**Comparative Analysis of SWAT Model Performance Under Varying Land Use and Soil Data Resolutions in eastern India**

**Abstract**

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| This study investigated the impact of land use/land cover (LULC) and soil data resolution on hydrological modeling using the Soil and Water Assessment Tool (SWAT) in the Bargarh command area of the Mahanadi River Basin, India. Six scenarios combining different resolutions of LULC (1:250000, 1:50000, and 10m spatial resolution) and soil data (1:5000000 and 1:50000) were used to simulate streamflow. The SWAT model was calibrated (2000-2012) and validated (2013-2020) using the SUFI-2 algorithm. Model performance was evaluated using the Nash-Sutcliffe efficiency (NSE), coefficient of determination (R2), percent bias (P-bias), R-factor, and P-factor. The results showed that the simulated streamflow matched well with the observed data for all scenarios, with the D1L1S1, D1L3S1, and D1L3S2 setups exhibiting the best agreement. The NSE values ranged from 0.76 to 0.89, R2 from 0.86 to 0.91, P-bias from -3.8% to 31.7%, R-factor from 0.56 to 1.20, and P-factor from 0.73 to 0.91 during calibration and validation. This study highlights the importance of the combination and classification of datasets in hydrological modeling, indicating that fitted parameter values do not adjust uniformly for all uncertainty sources. These findings provide guidance for selecting appropriate precision levels of input data for future SWAT applications to improve the accuracy and reliability of hydrological predictions. This study also highlights the practical relevance of hydrological modeling for water resource planning and management. The findings provide guidance on selecting appropriate input data resolutions to improve the accuracy and reliability of streamflow predictions using the SWAT model. |

**Keywords** *Hydrological Modelling, Soil parametrization, Runoff, SWAT*

**1.Introduction**

Water availability and quality are global concerns, presenting challenges for water resource managers and decision-makers (Muller et al., 2007; Bhandari et al., 2018). Computer-aided hydrological models have become increasingly prevalent in water resource research, using various tools available for hydrological and hydraulic simulations (Thakali et al., 2016; Murty et al.,2020; Sedighkia et al., 2022). Watershed responses to hydrological events are influenced by land use/land cover, soil type, and climate, necessitating the collection of diverse soil data for modeling purposes. Spatially dispersed hydrological models enable the design and evaluation of water management strategies (Romanowicz et al., 2005), allowing for multi-objective assessment of regional forcing terms and command variables on hydrological responses. Well-parameterized models can inform policy development, effective watershed management plans, support sustainable livelihoods, and environmental protection (Zhang et al., 2015). Such modeling studies have consistently aided decision-making processes (Goodchild et al., 1992; Uniyal et al., 2020). The Soil and Water Assessment Tool (SWAT) is a widely used conceptual semi-distributed hydrological model that simulates runoff and sediment yield (Geza et al., 2008). The accuracy of hydrological models depends heavily on the precision of the input data, particularly land use land cover (LULC) data for semi-distributed models such as SWAT (Arnold et al., 2012; Chen et al., 2016). Research has focused on the impact of land cover change on streamflow, water quality, and sedimentation (Kumar et al., 2009). However, the effects of LULC data categorization systems and spatial resolution on hydrological modeling require further investigation. Spatially dispersed hydrological models offer advantages in assessing land and water management decisions but also present challenges, including extensive data requirements, computational power needs, and questions regarding model resilience, sensitivity, and validity (Abbot & Refsgaard, 1996; Kassaye et al., 2024; Zhao et al., 2024). There is a gap in understanding how different resolutions of input data interact to influence model performance. Further research could explore optimal combinations.

Studies have demonstrated that GIS data resolution and aggregation significantly impact rainfall-runoff process modeling (Becker & Braun, 1999). Consequently, a detailed examination of the soil, vegetation, and climatic parameterization is essential before model calibration (Moriasi et al., 2011). The sensitivity of the SWAT model to soil parameterization, particularly the available water capacity, has been established in previous research (Muttiah & Wurbs, 2002).LULC datasets play a crucial role in assigning hydrological and water quality features to the USLE (Asante et al., 2017). This study employed three types of land use/land cover datasets and two types of soil dataset. These include ISRO's Natural Resources Census program data, Bhuvan-LULC 250 K information, and a global LULC map with 10-meter spatial resolution based on ESA Sentinel-2 imagery. Soil data sources included the Harmonized World Soil Database and the National Bureau of Soil Survey and Land Use Planning's national soil resource map. Additionally, high-spatial-resolution IMD Gridded Daily Rainfall data were incorporated (Pai et al., 2014). This study aimed to examine the sensitivity of the SWAT model to soil and LULC inputs for simulating surface runoff, which can be used in further studies. It examines the difference in the predictive reliability of the SWAT model for streamflow simulation under parameter uncertainty resulting from varying degrees of complexity and resolution of the input data.

**2. Materials and methods**

**2.1 Study area**

The study area for the current research was the Bargarh Canal command in the middle reach of the Mahanadi River Basin. This region spans 11 blocks across the Balangir, Subarnapur, Sambalpur, and Bargarh districts. Geographically, it is positioned between the latitudes of 20°43' and 21°41' N and longitudes of 83°39' and 83°58' E (Fig.1). With an average height of 185 m above sea level, the land terrain is flat to reasonably high and covers an area of 2085 km2. The sub-elevation basin ranges from 166.0 to 1096.0 meters with an average annual rainfall of 1660 mm. Clay loam is the most common soil type in the basin and has a high water holding capacity. This soil type is rich in nutrients and is ideal for growing rice, lentils, oilseeds, and cotton. Summer temperatures ranged from 25 °C to 45 °C, while winter temperatures ranged from 11 °C to 27 °C.



 **Fig. 1** Location of Bargarh canal command area

The Soil and Water Assessment Tool (SWAT) model primarily requires four major input data: topographic data (DEM), land cover data, soil data, and meteorological data (rainfall, temperature) (Arnold et al., 2012). The sources and data formats for all datasets used in this study are listed in Table 1.

**Table 1** Overview of primary input data

|  |  |  |
| --- | --- | --- |
| Data | Data Format/Scale | Data Source |
| DEM | Grid (cell size 30 × 30 m) | ASTER Global DEM from USGS |
| Land use/Land cover map | 1:2500001:5000010m × 10m  | NRSC, ISRO,HyderabadESRI Global LandCover Map |
| Soil map | 1:50000001:50000 |

|  |
| --- |
| FAO World soil database |
| NBSS & LUP-ICAR, Govt. of India |

 |
| Meteorological data | Table (.dbf and text) | Indian Meteorological Department (0.250) |

**2.2 Preparation of model input**

The Arc-SWAT model was established using input data with varying geographical resolutions and combinations. DEM, LULC, and Soil data were selected for each setup, and the model was run. Six combinations were made using two types of soil type and three types of land use/land cover datasets.1:250000 land use data were taken as L1, 1:50000 as L2, and 10 m spatial resolution as L3. Similarly, 1:5000000 as S1, 1:50000 as S2, and DEM as D1.

**2.2.1 Digital elevation model**

SWAT's automatic watershed delineation tool, Arc SWAT, employs a digital elevation model (DEM) as a geographic input dataset to identify sub-watersheds within the study area. The resolution of the DEM affects watershed delineation, stream networks, and sub-basin classification (Chaubey et al., 2005). A DEM map, comprising tiles from the global database, is accessible with a resolution of 30 m x 30 m from USGS Earth Explore. Before integrating the tiles with Arc SWAT, mosaicking and projection into the Universal Transverse Mercator (UTM) coordinate system were conducted, employing the WGS 1984 spheroid type and the WGS 1984 UTM Zone 44 N projection.

**2.2.2 Land use/land cover data**

In the watershed/command area, LULC affects streamflow transit. The satellite land use land cover thematic database maps for 1995, 2005, and 2015 were collected from the NRSC and ISRO Hyderabad in the current study. The georeferenced contour boundary of the basin was used as the AOI for sub-setting satellite images using this database map and the DEM (area of interest (DEM). Using the AOI and signature editor tools, individual agricultural land, water bodies, woodland, wasteland, built-up, and town shape files were created in the ERDAS Imagine. The use and land cover of the sub-land basin were divided into five categories: built-up areas where people have grown due to non-agricultural activities, such as construction, industry, commerce, and transportation. These features have rough roughness. Field, commercial, plantation, and horticultural crops are all grown on agricultural land. The land use maps for the Bargarh command at scales of 1:250000 and 1:50000 were mosaiced and classified into 7 and 15 classes, respectively.

**2.2.3 Soil data**

To determine the characteristic soil for runoff estimation, the Harmonized World Soil Database provided a digitalized vector-dataset-based soil map of the world at a scale of 1:5000000. To create the requisite soil map, this soil map was geo-referenced and then clipped with a shape file of the research region, and a scale of 1:50000 was obtained from the National Bureau of Soil Science and Land Use Planning (NBSS and LUP). They were then reclassified into eight classes. A lookup table for both soil types was created for the SWAT model (Sahu et al., 2016).

**2.2.4 Hydrological and Meteorological data**

Daily climatic inputs, including precipitation, maximum and minimum temperatures, and daily gridded rainfall data with 0.25° geographic resolution, were obtained from the IMD, Pune, India. The gridded binary weather data were converted into CSV/Excel using Python and QGIS. Hydrological data are necessary for model calibration, validation, uncertainty, and sensitivity analysis (Mohapatra et al.,2023). Daily discharge statistics for the study command area (2000-2020) were acquired from the Water Resource Information System of India (India-WRIS). Additionally, long-term daily flow data (2004-2014) for the Bargarh command outlet were obtained from the Central Water Commission (CWC) office in Bhubaneswar and downloaded from the India-Wris website.

**2.3 Generation of hydrological response units**

Land cover, soil, and slope data are required to determine hydrological response units (HRUs). A subthreshold basin value then determines the number. The threshold value specifies the minimum percentage that the model can exclude from land coverage. Consequently, the model ignores any coverage below the threshold. The HRU was generated for each intersecting unique combination of land use, soil type, and topography with a 10% threshold value (Uniyal et al.,2020). Table 2 lists the number of HRUs generated for each model setup.

**Table 2** Number of HRUs for each criterion

|  |  |
| --- | --- |
| **CRITERIA** | **HRU**  |
| D1L1S1 | 151 |
| D1L2S1 | 170 |
| D1L3S1 | 163 |
| D1L1S2 | 192 |
| D1L2S2 | 222 |
| D1L3S2 | 263 |

**2.4 Model efficiency evaluation**

In this study, the model efficiency was calculated using the coefficient of determination (R2), Nash-Sutcliffe efficiency index (NSE), P-factor, R-factor and Percent Bias (Jakada et al., 2020).

**2.4.1 Coefficient of determination (R2 )**

R2 is a key metric for evaluating the agreement between the observed and simulated data. It ranges from 0 to 1, with 1 indicating a better correlation and 0 indicating no correlation. R2 was calculated using the equation provided in Eq.1. Generally, R2 values exceeding 0.5 are considered acceptable, demonstrating a reasonable fit between the observed and simulated data.

$R^{2}=\frac{\left[\sum\_{i=1}^{n}\left(S\_{i}-\overbar{S}\right)\left(O\_{i}-\overbar{O}\right)\right]^{2}}{\sum\_{i=1}^{n}\left(S\_{i}-\overbar{S}\right)^{2}\sum\_{i=1}^{n}\left(O\_{i}-\overbar{O}\right)^{2}}$ (1)

**2.4.2 Nash–Sutcliffe efficiency**

The Nash-Sutcliffe Efficiency (NSE) is a normalized statistical approach used to forecast the noise level in relation to the information content. The NSE values ranged from 0 to 1, reflecting the degree of alignment between the simulated output and observed data along a 1:1 line (Arnold et al., 2012). This efficiency metric was presented by Nash and Sutcliffe in Eq. (2).

$NSE=1-\frac{\sum\_{i=1}^{N}(O\_{i}-S\_{i})^{2}}{\sum\_{i=1}^{N}(O\_{i}-\overbar{O})^{2}}$ (2)

where $O\_{i}$ - observed parameter and $S\_{i}$ is the predicted parameter.

**2.5 Model calibration as well as validation**

 The calibration technique aims to minimize the discrepancy between the observed and model-simulated values by optimizing the model parameters(Arnold et al., 2012). For model calibration and validation, we utilized monthly streamflow data from 2000 to 2020. The model underwent a 13-year calibration period (2000-2012), including a three-year warm-up phase, followed by an eight-year validation period (2013-2020) using the SUFI-2 algorithm. The parameters used for calibration are listed in Table 3.

**Table 3** Parameters and Descriptions Used for Calibration as well as validation

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Sensitivity Rank** | **Calibration****parameters** | **Description** | **Qualifier** | **Minimum value** | **Maximum value** | **Fitted Parameters** |
| 1 | CN2.mgt | Curve number (II) | r | -0.169 | 0.110 | 0.062 |
| 2 | ALPHA\_BF.gw | Base flow recession constant | v | -0.307 | 0.564 | 0.276 |
| 3 | GW\_DELAY.gw | Groundwater delay | a | 79.451 | 359.838 | 228.056 |
| 4 | GWQMN.gw | The threshold water level in the shallow aquifer for base flow | v | 1583.575 | 4751.424 | 1995.395 |
| 5 | ESCO.hru | Soil available water capacity | v | 0.392 | 0.535 | 0.303 |
| 6 | SOL\_AWC(..).sol | Soil available water capacity | r | -0.109 | 0.171 | 0.028 |
| 7 | CH\_K2.rte | Channel hydraulic conductivity | v | 67.007 | 201.042 | 89.793 |
| 8 | SOL\_K(..).sol | Saturated hydraulic conductivity | r | -0.083 | 0.248 | -0.098 |
| 9 | SURLAG.bsn | Surface runoff lag | v | 2.015 | 5.046 | 4.894 |
| 10 | CH\_N2.rte | Channel Manning’s n | v | 0.088 | 0.246 | 0.229 |

(i) a\_ represents the fitted value is added to the existing parameter value; (ii) r\_ represents the current parameter value is multiplied by (1+the given value); (iii) v\_ represents the current value of the parameter is to be replaced by the fitted value.

**3. Results and discussion**

Figure 2-7 show the graphs of all the simulated streamflows for the six different combinations. Six model configurations were built using 1:250000 scale, 1:50000 and 10m spatial resolution land use/land cover data, and 1:5000000 and 1:50000 soil data. From the time series plot, it was observed that the simulated streamflow under all scenarios matched well with the observed streamflow, but D1L1S1, D1L3S1, and D1L3S2 were in better agreement with the observed streamflow. All parameters, such as NSE, R-squared, P-bias, P-factor, and R-factor, are shown in Tables 4 and 5. After calibration and validation of the six model setups, Fig. 8 summarizes the NSE data, Fig. 9 represents the R-squared values, Fig. 10 depicts the P-bias value being influenced, and Fig. 11 and 12 show the P-factor and R-factor, respectively.

**3.1 Evaluation of Model Performance**

The results from the calibrated and validated SWAT model were adequate despite the uncertainty caused by the input data. The ten parameters listed in Table 3 were used to calibrate the model, and those in Table 4 were used to validate the model. SUFI-2 optimization approaches employ these characteristics to calibrate the streamflow every month. The streamflow simulation of the SWAT model is affected by both surface runoff and groundwater flow mechanisms, which is why both are important.

Several essential variables, including (ALPHA BF, CH N2, GW DELAY, ESCO, CH K2, SOL K, and CN2), were selected because they were used in this analysis in other Indian commands. The results of this investigation are consistent with seven of the ten sensitive parameters mentioned in this research. This study examined the need for a thorough understanding of hydrological models and GIS data input techniques. This necessitates the development of a model application methodology that is accessible to all users. As a result, extra attention must be paid to how the applied model creates, manipulates, and transforms GIS data. Preprocessing data for which the model user has little or no control should be given special care.

**Fig. 2** Hydrograph of Streamflow during Calibration as well as validation periods under D1L1S1

**Fig. 3** Hydrograph of Streamflow during Calibration as well as validation periods under D1L2S1

**Fig. 4** Hydrograph of Streamflow during Calibration as well as validation periods under D1L3S1

**Fig. 5** Hydrograph of Streamflow during Calibration as well as validation periods under D1L1S2

**Fig. 6** Hydrograph of Streamflow during Calibration as well as validation periods under D1L2S2

**Fig. 7** Hydrograph of Streamflow during Calibration as well as validation periods under D1L3S2

**Table 4** Model performance and Weightage assignment to scenarios during calibration

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Criteria | D1L1S1 | D1L2S1 | D1L3S1 | D1L1S2 | D1L2S2 | D1L3S2 |
| NSE | 0.88 | 0.89 | 0.88 | 0.88 | 0.87 | 0.89 |
| R2 | 0.88 | 0.90 | 0.88 | 0.90 | 0.88 | 0.89 |
| P-BIAS | -1.3 | 13.5 | -1.9 | -2.9 | 5.7 | -3.8 |
| R-Factor | 1.12 | 0.98 | 0.70 | 0.82 | 1.03 | 0.94 |
| P-Factor | 0.91 | 0.84 | 0.74 | 0.86 | 0.89 | 0.85 |

**Table 5** Model performance and Weightage assignment to scenarios during validation

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Criteria | D1L1S1 | D1L2S1 | D1L3S1 | D1L1S2 | D1L2S2 | D1L3S2 |
| NSE | 0.86 | 0.82 | 0.87 | 0.87 | 0.76 | 0.89 |
| R2 | 0.91 | 0.89 | 0.91 | 0.88 | 0.86 | 0.89 |
| P-BIAS | 8.4 | 31.7 | 15.5 | 10 | 35.5 | 8.5 |
| R-Factor | 1.20 | 0.96 | 1.14 | 0.56 | 1.03 | 1.01 |
| P-Factor | 0.86 | 0.73 | 0.84 | 0.59 | 0.89 | 0.81 |

**Fig. 8** Fitting discharge observation results of NSE after calibration as well as validation

**Fig. 9** Fitting discharge observation results of R-square after calibration as well as validation

**Fig. 10** Fitting discharge observation results of Percent Bias after calibration as well as validation

**Fig. 11** Fitting discharge observation results of R-Factor after calibration as well as validation

**Fig. 12** Fitting discharge observation results of P-Factor after calibration as well as validation

**3.2 Sensitivity analysis**

Sensitivity analysis, which is often conducted during calibration, identifies the parameters that have the greatest impact on model output. For the stream flow, this analysis considered ten parameters. These parameters were evaluated to determine their influence on runoff. The flow calibration ranges were established based on the SWAT CUP manual and relevant published literature. Table 3 presents a comprehensive list of the sensitive parameters identified in this analysis.

**3.3 Comparison of different Model Setups**

This section evaluates the performance of the six model configurations in the uncertainty analysis using SUFI-2. The NSE values for all model configurations range from 0.76 to 0.82 (Fig. 12), indicating satisfactory performance. The minimal variation in NSE values suggests that high-flow events are not markedly sensitive to variations in the assessed spatial input data. Nevertheless, a more detailed soil map (S2) resulted in higher NSE values and a more accurate representation of high-flow events. The primary distinction between soil maps S1 and S2 is soil depth, which is essential for hydrological models to accurately predict water storage volume and retention time.

 It can be concluded that because the pasture, forest, and agricultural categories on our LULC map predominantly varied, these three LULC selections had a noticeable impact on evapotranspiration and, in turn, on our command's water balance. Combined with L1 of resolution 1:250000 and L3 of 10 m spatial resolution with S1 of 1:5000000 resolution gives a better result fulfilling all criteria of NSE, P-bias, R2, R-factor, and P-factor. However, L3 with S2 on a 1:50000 scale has given the best combined results.

This study demonstrates the significant influence of spatial resolution on land use/land cover and soil data on hydrological modeling outcomes. By comparing six different model configurations using varying scales of input data, we revealed that certain combinations yielded superior results in simulating streamflow. Specifically, configurations D1L1S1, D1L3S1, and D1L3S2 showed the best agreement with the observed streamflow, highlighting the importance of selecting appropriate data resolutions for accurate hydrological predictions. The results of this study can guide researchers and practitioners in selecting optimal data resolutions for their specific modeling needs, potentially improving the accuracy and reliability of hydrological predictions across various scales and regions.

This analysis highlights the importance of input data resolution on SWAT model performance, while also revealing the complexity of interactions between different input datasets. Further research could help establish more definitive guidelines for optimal input data selection in different modeling contexts.

**4. Conclusion**

According to this study, the SWAT model is susceptible to internal and external soil and land-use data pre-processing. Because some input transformations affect the model outputs, examining how the model pre-processes the soil and land use data is crucial. The sub-command size threshold of the SWAT model is a crucial variable because it regulates internal aggregation and, consequently, the model's performance. However, parameterization techniques based on freely available data should be thoroughly investigated. According to the modeling performance analysis, the derived soil properties should be calculated directly from the fundamental soil data before averaging. To use the Arc-SWAT model effectively, the user must first analyze and prepare the input maps. Consequently, the land use and soil map overlay for the application of the hydrological model is more reliable. The NSE scores for all scenarios changed between 0.87 to 0.89 during calibration and 0.76 to 0.89 during calibration, indicating that all six combinations  were within acceptable limits. During calibration, the R2 value of all scenarios ranged from 0.88 to 0.90, and during validation, it ranges from 0.86 to 0.91, indicating that the simulated results were near the observed stream flow. According to the analysis, the PBIAS value ranges from -3.8 percent to 13.5 percent during calibration and 8.4 percent to 31.7 percent during validation, with most cases having a simulation bias of less than 20%. During calibration, the R-factor of all scenarios ranged from 0.70 1.12. In contrast, during validation, it ranges from 0.56 to 1.20, indicating that the dispersion of simulated data is not particularly wide compared to the observed data set. The P factor score for all situations ranges from 0.74 to 0.91 during calibration and from 0.73 to 0.89 during validation, resulting in a satisfactory result for both calibration as well as validation of six model setups, with the majority of simulated data sets falling within the 95 percent PPU zone. Among the six model setups, the D1L1S1, D1L3S1, and D1L3S2 model setups are the most effective. Hydrological modeling depends entirely on the combination and classification of datasets.

**DISCLAIMER (ARTIFICIAL INTELLIGENCE)**

Author(s) hereby declare that no generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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