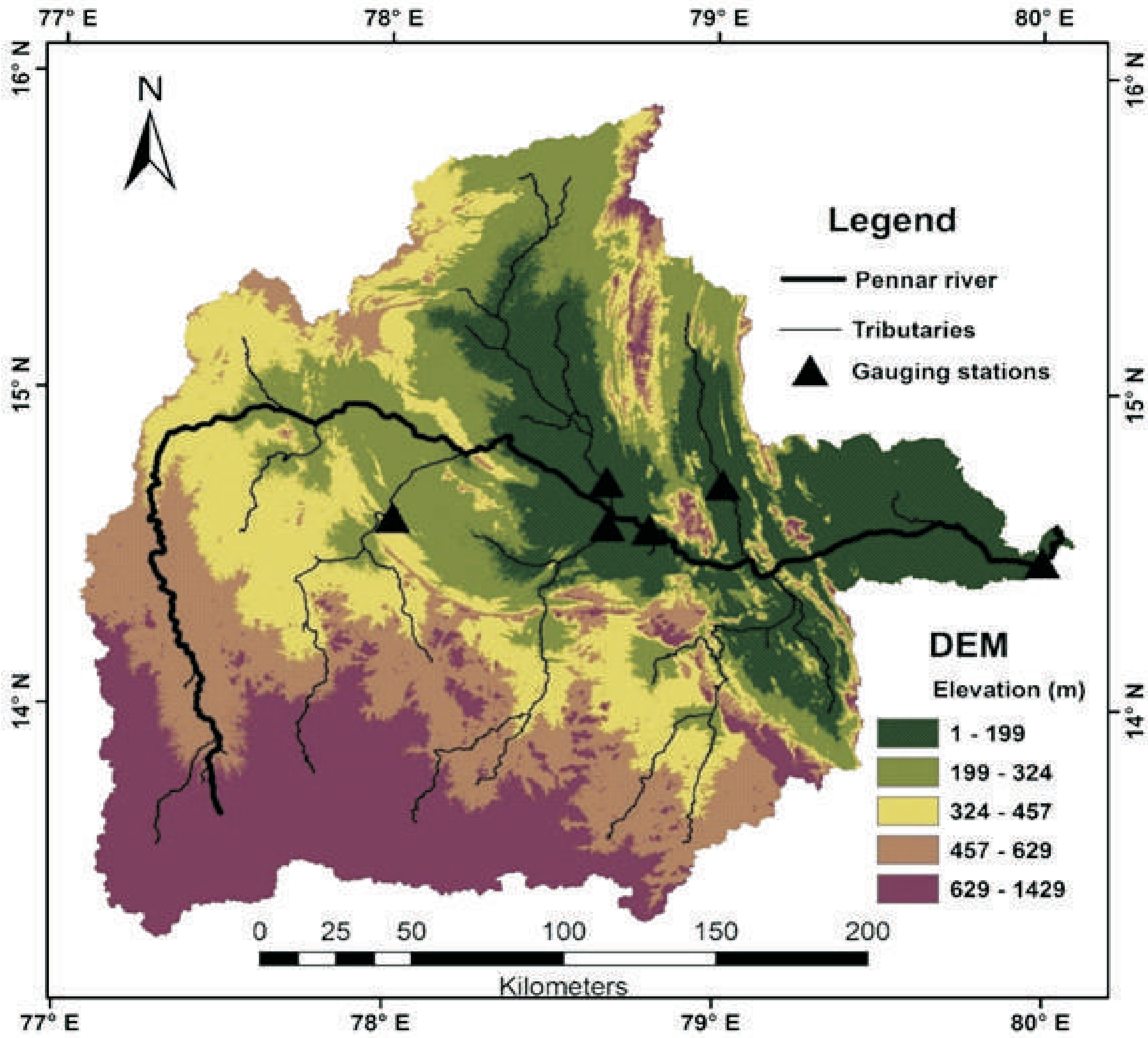

Fig. 2. Map showing the digital elevation model (DEM) and the gauging stations in the Pennar basin

2.4 .2. Land use

A land use grid for the Pennar basin was created using AWiFs imagery from the IRS-P6 satellite, classified with ERDAS IMAGINE 9.0 and ground truth data (Fig. 3). The primary land uses are agricultural land (82.9%), forested areas (13.8%), and wetlands/fallow lands (2.8%) followed by other land uses of 0.5%. During the *kharif* season, rice, groundnut, jowar, and finger millet are grown, while *rabi* season cultivation dominates with mustard, chili, and sunflower.

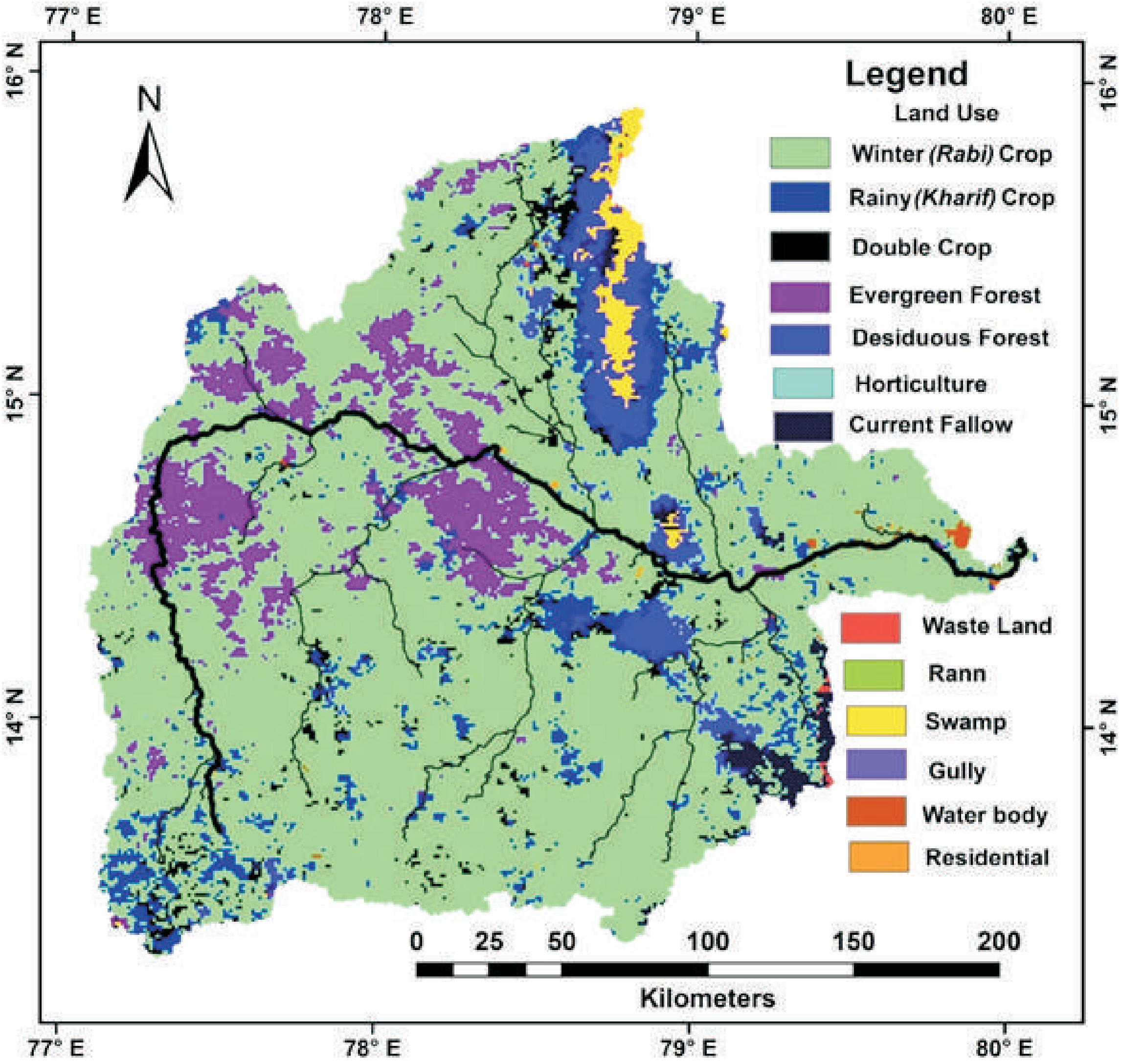

Fig. 3. Map showing the present land use followed in the Pennar basin

2.4 .3. Soil

The soil series map of undivided Andhra Pradesh at a 1:250,000 scale by NBSS&LUP (2005) provided the soil database for the Pennar basin (Fig. 4). Soil hydraulic data were estimated using pedotransfer functions for Indian soils (Adhikary et al., 2008) due to data unavailability in the report. The map indicates that 69% of the basin's soil is heavy-textured.

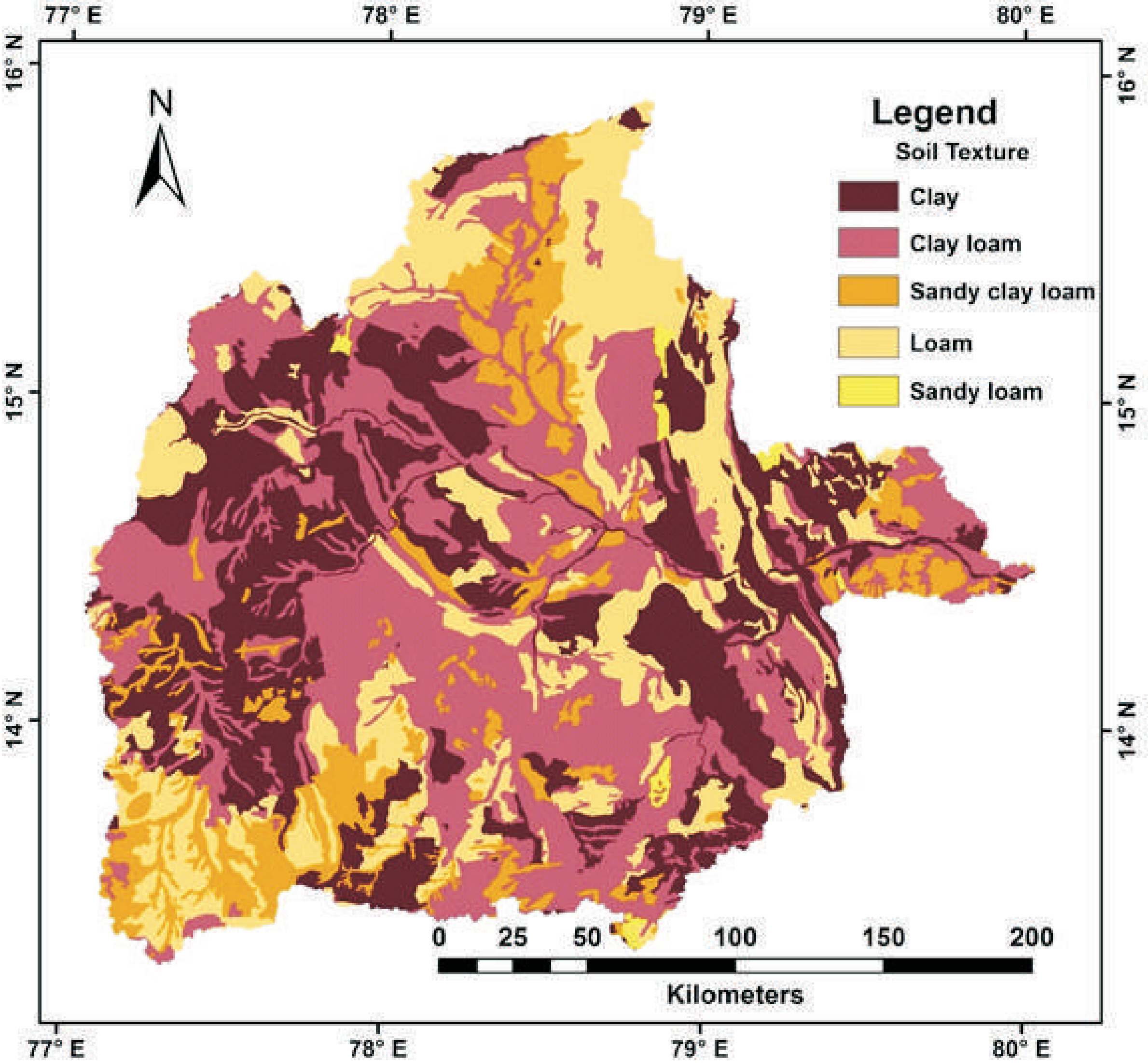

Fig. 4. Map showing the spatial distribution of predominant soil textures in the Pennar basin

2.4.4. Weather

The SWAT model requires daily weather data inputs, which can be observed or simulated. This study obtained 37 years (1969-2005) of observed data for rainfall, temperature, humidity, and wind speed from the India Meteorological Department (IMD). Solar radiation, not available from IMD, was calculated using temperature data (Hargreaves and Samani, 1985). Observed data were used for simulation, with the weather generator filling missing values, when necessary, by using the maximum likelihood-based expectation maximization method.

2.5. Model Setup

The ASTER DEM was utilized for watershed delineation and for creating stream networks and outlets. The SWAT generated the Hydrological Response Units (HRUs) by integrating pre-prepared land use and soil maps by reclassifying and overlaying soil, land use, and slope classes accurately. Given the watershed's size, thresholds of 5% for land use, 10% for soil, and 10% for slope were set to form HRUs, resulting in 73 sub-watersheds and 1,410 HRUs. Smaller sub-basins increase drainage network detail, while larger ones reduce it. Bingner et al. (1997) noted that SWAT's erosion model runoff volume is not significantly affected by sub-watershed size.

Climate data inputs included precipitation, minimum and maximum temperature, wind speed, solar radiation, and relative humidity, formatted and imported into SWAT. The model was run over 14 years (1992-2005), including a three-year warm-up, with results produced monthly.

2.6. Model Calibration and Validation

Calibration, validation, and sensitivity analysis of the SWAT model were conducted using SWAT-CUP. Observed outflow data from 1995 to 2000 with a warm-up period of three years, were provided for model calibration at six gauging stations. To achieve proper calibration, 15 sets of parameters were individually applied to each gauging station, using the utility program option in SWAT-CUP called "upstream sub-basins" to separate upstream sub-basins and assign different parameter ranges to different sub-basins. This method involved using 90 parameters to calibrate the entire Pennar basin, encompassing the six gauging stations. By subcategorizing 15 sets of parameters into 90 sets, the calibration was fine-tuned to account for the diverse ecological regions within the watershed, improving the sensitivity analysis and overall calibration accuracy.

The effectiveness of the calibration was evaluated using several statistical metrics: the Nash-Sutcliffe coefficient of efficiency (NSE), the coefficient of determination (R^2), the ratio of the root mean square error to the standard deviation of the measured data (RSR), and the percentage bias (PBIAS). These metrics are described below:

NSE measures how well the predicted values match the observed data, with values closer to 1 indicating better performance.

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

Where,
n is the number of measured data
O_i and P_i are measured and predicted data at time i
O' is the mean of the measured data.
R^2 indicates the proportion of the variance in the observed data explained by the model, with values closer to 1 signifying a better fit.

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

Where,
n is the number of measured data
O_i and P_i are measured and predicted data at time i
O' and P' are mean of the measured data and predicted data
RSR combines error index statistics and the standard deviation of the observations, with lower values indicating better model performance.

$$RSR = \frac{RMSE}{STDEV_{obs}} = \left[\frac{\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - O')^2}}\right]$$

Where, n is the number of measured data
O_i and P_i are the measured and predicted data at time i
O' is the mean of measured data
PBIAS measures the average tendency of the simulated values to be larger or smaller than their observed counterparts, with values closer to 0 indicating more accurate model predictions.

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

Where, n is the number of measured data
O_i and P_i are the measured and predicted data at time i.

2.7. Sensitivity Analysis

In the present study, sensitivity analysis was conducted using the Latin Hypercube Sampling and One-At-a-Time (LHS-OAT) method. This technique allows us to observe the impact of individual parameters on the model output by measuring the rate of change in response to variations in input parameters. For the calibration of runoff estimation, a total of 90 parameters were utilized, with 15 sets assigned to each of the six gauging stations. These parameters were varied within their absolute ranges. Some parameters, such as curve number, available water content, bulk density, hydraulic conductivity, and average slope length, were adjusted using relative methods, while others were replaced or set using absolute methods. A wide range of parameters were provided to the model for calibration due to the limited understanding of parameter behaviour within the watershed.

During the calibration process, parameters were adjusted in a trial-and-error manner based on observations from global analysis graphs, dotty plots, and the 95% prediction uncertainty (PPU) graph to achieve a good fit between simulated and observed streamflow. The goal was to obtain simulated streamflow output that closely matched observed data.To predict uncertainty, the p-factor (percent of observations bracketed by the uncertainty band) and r-factor (achievement of a small uncertainty band) were calculated. A p-factor close to 1 and a small r-factor indicate better results in predicting uncertainty (Luo et al., 2011).

3.0. Result and Discussion

3.1. Flow calibration and validation using SUFI-2 algorithm

The calibration phase of hydrological models like SWAT involves adjusting model parameters to minimize the difference between simulated and observed hydrological behaviour. In this case, after 500 simulations, Table 1 displays the optimized values of 15 parameters, revealing a narrower range compared to the default SWAT recommendations. This narrowing suggests reduced parameter uncertainty and indicates a stable model capable of accurately representing hydrological processes within the Pennar basin. The fact that uncertainties are categorized as epistemic implies that they arise from a lack of knowledge rather than inherent variability in the system. Notably, the uncertainty in predictions, as indicated by the 95 percent prediction uncertainty (PPU) band, suggests greater uncertainty for higher discharge rates, which is crucial for understanding potential model limitations and informing decision-making processes. The optimized parameter values, coupled with the narrowed parameter range, indicate the model's capability to simulate hydrological behaviour under different conditions, including potential impacts of climate change. Previous studies (Gosain et al., 2006; Narsimlu et al., 2015; Mandal et al., 2021) support the suitability of the SWAT model for predicting hydrological behaviour in various river basins under different climate change scenarios, further validating the findings and conclusions drawn from this study. Overall, the narrowed parameter range and optimized parameter values enhance confidence in the model's predictive capabilities, providing valuable insights for water resource management and climate change adaptation strategies in the Pennar basin.

Table 1: Input parameters for calibrating and validating the SWAT model

Parameter Name	Description	Initial parameter distribution		Final parameter distribution		Fitted value	
		Min value	Max value	Min value	Max value	Upper Pennar	Lower Pennar
R__CN2.mgt	SCS Curve number for soil moisture condition II	-0.2	0.2	-0.2	0.2	0.002	-0.02
V__ESCO.hru	Soil evaporation compensation factor	0	1	0	1	0.23	0.35
V__GW_DELAY.gw	Groundwater delay time	1	30	1	30	11	14
R__SOL_AWC(..).sol	Available water capacity of the soil layer	-0.2	0.2	-0.2	0.2	0.14	0.18
V__RCHRG_DP.gw	Deep aquifer percolation fraction	0	1	0	0.5	0.33	0..23
V__GW_REVAP.gw	Groundwater revaporation coefficient	0.02	0.25	0.02	0.25	0.18	0.08
R__SOL_K(..).sol	Saturated hydraulic conductivity	-0.2	0.2	-0.15	0.15	-0.13	0.02
V__GWQMN.gw	Threshold water depth in shallow aquifer for return flow to occur	0	6000	1000	6000	2135	34 75
R__SOL_BD(..).sol	Soil bulk density	-0.2	0.2	-0.2	0.18	-0.18	-0.16
V__ALPHA_BNK.rte	Bank flow recession constant or constant of proportionality	0	1	0	1	0.98	0.33
A__ALPHA_BF.gw	Alpha base flow factor	0	1	0	1	0.89	0..74
R__SLSUBBSN.hru	Average slope length (m)	-0.2	0.2	-0.2	0.1	-0.04	0.07
V__EPCO.hru	Plant uptake compensation factor	0	1	0	1	0.53	0.75
V__REVAPMN.gw	Threshold depth of water in the shallow aquifer for “revap” to occur (mm)	0	500	0	4 00	51	186
V_OV_N.hru	Manning’s “n” value for overland flow	0.01	30	0.01	20	2.5	12

Calibration and validation, using the temporal split sample approach, occurred from 1995 to 2000 and 2001 to 2005, respectively, in the Pennar basin. Performance metrics included NSE, R^2, RSR, and PBIAS. The Pennar basin underwent calibration and validation through spatially distributed outlet. Distributed parameter calibration from 1995 to 2000 and validation from 2001 to 2005 at six gauging stations improved results, especially for four main tributaries and upper and lower Pennar. Calibration results are summarized in Table 2. As the four main tributaries in the Pennar benefited from the distributed approach, reflecting the true conditions of each sub-basin with varied parameter values, thus enhancing model performance. Fig. 5 displays observed and simulated monthly stream flow patterns alongside their upper and lower PPU ranges during calibration and validation. During the six-year calibration period, observed and simulated discharges aligned well across sub-basins. Although some sub-basins, including lower Pennar, exhibited higher bias due to the basin's dryness, overall performance remained satisfactory.

Table 2: Performance statistics of the SWAT model for simulating monthly stream flows using SUFI-2 during calibration and validation periods in the Pennar basin

Parameters	Upper Pennar		Lower Pennar	
	Calibration	Validation	Calibration	Validation
R^2	0.88	0.90	0.51	0.88
NSE	0.72	0.88	0.52	0.67
RSR	0.52	0.35	0.68	0.27
PBIAS (%)	-31.3	-1.3	-17.5	-6.2
p-factor	0.73	0.69	0.57	0.46
r-factor	0.79	0.53	0.55	0.74

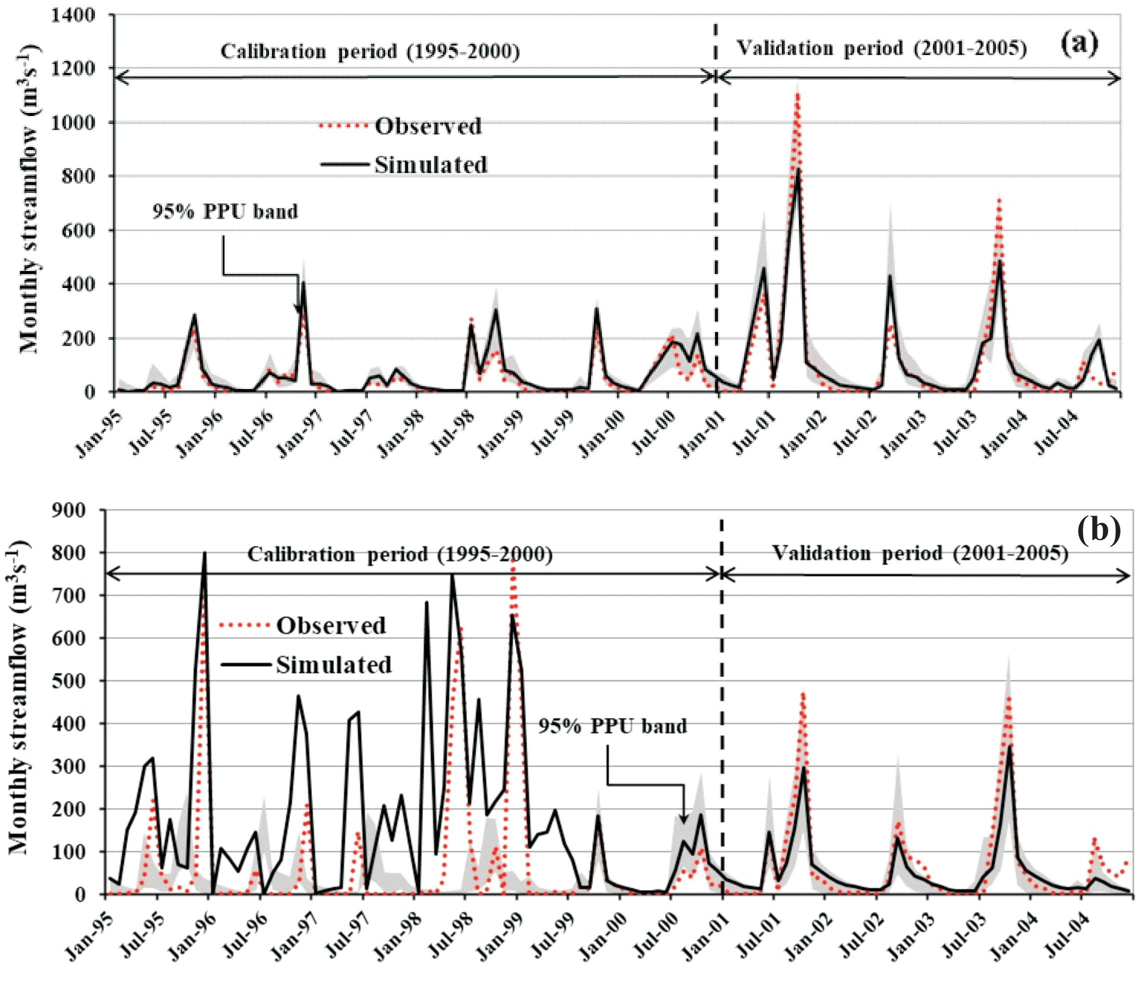

Fig. 5. Observed and simulated daily stream flow hydrographs by SUFI-2 for calibration and validation periods in the (a) Upper Pennar and (b) Lower Pennar sub-basins of the Pennar River

The validation performance of Kunderu, Sagileru, Chitravati, Papagni tributaries, upper Pennar, and lower Pennar displayed high values of R^2, NSE, and low PBIAS, indicating their significant contribution to the basin′s runoff. Kunderu River notably contributed sufficient runoff, with satisfactory performance in both calibration and validation, albeit, slight discrepancies in some months. Overall, the simulation for stream flow in the upper Pennar basin was deemed satisfactory.

The Sagileru tributary demonstrated consistent and satisfactory performance in both calibration and validation phases, with R^2 values of 0.7 and NSE values around 0.6. Despite its low runoff, Sagileru maintained stable flow patterns throughout seasons, with occasional discrepancies, notably in 1996. Similarly, the Chitravati and Papagni rivers, contributing to the southern Pennar basin, exhibited comparable patterns, with calibration generally outperforming validation. Chitravati displayed an impressive calibration R^2 of 0.9_4 but declined during validation. Papagni showed similar trends, indicating sensitivity to model parameters and observational uncertainty. The p-factor, reflecting the percentage of observations within the 95PPU, varied across tributaries, with improved results during validation, suggesting model refinement over time. Despite challenges in semi-arid regions, the basin′s tributaries and main river basin demonstrated satisfactory performance. Discrepancies between calibration and validation underscored the need for enhanced data quality and consideration of external factors in future modeling endeavours, particularly in addressing uncertainties arising from anthropogenic water usage and runoff observation errors.

In both upper and lower Pennar, validation outperformed calibration. Upper Pennar displayed an R^2 of 0.90 in validation, indicating a near-unbiased result, contrasting with its biased calibration phase (Fig. 5). The model was occasionally overpredicted, possibly due to input errors or hydrological variations. Lower Pennar′s SUFI-2 algorithm showed lower capture rates during calibration, resulting in decreased statistical parameters. While R^2 and RSR suggest good model performance, NSE and PBIAS reveal discrepancies between observed and simulated runoff. Uncertainties arise from factors like climatic data errors, downstream activities, or soil properties. Despite challenges, the overall basin performance, including its tributaries, remains satisfactory. Improved data quality and accounting for external factors are crucial for accurately simulating large basins using SWAT.

3.2. Sensitivity of model parameters

Before model calibration, sensitivity analysis is crucial to identify significant parameters, reducing their number for manageable handling in the SWAT model. The SUFI-2 optimization technique′s outcomes, include best-fit estimations and parameter uncertainty ranges, denoted by "v" for replacement, "r" for percentage change, and "a" for addition. Sensitivity analysis in SWAT-CUP, using SUFI-2 optimization, employs t-stat for sensitivity measurement and p-value for significance determination. Table 3 summarizes values for t-stat and p-value within the Pennar basin. High absolute t-stat values indicate greater sensitivity, while values close to zero in p-value indicate significance (Abbaspour 2011).

Table 3: Sensitivity analysis of SUFI-2 model parameters for monthly stream flow simulation in the Pennar basin

Parameter Name	Calibration		Validation	
	t-Stat	p-Value	t-Stat	p-Value
R__CN2.mgt	2.07	0.009	-1.83	0.068
V__ESCO.hru	0.32	0.748	0.40	0.686
V__GW_DELAY.gw	1.04	0.301	-1.42	0.155
R__SOL_AWC(..).sol	1.57	0.116	1.50	0.133
V__RCHRG_DP.gw	1.14	0.255	-3.16	0.002
V__GW_REVAP.gw	0.98	0.330	0.37	0.709
R__SOL_K(..).sol	-1.49	0.137	1.33	0.185
V__GWQMN.gw	0.45	0.656	-0.59	0.555
R__SOL_BD(..).sol	-1.00	0.317	-0.13	0.893
V__ALPHA_BNK.rte	-0.68	0.497	-0.01	0.989
A__ALPHA_BF.gw	1.79	0.074	1.18	0.238
R__SLSUBBSN.hru	-0.48	0.629	0.24	0.813
V__EPCO.hru	1.13	0.261	-1.02	0.306
V__REVAPMN.gw	-0.71	0.476	1.27	0.205
V__OV_N.hru	-1.49	0.136	1.33	0.185

Sensitivity analysis, conducted using the latin hypercube one-factor-at-a-time (LH-OAT) technique (Van Griensyen et al., 2006) in SUFI-2, highlighted parameters like GW_DELAY, GW_REVAP, GWQMN, RCHRG_DP, REVAPMN, ALPHA_BF, SOL_AWC, SOL_K, SOL_BD, ESCO, EPCO.hru, OV_N, SLSUBBSN, CN2, and ALPHA_BNK as sensitive. In the Kunderu sub-basin, parameters such as CN2, ESCO, GW_DELAY, SOL_AWC, RCHRG_DP, GW_REVAP, SOL_K, GWQMN, and SOL_BD are highly sensitive, indicating their crucial role in regulating stream flow. These parameters, linked to soil and groundwater dynamics, heavily influence the sub-basins hydrology. For instance, the relatively low GW_REVAP value suggests efficient capillary water movement to the root zone, while RCHRG_DP′s low value indicates limited deep aquifer recharge. Overall, soil characteristics and aquifer properties significantly impact runoff generation in the Kunderu sub-basin. In the adjacent Tungabhadra River basin, Singh et al. (2013) identified ten highly sensitive hydrological parameters, and eight of these were also found to be sensitive in the current study.

Sensitivity analysis of the Sagileru sub-basin, contrasting with the Kunderu sub-basin, reveals significant parameter differences due to geological, geomorphic, soil, and climatic variations. Key parameters include CN2, GW_REVAP, ESCO, SOL_K, SOL_BD, ALPHA_BF, RCHRG_DP, REVAPMN, GW_DELAY, and OV_N, with groundwater parameters notably sensitive. Despite being in the rain shadow of the Eastern Ghats, high evapotranspiration occurs. A high GW_REVAP value (0.24) indicates a shallow aquifer, leading to rapid water flow due to the area′s sloping terrain. The Chitravati sub-basin exhibits sensitivity patterns akin to the Kunderu sub-basin. Key sensitive parameters include RCHRG_DP, CN2, ESCO, GWQMN, GW_REVAP, SLSUBBSN, SOL_AWC, SOL_BD, SOL_K, GW_DELAY, with average slope length also influential. High evapotranspiration is observed, reflected in a notable GW_REVAP value (0.25), suggesting a shallow aquifer presence and capillary rise, with predominant sheet flow and overland runoff.

In the Papagni sub-basin of the Pennar basin, all hydrological parameters are highly sensitive, making it the most sensitive sub-basin. Key parameters include HRU, soil, and groundwater factors like GWQMN, RCHRG_DP, CN2, EPCO, ESCO, SOL_BD, GW_DELAY, GW_REVAP, ALPHA_BF, OV_N, SOL_AWC and REVAPMN. Notably, EPCO, dependent on soil water availability, is crucial, with a sensitivity of 0.29 indicating minimal deviation from the original distribution.

In the lower Pennar basin, ALPHA_BF, SOL_AWC, OV_N, RCHRG_DP, EPCO, and SOL_BD are sensitive parameters. Conversely, in the upper Pennar basin, GW_REVAP, REVAPMN, and ALPHA_BNK show sensitivity. The movement of water from the shallow aquifer into the unsaturated zone appears significant in the upper Pennar, indicated by GW_REVAP's value of 0.18. However, the lower Pennar's ample rainfall reduces the need for direct aquifer water uptake, lessening GW_REVAP and REVAPMN's significance. Overall, differences in hydrological processes due to varying rainfall patterns influence parameter sensitivity between the upper and lower Pennar basins.

The sensitivity analysis reveals that the soil evaporation compensation factor (ESCO) is crucial for all tributaries except the lower Pennar. In Tungabhadra River basin also, ESCO was a crucial sensitive parameter (Singh et al., 2013). Low coefficients in Kunderu, Sagileru, Chitravati, and Upper Pennar suggest adequate moisture extraction from lower soil layers, contrasting with high coefficients in Papagni and lower Pennar, indicating insufficient moisture for plant uptake (Adhikary et al., 2019). Soil parameters like SOL_AWC and SOL_BD are universally sensitive. Curve number, key for runoff, varies across HRUs due to soil permeability and land use, influencing runoff potential. With only 14.9% stream flow from total precipitation (Table 4), the basin's low runoff potential aligns with its predominantly medium-textured soil.

3.3. Water balance in Pennar basin

The simulated water balance components for the Pennar basin, as derived from the SWAT model, provide valuable insights into its hydrological conditions (Table 4). With a precipitation input of 813.3 mm, the basin receives a substantial amount of rainfall, which drives various hydrological processes. Surface runoff, totalling 121.83 mm, signifies the portion of rainfall that directly flows over the land surface, indicating potential risks of soil erosion and surface water runoff. Lateral flow, at 10.52 mm, demonstrates limited horizontal movement of water within the soil profile (Adhikary et al., 2019). Groundwater flow, accounting for 20.27 mm, suggests modest recharge of groundwater resources within the basin. The total water yield, calculated at 215.49 mm, signifies the combined availability of surface water and groundwater. Evapotranspiration is notably high at 538.5 mm, indicating significant water loss to the atmosphere, likely driven by warm temperatures and vegetation activity. Percolation out of the soil, with a value of 132.98 mm, indicates substantial water infiltration into the soil profile, which is essential for groundwater recharge and sustaining soil moisture levels. Deep aquifer recharge, totalling 21.88 mm, suggests a moderate replenishment of deep aquifers with water, indicating potential limitations in groundwater replenishment processes within the basin. Variations in topography and soil physical properties significantly influence the hydrological process (Shivakoti et al., 2008). Different land uses affect the water balance by controlling transpiration, interception storage, throughfall, plant water uptake, and infiltration capacity (Breuer et al., 2009). Overall, the analysis of these hydrological fluxes provides valuable insights into the water balance dynamics of the Pennar basin, essential for informed water resource management and conservation efforts in the region.

Table 4: Simulated water balance components (mm) for the Pennar basin using the SWAT model

Hydrological fluxes	Amount (mm)
Precipitation	813.3
Surface Runoff	121.83
Lateral flow	10.52
Groundwater flow	20.27
Total water yield	215.49
Evapotranspiration	538.5
Percolation out of soil	132.98
Deep Aquifer recharge	21.88

4.0. Conclusion

The assessment of hydrological processes and water balance in the Pennar River basin using the SWAT model has provided valuable insights into the basin's hydrological dynamics. The model's ability to simulate runoff with high accuracy, as reflected in strong statistical performance, underscores its reliability as a tool for hydrological analysis in complex river basins. The sensitivity and uncertainty analyses further validated the robustness of the model, highlighting critical parameters influencing runoff generation.The findings reveal that surface runoff accounts for only 14 % of total precipitation, emphasizing the basin's low runoff potential and the need for focused water conservation efforts. The results indicate that unsustainable human activities and the effects of climate change are likely to exacerbate water scarcity issues in the region. This calls for the implementation of effective water management strategies, including the adoption of best management practices (BMPs) to mitigate water stress and ensure sustainable water use.The SWAT model's effectiveness in capturing the key components of the water balance makes it a valuable tool for future studies on the impacts of climate change and land-use dynamics on water resources. These findings can guide decision-makers in developing long-term conservation strategies to preserve the basin's water yield, supporting both ecological health and human needs in the face of growing environmental challenges.

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