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Comparison of the performance of SWAT and hybrid M5P tree models in rainfall–runoff simulation

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ABSTRACT

Stream flow forecasting is a crucial aspect of hydrology and water resource management. This study explores stream flow forecasting using two distinct models: the Soil and Water Assessment Tool (SWAT) and a hybrid M5P model tree. The research specifically targets the daily stream flow predictions at the MH Halli gauge stations, located along the Hemvati River in Karnataka, India. A 14-year dataset spanning from 2003 to 2017 is divided into two subsets for model calibration and validation. The SWAT model's performance is evaluated by comparing its predictions to observed stream flow data. Residual time series values resulting from this comparison are then resolved using the M5P model tree. The findings reveal that the hybrid M5P tree model surpasses the SWAT model in terms of various evaluation metrics, including root-mean-square error, coefficient of determination (R^2), Nash–Sutcliffe efficiency, and degree of agreement (d) for the MH Halli stations. In conclusion, this study shows the effectiveness of the hybrid M5P tree model in stream flow forecasting. The research contributes valuable insights into improved water resource management and underscores the importance of selecting appropriate models based on their performance and suitability for specific hydrological forecasting tasks.

Key words: forecasting, M5P model, runoff, SWAT model

HIGHLIGHTS

- Stream flow forecasting issues have been effectively solved using the M5P model tree and the Soil and Water Assessment Tool (SWAT).
- The 14-year (2003–2017) data were split into two sets to calibrate and validate the models.
- The SWAT model's output was compared to the stream flow data that had been acquired.
- The hybrid M5P tree model outperformed the SWAT model.

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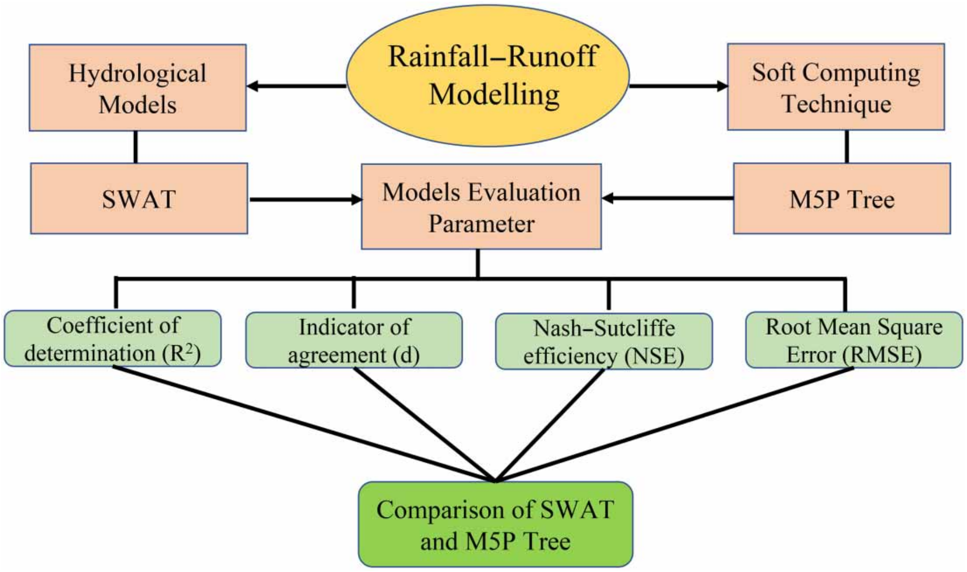
GRAPHICAL ABSTRACT



1. INTRODUCTION

One of the most crucial hydrological processes, particularly for large-scale operations, is modelling of rainfall and runoff. In addition, nonlinearity and multidimensionality make it very difficult to calculate how rainwater turns into runoff (Ishtiaq *et al.* 2010). Although there are many different classifications for hydrological models, they have generally been grouped into three categories: empirical or data-driven models, conceptual or grey box models, and physically based or white box models (Willems 2000). Empirical or data-driven models simply link the input conversion functions to the output functions rather than explicitly using rules and processes (Leavesley *et al.* 2002). The second category comprises conceptual models that are created by understanding the designer of the system model's behaviour rather than on the basis of all physical processes. The third category, theoretical models (physically based models), tries to account for all of the operations in the necessary hydrology system by incorporating physical senses (Moore *et al.* 1988).

The American Agricultural Research Organization created the hydrological model known as the Soil and Water Assessment Tool (SWAT). The basin-scale framework uses the SWAT model, a conceptual semi-distributed model. This model includes a number of processes such as those related to the weather, hydrology, nutrients, erosion, vegetation, management techniques, and flow direction. As a result, it is widely used everywhere (Gassman *et al.* 2007). A substantial advancement in the predictors of hydrological events has also been made recently thanks to the development of artificial intelligence techniques like artificial neural networks (ANNs), support vector machine (SVM), and others (Kisi & Cigizoglu 2007; Kisi *et al.* 2009; Kocabasa *et al.* 2009; Yang *et al.* 2009). M5P model tree, a machine learning approach, has gained much popularity in water resources for streamflow prediction in recent years. This is a tree-based model analogous to the linear regression model where parameter spaces are discredited to subspaces for which a local specialized linear regression model is built (Bhattacharya & Solomatine 2005). The approach has wider application in hydrology ranging from stream flow prediction to sediment yield prediction. Shamshirband *et al.* (2020) used the approach for predicting the hydrological drought index and concluded its superiority over the support vector regression method. The M5P method also performed better in short-time flood forecasting than the ANN method. Similarly, the method has been used to predict the water level of lakes where they edged over random forest, random tree, and k-nearest neighbour methods (Nhu *et al.* 2020; Ditthakit *et al.* 2021). M5P has been used both in low-flow forecasting as well as daily flow forecasting with less computation time and reasonable accuracy (Štravs & Brilly 2007; Taghi Sattari *et al.* 2013).

In river basins all over the world, the SWAT model has been widely used to simulate different types of hydrological processes (Abbaspour *et al.* 2015; Francesconi *et al.* 2016; Liu *et al.* 2016; Malagò *et al.* 2016; Tuo *et al.* 2016; Golmohammadi *et al.* 2017; Duan *et al.* 2019; Nguyen *et al.* 2019; Rahman *et al.* 2020). SWAT is also widely used to evaluate how snow affects the water cycle in mountainous basins (Rostamian *et al.* 2008; Debele *et al.* 2010; Troin & Caya 2014;

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Grusson *et al.* 2015; Shahid *et al.* 2021). Many studies have shown that the temperature-index technique, which has been widely utilized to model snow processes in various basins utilizing SWAT (Hock 2003; Walter *et al.* 2005; Zhang *et al.* 2008), is astonishingly accurate (Debele *et al.* 2010; Luo *et al.* 2013). Although SWAT has demonstrated its ability to simulate hydrological processes, it still requires a variety of geographical data and a thorough description of the numerous physical processes that affect a watershed's hydrological behaviour. ANN models, in contrast, are data driven and do not require spatial information. This is another disadvantage; however, ANN models are useful for assessing and contrasting the modelling of discharge at a single watershed outlet.

Morid *et al.* (2010) used the ANN and SWAT models simultaneously. They found that ANN outperformed SWAT for basic flow rates in summer, fall, and winter. On the contrary, the SWAT model could perform better modelling in spring when rainfall and sudden peak flow rates were frequent. Bhagwat & Maity (2012) studied the potential to use the least-square SVM to forecast the river flow rate in a catchment basin in India. In Iran, SVM was used to forecast data measurement in the Kashkan catchment basin. The results showed the high accuracy of the model. The artificial neural fuzzy inference system method according to C_means fuzzy clustering. According to frequent applications of the SWAT hydrological model and the time series tool, the main objective of this article is to evaluate the accuracy of SWAT and hybrid M5P tree models in reproducing observed rainfall–runoff patterns and compare the models' performance in predicting runoff in the MH Halli gauging site in the Hemavati River.

2. MATERIALS AND METHODOLOGY

2.1. Study area and dataset

The Hemavati River which is a major tributary of the Cauvery River, originates from the Western Ghats at an elevation of about 1,219 m amsl near the Ballalarayanadurga village in the Chikmagalur District of the Karnataka state, India. It passes from Hassan District and joins its chief tributary, the Yagachi River at Hemavati Dam and then into Mysore District before joining the Cauvery River near Krishnarajasagara. It is approximately 245 km long and has a drainage area of about 5,410 km². In this study, the study area for hydrological simulation has been taken up to its gauging site located at MH Halli station. Geographically the study area has an extent of latitude from 12°37′8″ N to 13°23′24″ N and a longitude from 75°29′23″ E to 76°10′2″ E. The study area falls under humid climatic conditions with an average annual rainfall of 1,530 mm (Shekar & Hemalata 2021) and the average annual maximum temperature of 29.35 °C and minimum temperature of 18.68 °C. The soil type was found to be loamy, clay, and clay skeletal textures with deep in depth and well drainage class and the elevation profile falls between 733 and 1,778 m amsl (Figure 1).

For the period 2003–2017, discharge (m^3/s), rainfall (mm), and temperature (°C) data on a daily scale from the MH Halli station were used. The first 8 years of data for temperature, precipitation, and discharge were used to create and calibrate the model; the final 7 years were used to test and assess the model's performance. Figure 2 displays the time series of the total data that were used for the MH Halli station. Table 1 presents a list of the statistical parameters for the outcomes.

2.2. Model descriptions

In this study, the SWAT model and the M5P model were applied to simulate discharge in the MH Halli station.

2.2.1. Soil and Water Assessment Tool

SWAT is a semi-distributed hydrologic model that can simulate surface runoff, evapotranspiration, sediment yields, the dissemination of nutrients and pesticides, plant growth, groundwater movement, and estimate reservoir storage over the long term (Grusson *et al.* 2015). In this study, ArcSWAT 2012 (Arnold *et al.* 2012) has been used for runoff simulation. After a good model design, the model can effectively mimic vast and complicated watersheds with various management techniques and best management practices. To ensure the reproducibility of research involving the SWAT or similar hydrological models, a 'proper setup' encompasses several key steps. It entails comprehensive data collection, including topography, land use, soil properties, and climate data, while ensuring data quality through validation and quality control procedures. It involves characterizing the study area by understanding its physical characteristics, such as size, shape, and topography, mapping the drainage network, analysing land use and land cover, and collecting soil data. A proper parameterization of the hydrological model is essential, involving the configuration of model parameters, calibration, and validation using observed streamflow data. The input data must be meticulously prepared, organized, and formatted for the model, including spatial data input into the SWAT model setup. The researchers should conduct scenario testing and sensitivity analysis to assess various

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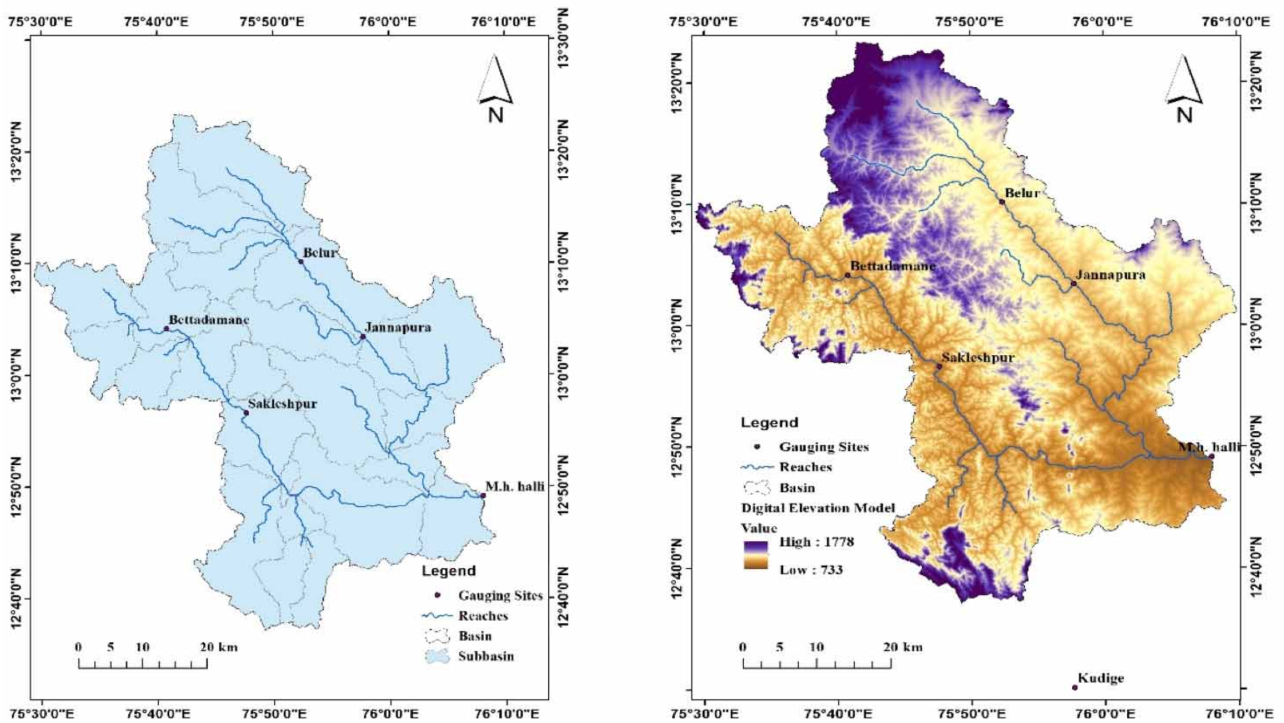

Figure 1 | Location map and digital elevation model of the study area

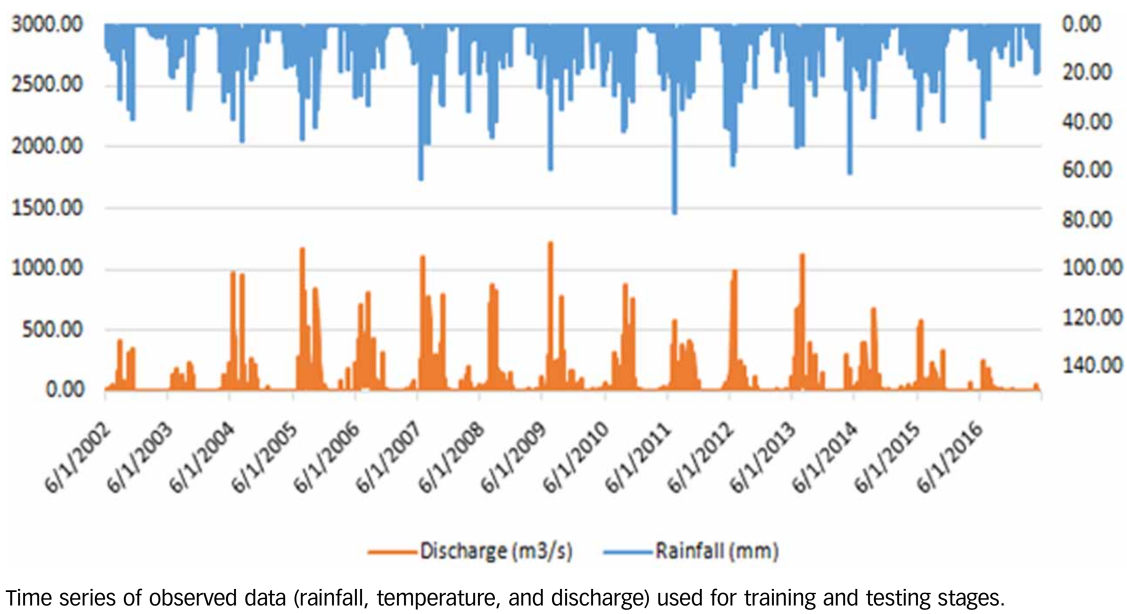

Figure 2 | Time series of observed data (rainfall, temperature, and discharge) used for training and testing stages.

land use or management practices' impact and identify influential model parameters. The model execution and analysis involve running the SWAT model with prepared data, evaluating outputs against observed data, and analysing results. Thus, thorough documentation and reporting of data sources, parameter values, and procedures ensure transparency and facilitate replication by other researchers. This comprehensive approach ensures the rigor and reproducibility of SWAT modelling studies. So it is important that while creating the sub-basins in the SWAT model the study area should thoroughly be

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Table 1 | Statistics of the data

Dataset	Data type	Data no.	Mean	STD	CV	Max	Min
Calibration (2003–2010)	Rainfall (mm)	1,346	6.12	8.34	1.36	62.415	0.000
	Discharge (Cumec)		95.13	167.47	1.76	1,203.000	0.023
	Temperature (°C)		23.23	1.01	0.05	27.733	19.920
Validation (2010–2017)	Rainfall (mm)	1,198	6.33	8.67	1.37	76.940	0.000
	Discharge (Cumec)		68.53	123.19	1.80	1,102.000	0.040
	Temperature (°C)		23.47	1.14	0.09	29.135	19.804

investigated, i.e. in a physical sense the distribution of the drainage network and the shape of the basin up to its outlet along with the land use pattern and the soil type.

While generating the sub-basins in the SWAT model, care should be taken that the number of the generated sub-basins neither be very much nor very little because it affects the runoff generation and separation process as well as the simulation of computation time and also creates difficulties while writing the output results. While creating the Hydrologic Response Unit (HRU), it is most important to understand the HRU thresholds and HRU's definition first. HRU is an abbreviation for hydrologic response unit. In hydrology and watershed modelling, an HRU is a fundamental concept used to represent a spatial unit within a watershed. It is a way to partition a watershed into smaller, manageable units based on various landscape characteristics that influence hydrological processes. The HRU concept is essential in models like the SWAT for simulating how water moves through the landscape. Each HRU typically encompasses a specific combination of land use, soil type, slope, and other factors that affect the movement of water, sediment, and nutrients within that unit. HRUs are used to model how rainfall is transformed into runoff, how sediment is eroded and transported, and how nutrients are transported within the watershed. Properly defining HRUs is crucial for accurately representing the complexity of hydrological processes in a watershed. Depending on the modelling needs and data availability, HRUs can be defined in different ways, such as by dominant land use, soil type, slope class, or a combination of these factors. The choice of HRU definition depends on the specific characteristics of the study area and the goals of the modelling exercise.

The SWAT model facilitates the four HRU definitions and two threshold criteria, and in this way as per the thresholds selected, i.e. percentage or area, HRU's definition can be chosen depending on the study area; therefore, a proper investigation of the study area is essential prior to selecting HRU's definition. In the SWAT model, the HRU's definition may be dominant of land use, soils and slopes, dominant of HRUs, target no. of HRU, and multiple HRUs. In this study, we have used multiple HRUs and percentage of thresholds. According to the standards outlined by Her *et al.* (2015), the values for land use % over sub-basin area, soil class percentage over land use area, and slope class percentage over soil area have been determined. For the SWAT model setup of this study area, we have taken land use and soil data from https://swat.tamu.edu/data/india-dataset/. Since this dataset is easily available and ready to use otherwise, finding out the HSG (Hydrologic Soil Group) is a tedious job which needs an in-depth field investigation of the soil type and multiple infiltration tests for each and every soil type found in the study area. The digital elevation model of 30 m resolution from SRTM has been used for preparing the Shuttle Radar Topography Mission (SRTM) model setup. The Hargreaves method has been used as the potential evapotranspiration (PET) method since this method requires only the temperature as an input for estimating the PET. For reaching channel routing, the Muskingum method has been selected with its default parameter value.

The calibration of model parameters for any hydrological model is an essential part only if the first simulation results are unsatisfactory or expecting more improvements. In this study, we found that the results were satisfactory which are discussed in Section 3. Such type of performance from the model can be obtained only if the model setup has been done in a proper manner as we have explained earlier. Therefore, it was decided that for this setup of the SWAT model and for this study area, no calibration of the parameters is required, which shows that the understanding of the physical meaning of all the input required to the model is necessary while setting up the model.

2.2.2. M5P model

Quinlan (1992) introduced the M5 tree as a regression decision tree learner (Quinlan 1992). Regression analysis functions are assigned to the terminal nodes of this tree approach, and a multivariate linear regression analysis is fitted to each subspace. The M5 tree scheme, rather than discrete groups, deals with continuous class problems and can handle high-dimensional

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problems. It shows the piecewise information for each linear model that was used to estimate nonlinear relationships in the dataset.

Information about the M5 model tree's splitting criteria is gathered using error calculations at each node. To evaluate the error, the standard deviation of the class values that arrive at a node is used. As a consequence of checking each property at that node, it is determined which attribute for splitting at that node maximizes the projected error reduction. The following formula is used to calculate the standard deviation reduction (SDR):

$$\mathrm{SDR} = \mathrm{sd}(K) - \sum \frac{|K_i|}{|K|}\mathrm{sd}(K_i) \tag{1}$$

where K = set of instances; K_i = the subset of illustrations that have the ith product of the possible set; and sd is the standard deviation.

2.2.3. Model results evaluation

For the best forecasting model, a number of criteria were developed to evaluate the prediction performance based on hydrological forecasting standards. Three statistical measures – the coefficient of determination (R^2), the indicator of agreement (d), the Nash–Sutcliffe efficiency (NSE) – and the root-mean-square error (RMSE) are employed in this study. The formulation can be expressed as follows:

$$R^2 = \left(\frac{1}{n} \times \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{(\sigma_x)(\sigma_y)}\right)^2 \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}} \tag{3}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (|y_i - \bar{x}| + |x_i - \bar{x}|)^2} \tag{4}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{5}$$

where n is the number of data, x and y are observed and estimated values, and σ_x and σ_y are the standard deviations of the observed and estimated data, respectively. It is important to note that a low value (closer to zero) for the root mean square error (RMSE) indicates a good agreement between the observed and modelled estimation data. Conversely, a high value (closer to unity) for the variables d and R2 also signifies a good agreement between the observed and modelled estimation data.

3. RESULTS

This study has used daily discharge, rainfall, and temperature data from the MH Halli station in India. As stated earlier, two models, i.e., SWAT and M5P, have been developed for discharge forecasting. A general view of the study is given Figure 3.

3.1. Statistical analysis of data

Daily data on discharge, precipitation, and temperature were first split into two categories: calibration/training and validation/testing. Eight years' worth of data were chosen from the total for calibration, and the remaining 7 years' worth was chosen for testing the constructed models. The statistical parameters for the discharge, rainfall, and temperature datasets' calibration, training, validation, and testing were computed as given in Table 1.

Although the mean and standard deviation for the discharge testing datasets were lower than those for the training, the coefficient of variation (CV) values for the temperature, discharge, and rainfall testing/validation datasets were higher

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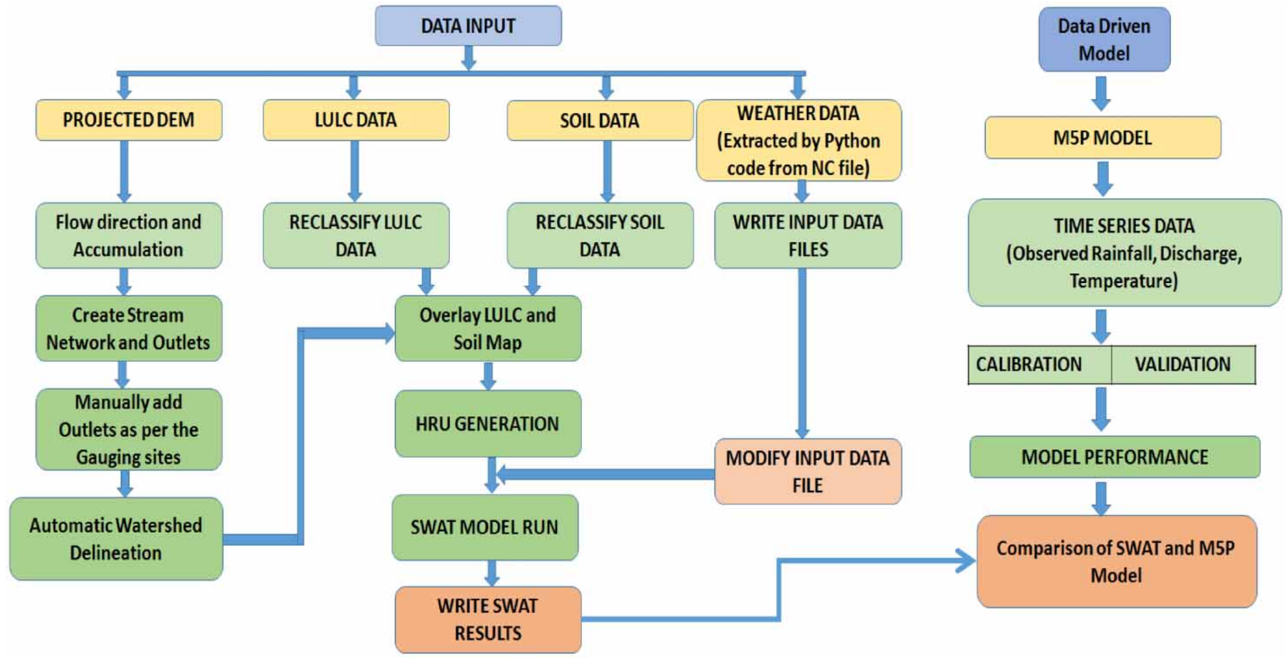

Figure 3 | Flowchart of the modelling procedure.

than those for the training (Table 1). In addition, the training dataset has a higher maximum value for the discharge variable. The maximum values in the testing dataset for temperature and rainfall were higher than those in the training dataset.

3.2. Discharge prediction with SWAT hydrological model

3.2.1. Model application

In fact, the simulation process, which is used to estimate model expectation results, is not possible without model calibration and validation. We have split the available daily time series of the observed flow into two parts, i.e. one for the calibration and the second for a validation process.

3.2.2. Model calibration

The model was calibrated using monthly flow records to further the calibration for the entire basin. In fact, over a period of 7 years, the SWAT model in the MH Halli station was calibrated by contrasting the measured discharges with the simulated discharges in the hydrometric station under consideration. The comparison study demonstrates a reasonable level of sufficiency. The results of the model accuracy evaluation have suggested that the overall values of R^2 is within the criteria ' very good' (0.94), NSE is 'very good' (0.88) (88% of the simulated discharges are similar to the discharges observed), and RMSE and d are 'good' (47.71 and 0.98, respectively). For compatibility between the model results and the actual observed values of discharge at the MH Halli station, the daily hydrograph is shown in Figures 4 and 5, respectively. The results indicated that the SWAT model can be applied to assess discharge with acceptable accuracy.

3.2.3. Model validation

By comparing the discharges of the measured flow to the simulated flow in the hydrometric station under consideration, SWAT model validation was carried out over additional periods of the dataset. The validation enabled us to acquire a good model performance for discharges with RMSE and 'd' of, respectively, 50.54 and 0.95, in accordance with the performance assessment criteria of the model advised for a monthly time step (Moriasi *et al.* 2007). The NSE and R^2 thresholds are 0.74 and 0.91, respectively, and it also assesses the relationship between the two statistical series. The good model calibration and capacity to accurately reflect the flow estimation is also demonstrated by the good agreement between simulations and observations throughout the validation process.

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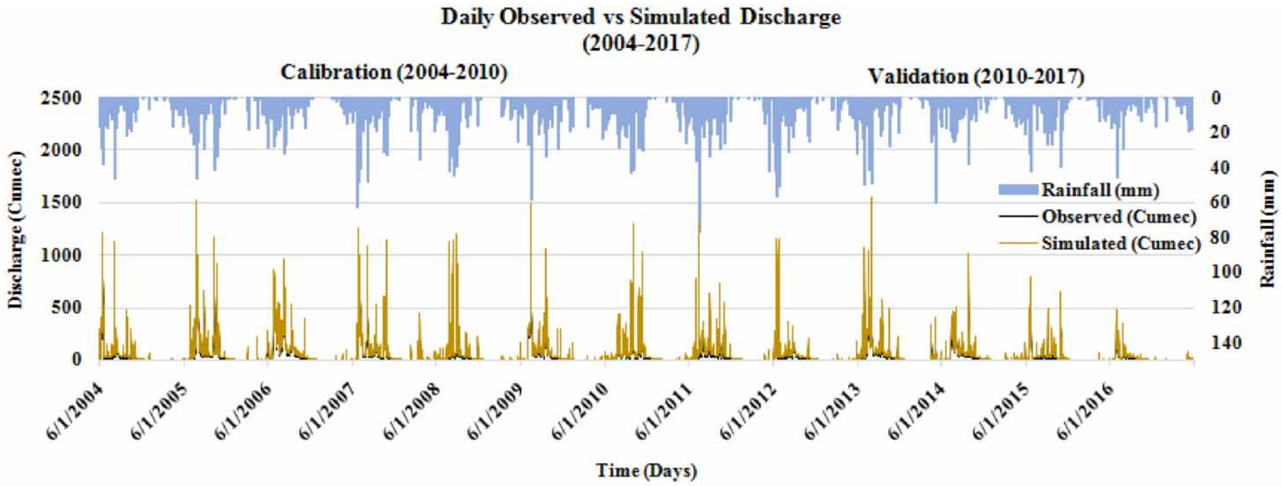

Figure 4 | SWAT model performances in terms of comparison of observed and simulated discharge.

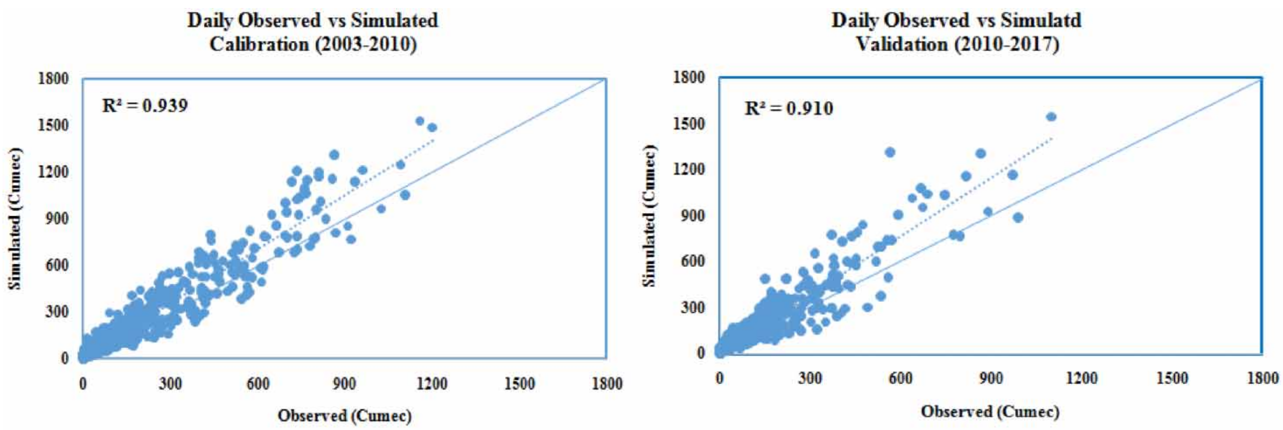

Figure 5 | SWAT model scatter plot between observed versus simulated discharge during calibration and validation stage.

3.3. Discharge prediction with M5P model

Weka software was used to build the M5P model tree. The user-defined parameter (M) had the best value of 4. As mentioned previously, the training and testing dataset were randomly selected from the 50–50 split. For the sake of simplicity and more precise prediction of the flow, the M5P model itself has been run under two parameter settings named scenario 1 and scenario 2. These scenarios' results were then evaluated using R^2, RMSE, NSE, and d. The fitting accuracy of the used models for each input composition over the training phase is summarized in Table 2. As given in Table 2, the efficiency fluctuated from one compound to another. The primary reasons for the oscillation are the differences between the effects of each selected

Table 2 | Comparison of SWAT and M5P models in terms of R^2, RMSE, NSE, and d

	Calibration				Validation			
Models	R^2	**RMSE**	**NSE**	d	R^2	**RMSE**	**NSE**	d
SWAT	0.94	47.71	0.88	0.98	0.91	50.54	0.74	0.95
Data-driven model								
Rain, temp, discharge (first scenario)	0.81	73.00	0.75	0.86	0.79	60.34	0.63	0.84
Rain, temp, D-1, D-2 (second scenario)	0.97	29.12	0.91	0.99	0.92	37.02	0.76	0.96

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input variable on the stream flow prediction. According to Table 2, the best correlation coefficient to estimate discharge in training data was 0.97 for the second scenario.

Figure 6 delineates the performance of the M5P models. Table 2 shows the effects of the M5P approach in terms of R^2, RMSE, NSE, and d for both (calibration and validation) phases. According to Table 2, the performance criteria for scenario 2 are $R^2 = 0.97$, RMSE = 29.12, NSE = 0.91, and $d = 0.99$ in the calibration stage, while the performance criteria for scenario 2 are $R^2 = 0.92$, RMSE = 37.02, NSE = 0.76, and $d = 0.96$ in the validation stage. Figure 7 shows the M5P model scatter plot between observed and simulated discharge during the calibration and validation stages.

According to R^2 values, the Random Forest (RF) model from the second scenario produced the best performance during calibration, followed by the first scenario. Because R^2 is tuned for differences between the mean and variance of measured and expected quantities, it is vulnerable to outliers and should not be used only for evaluating created models (Legates & McCabe 1999; Kisi & Shiri 2012). As a result, different error measurement indices were used to evaluate the model's performance. Based on RMSE, NSE and d, the M5P (second scenario) was superior to the other types.

3.4. Comparison of prediction models

We investigated the SWAT model's capacity for predicting runoff and contrasted it with the M5P model. Using R^2, RMSE, NSE, and d, the accuracy of the SWAT and M5P models was compared. The training and testing outcomes for the MH

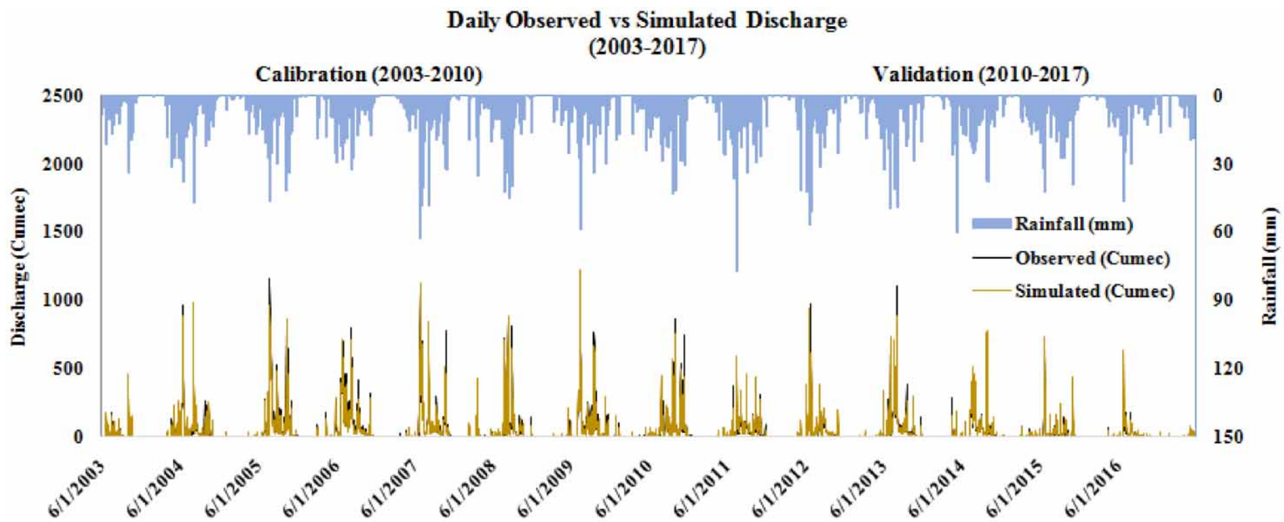

Figure 6 | M5P model performances in terms of comparison of observed and simulated discharge.

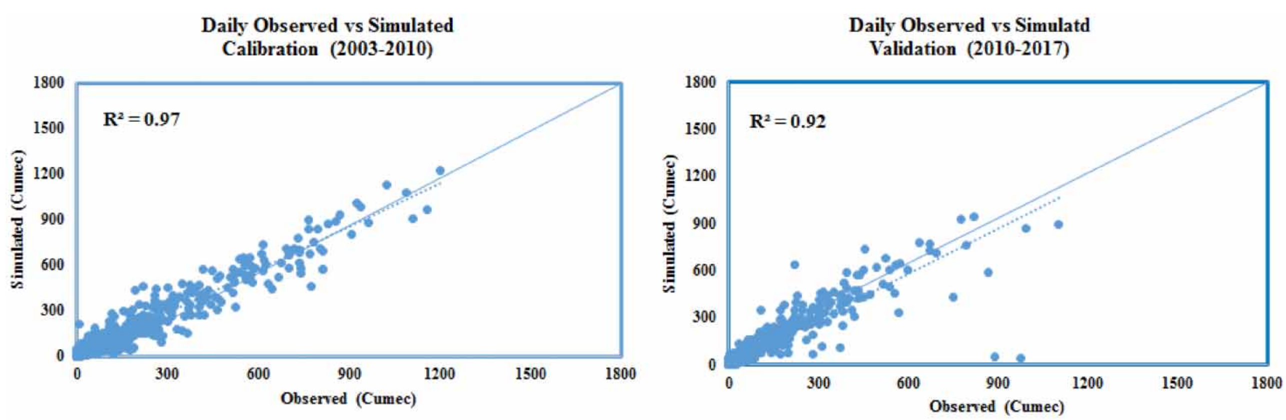

Figure 7 | M5P model scatter plot between observed versus simulated discharge during calibration and validation stage.

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Halli station are presented in Table 2. The M5P model obtained the best R^2, RMSE, NSE, and d during the calibration and validation phases, as shown in Table 2. Figure 8 shows how the SWAT and M5P models compare. In the testing stage, the M5P model's accuracy significantly outperformed the SWAT model. The M5P model may offer a substitute for the SWAT models for predicting runoff, according to the results.

4. DISCUSSION

In this section, we provide an in-depth discussion of the simulation results obtained from both the SWAT and the M5P models. We aim to elucidate implications of these results and draw meaningful conclusions.

4.1. Interpretation of SWAT model results

The calibration and validation phases demonstrated a reasonable level of model accuracy, as evidenced by the goodness-of-fit statistics (R^2, NSE, RMSE, and d). Notably, the model showed its ability to replicate the observed flow observations. The daily hydrographs presented in Figures 4 and 5 further illustrate the model's capability to simulate streamflow. These results indicate that the SWAT model can be applied with acceptable accuracy for discharge assessment in the MH Halli station of the Hemavati River watershed.

4.2. Interpretation of M5P model results

Now, we discuss the performance of the M5P model, emphasizing its advantages over the SWAT model. The M5P model, developed using Weka software, exhibited variable efficiency across different input compositions. The best correlation coefficient was achieved in the second scenario of the M5P model as depicted in Table 2, demonstrating the model's sensitivity to input variables. Evaluation metrics (R^2, RMSE, NSE, and d) revealed the M5P model's superior accuracy during the calibration and validation phases, particularly in the testing stage.

4.3. Comparison of prediction models

The results clearly indicate that the M5P model outperforms the SWAT model in terms of accuracy, especially in predicting runoff during the testing phase. The evaluation metrics in Table 2 highlight the M5P model's superior performance. This suggests that the M5P model could serve as a promising alternative to the SWAT model for runoff prediction in the MH Halli station.

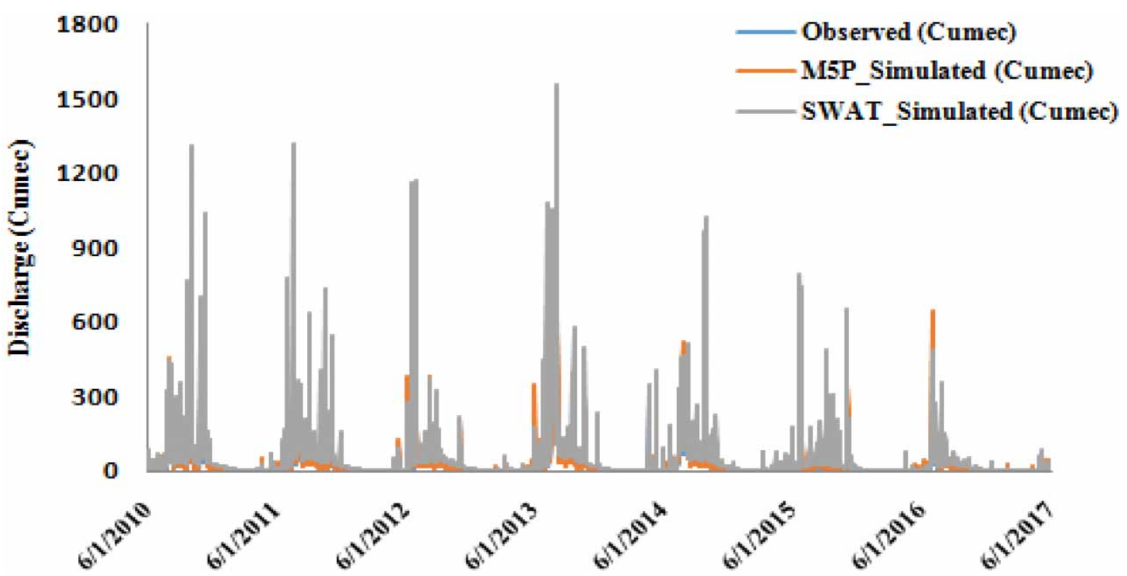

Figure 8 | Comparison of SWAT and M5P model.

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4.4. Implications and conclusions

The superior accuracy of the M5P model during the testing phase underscores its potential as a valuable tool for discharge forecasting in similar watersheds. This study highlights the importance of considering alternative modelling approaches and the need to select the most suitable model based on the specific characteristics of the study area. Finally, this section aims to provide a comprehensive understanding of the simulation results, their significance, and the implications for future research and practical applications. It strengthens the link between the results and the conclusions drawn from this study, ensuring that readers can grasp the key takeaways and their relevance.

5. CONCLUSIONS

The study presented a comparative analysis of the SWAT and the hybrid M5P model for rainfall–runoff simulation in the MH Halli station, Hemavati River watershed, Karnataka, India. While the results and discussion sections have elaborated on the simulation outcomes, let us delve into the rationalization of the conclusions and highlight the advantages of the hybrid M5P model.

5.1. Rationalization of conclusions

Both the SWAT and M5P models demonstrated commendable performance in modelling rainfall and runoff, as evidenced by high correlation coefficients (R^2) and NSE values. However, these conclusions are based on the evaluation metrics alone. It is important to clarify that the selection of these models should be context dependent, taking into account the specific research goals and data availability. The assertion that the M5P model may be preferable for assessing the steam flow, particularly in data-scarce regions, needs further clarification. While the M5P model exhibited promising accuracy, the complexity and resource-intensive nature of the model should also be considered in the decision-making process.

The recommendation to use the SWAT model for flood routing and investigations into physical watershed characteristics is valid. However, its suitability is contingent on the availability of comprehensive physical and chemical data for the study area. The suggestion for future research to explore alternative hydrological models such as the MIKE NAM model and the HEC-HMS model is a valuable point. These models may offer further insights into rainfall–runoff processes and enhance water resource management strategies.

5.2. Advantages of the hybrid M5P model

The advantages of the hybrid M5P model over the SWAT model, as it is a significant aspect of this study that warrants detailed discussion. The hybrid M5P model's sensitivity to input variables allows for a more in-depth understanding of the factors influencing streamflow prediction. This adaptability is particularly valuable in situations where data availability is limited, as it can leverage available information effectively. The M5P model's superior performance, especially during the testing phase, highlights its potential as a robust tool for discharge forecasting. The model's accuracy, as reflected in metrics like R^2, RMSE, NSE, and d, positions it as a valuable asset in regions where precise runoff predictions are crucial. The study underscores the importance of considering alternative modelling approaches, and the hybrid M5P model stands out as a viable alternative to the SWAT model in specific scenarios. This flexibility allows researchers and water resource managers to adapt their modelling strategies to suit the unique characteristics of the study area.

In conclusion, this study has highlighted the capabilities and advantages of the hybrid M5P model in the context of rainfall–runoff simulation. While the conclusions are based on rigorous evaluation metrics, it is essential to exercise caution in model selection and to weigh the advantages and complexities associated with each model against the research objectives and data constraints. The hybrid M5P model's adaptability and superior accuracy positions it as a valuable tool in the hydrological modelling setups of hydrologists and water resource managers, particularly in data-scarce or changing climate environments. Future research endeavours should continue to explore and refine hydrological modelling approaches to advance our understanding of runoff processes and improve water resource management strategies.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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