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Assessment of Stream Flow of Hidkal Dam Catchment Area in Krishna Basin of India Using SIMHYD Model

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

A study was conducted to predict the stream flow from a catchment area of Hidkal dam situated in Krishna basin of India. The SimHYD model was selected to setup the stream flow model under limited data conditions. Daily rainfall, potential evapotranspiration (PET) and observed discharges

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were used as input data to setup the model. Sensitivity analysis was carried out to identify the more sensitive parameter and fixed final parameter values. A genetic algorithm was used for calibration and validation of the model with object function of Nash -Sutcliffe Equation (NSE). The performance of model during calibration and validation with monthly stream flow (m^3/s) was found to be very good in terms of NSE, R^2. The NSE and correlation coefficient were found to be 0.77 and 0.93 during calibration period and 0.90 and 0.95 during validation period respectively. The was a very good agreement between monthly observed and simulated stream flows of catchment area of Hidkal Dam. The NSE value of model during calibration period with daily runoff was found to be satisfactory at 0.51. It was observed that good agreement between observed and simulated daily runoff (in mm) with a correlation coefficient is 0.74. NSE and correlation coefficient during validation period using daily data are found to be 0.80 and 0.9 respectively. This study concluded that the SimHYD model can be used for assessment of stream flow with limited data.

Keywords: SIMHYD; stream flow; rainfall-runoff model; calibration and validation; sensitivity analysis.

1. INTRODUCTION

The stream flow can be simulated or modeled with the help of hydrological models. These hydrological models require huge data to conduct the hydrological studies such as stream flows of a given catchment. Rainfall characteristics influence the stream flow of a given area. These models are the tools that simulate the impact of various geomorphological, and weather parameters on the hydrological processes in a watershed or basin. These models may be classified as data-driven, conceptual, and physical models and are further classified as lumped, semi-distributed and distributed models based on the spatial attribute data. Fully distributed models are data intensive and lumped models use averaged data of the catchment. Semi-distributed models utilise both spatial data and averaged data of catchment.

Fully distributed models require more data and the catchment area with high-resolution data can be modeled. Empirical models did not consider the physical processes in the watershed. Simple Hydrology (SIMHYD), a lumped conceptual daily rainfall-runoff model, can be used to simulate runoff from the catchments successfully with limited data [1]. The SIMHYD model which is frequently used in Australia and China can also be used where limited data is available. Very limited studies on SIMHYD model were noticed in India. However, this model is a widely used conceptual model in the world. SIMHYD model is a daily conceptual rainfall-runoff model that uses daily rainfall and potential evapotranspiration data which estimates daily stream flow. It is one of the programmes embedded with Rainfall Runoff Library (RRL), in the eWater tool kit developed by the University of Canberra, Australia. The structure of SIMHYD model and model parameters and algorithms described in detail in the document are published by Zhang and Chiew [2]. Chiew and Siriwardena [1] compared calibration of several models, investigated whether the calibrated parameter values could be related to catchment characteristics and compared the runoff model using parameter values estimated from the regionalisation relationships. The results indicated that SIMHYD could be calibrated satisfactorily to reproduce the monthly recorded runoffs. The use of the five-parameter version of SIMHYD was sufficient for most catchments, with Nash-Sutcliffe model efficiency values greater than 0.7 obtained in more than 90% of the catchments. Siriwardena [1] used SIMHYD, a lumped conceptual daily rainfall-runoff model, on about 300 catchments across Australia and compared calibration results from several model types. The results indicated that SIMHYD can be calibrated satisfactorily to reproduce the monthly recorded runoffs. The SIMHYD model with five-parameter version was sufficient for most catchments, with Nash-Sutcliffe model efficiency values greater than 0.7 obtained in more than 90% of the catchments. The modelled monthly runoffs from both methods were reasonable in about three quarters of the catchments, where the Nash- Sutcliffe model efficiency was greater than 0.6 and the total modelled runoff was within 30% of the total recorded runoff. Srikanthan et al. [3] compared the simulated runoff of historical (1901-1998) and 2021-2050 climate situations in the study area using SIMHYD They found that decrease in mean annual rainfall and runoff in eastern and south-west Australia, but an increase in the extreme daily rainfall, in 2021-2050 relative to 1961- 1990.

Yu and Zhu [4] used conceptual models, AWBM and SIMHYD and simulated daily flows of two forest watersheds in France and USA. They evaluated their ability to model daily flows. They found that both models performed much better for the River Rimbaud watershed in France than for the Fernow W6 in the USA. They also found difference in model performance between AWBM and SIMHYD was small. Chiew et al. [5] predicted different characteristics of streamflow in ungauged catchments and under climate change with three rainfall-runoff models using a large data set from 780 catchments across Australia. They concluded that medium and high flows were relatively easier to predict and suggested to use a single unique set of parameter values from model calibration. The low flow characteristics were considerably more difficult to predict and required careful modelling consideration to specifically target the low flow characteristic of interest. The modelling results also showed that different rainfall-runoff models and different calibration approaches could give significantly different predictions of climate change impact on streamflow characteristics, particularly for characteristics beyond the long-term averages. Li et al. [6] evaluated the effect of length of calibration data on the performance of a hydrological model in data-limited catchments where data are non-continuous and fragmental. They used a calibrated SIMHYD model with non-continuous calibration periods for more independent streamflow data. They found that longer calibration data series do not necessarily result in better model performance and results could be useful for the efficiency of using limited observation data for hydrological model calibration in different climates. Ramezani et al. [7] used SIMHYD and AWBM for assessment of the effect of urbanisation on regional water balance. Bhasme and Bhatia [8] also used SIMHYD model to compare the results of Physical Informed Machine Learning (PIML) while studying stream flow from a managed and unmanaged catchment areas. With the background, a study was conducted to assess the stream flow of Hidkal Dam catchment area in the Krishna basin of India using the SIMHYD model.

2. MATERIALS AND METHODS

2.1 Study Area and Data Sets

The present study of catchment area of Hidkal dam is located in the Ghatprabha subbasin of Krishna basin in India with a catchment area of 1370 km^2. It is situated between a latitude of 15^o 48′ to 16^o 8′ N and a longitude of 74^o 0′ to 74^o 40′ E; The elevations of study area range from 1049 m to 640 m which reveals that the catchment area is highly undulating and hilly terrain. The rainfall ranges from 6250 mm to about 1000 mm and most of the rainfall received from June to September. The annual mean temperature is 20 °C (Tmin) to 40.5 °C (Tmax). The location map of the study area is presented in Fig. 1. The gross storage capacity of Hidkal dam is 1443 M m^3 with an irrigated area of 155559 ha. The rainfall, maximum & minimum temperatures were downloaded from the Indian Meteorological Department website. Daily rainfall data at grid interval of 0.25^o x 0.25^o for 10 years from 2009 to 2019 [9] was used. Maximum and minimum temperatures at grid intervals of 1^o x 1^o for the same years [10] were also used for this study. Stream flow data on daily time steps was downloaded from Indian water resource information system website (www.indiawirs. gov.in) from the year (2009 to 2019). This daily stream flow data was used to calibrate and validate the model outputs.

2.2 SIMHYD Model

The process flow chart is presented in Fig. 2. In this model, the interception store is filled with daily rainfall, which is emptied each day by evaporation. The excess rainfall is then subjected to an infiltration function which estimates the infiltration capacity. The surplus rainfall that exceeds the infiltration capacity becomes infiltration excess runoff. The moisture that infiltrates is subjected to soil moisture function which diverts water to stream (interflow), groundwater store (recharge), and soil moisture store. An interflow is first estimated as a linear function of the soil wetness (soil moisture level divided by soil moisture capacity). The groundwater recharge is then estimated as a linear function of the soil wetness and remaining moisture flows into the soil moisture store. An evapotranspiration from the soil moisture store is estimated as a linear function of the soil wetness. The soil moisture store has a finite capacity and overflows into the groundwater store. Base flow from the groundwater store is simulated as a linear recession from the store. The model therefore estimates runoff generation from three sources – infiltration excess runoff, interflow (and saturation excess runoff), and base flow.

The fundamental equations of the model are:

$$\text{Impervious ET} = \min\begin{bmatrix}\text{PET,}\\ (1-\text{Pervious fraction})\times\text{Pervious threshold,}\\ \text{Impervious incident}\end{bmatrix}$$

$$\text{Interception ET} = \min\begin{bmatrix}\text{Pervious incident,}\\ \text{PET,}\\ \text{Rainfall interception storage capacity}\end{bmatrix}$$

$$\text{Infiltration Capacity} == \text{Pervious fraction}\times\text{Infiltration coefficient}\times\exp\left(-\text{Infiltration shape}\times\text{Soil moisture fraction}\right)$$

$$\text{Infiltration} = \min\left(\text{Throughfall, Infiltration capacity}\right)$$

$$\text{Interflow Runoff} = \text{Interflow coefficient}\times\text{Soil moisture fraction}\times\text{Infiltration}$$

$$\text{Infiltration after Interflow} = \text{Infiltration} - \text{Interflow runoff}$$

$$\text{Recharge} = \text{Recharge coefficient}\times\text{Soil moisture fraction}\times\text{Infiltration after interflow}$$

$$\text{Soil input} = \text{Infiltration after interflow} - \text{Recharge}$$

2.3 Input Data Preparation

The model utilizes daily time series data of average rainfall, average potential evapotranspiration (PET), and observed stream flow. The daily average rainfall of the catchment was calculated from IMD grid data. Hargreaves method was used to calculate the daily PET. The input files were saved in a desirable format so that the model could read the files. SWAT “PCP” format is also one of the readable formats of the SIMHYD model. Daily time series data of average rainfall and PET were saved in. pcp (SWAT) format, mm/day. The daily time series data of observed stream flow was also saved in. pcp (SWAT) format, m^3/s. The daily discharge data from 2013 to 2019 at the outlet point was used for the model setup. The general details of the catchment and its area in km^2 were also required for the model.

2.4 Model Setup

The model setup was done with the help of the procedure mentioned in the Rainfall Runoff Library user manual (Podger, 2004). The SIMHYD model was selected from the list of models given in the Rainfall Runoff Library software of the eWater tool kit. The model setup started with a general description of the study area and catchment area in km^2. The selected catchment area of the Ghataprabha (Hidkal) dam was 1370 km^2 and the same is entered as input to the model. The time series data of daily rainfall (mm/day), daily PET (mm/day) and observed discharge data (m^3/s) from the years 2013-2019 were uploaded in the model (Fig. 3) Warmup period for the model was adjusted from 1/1/2013 to 31/12/2013, calibration period was taken from 1/1/2014 to 31/12/2016 and Performance verification (validation) period was adjusted from 1/1/2017 to 31/12/2019 in which 1/1/2017 to 31/12/2017 period (Fig. 4) was taken as warm period.

2.5 Calibration of Model and Parameter Sensitivity of SIMHYD Model

Calibration of the model comprises with fixation of maximum and minimum values of parameters, selection of optimization method, selection of objective function, calculation and their criteria. SIMHYD model has nine parameters that depict infiltration, storage, groundwater flow, and recharge characteristics. The details of parameters and their ranges are given in Table 1. RRL has three calibration procedures namely, manual, custom, and auto-calibration. SIMHYD supports auto-calibration and manual calibration and does not support custom calibration. The present model was calibrated using auto-calibration and manual calibration methods. Among the auto-calibration methods, genetic algorithm technique was selected for calibration of the auto-calibration method. The genetic algorithm is search procedure that uses principles of mechanics of natural selection and natural genetics. The genetic algorithm combines an artificial survival of the fittest with genetic operators abstracted from nature [11]. Nash-

Sutcliffe criterion was selected as the objective function of the model. This can be applied on daily or monthly time steps. The present model was calibrated on a monthly time steps.

Initially, the model was auto calibrated with default ranges of all the parameters using a genetic algorithm optimizer. As a result of auto-calibration, a set of parameter values was found. While running the auto-calibration, dynamic update option was selected. This option is very useful for investigate the model behaviour against different parameter values. It also gives an idea of how sensitive the model is against the change of each parameter value. Further, the calibration of model was improved with the help of manual calibration until it attains desirable threshold values of objective function [12].

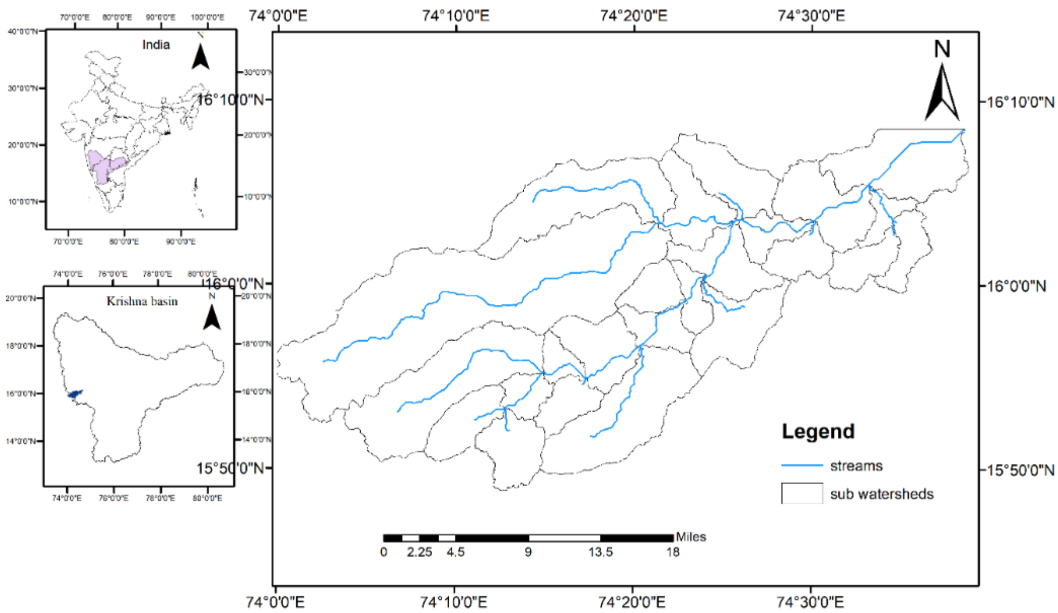

Fig. 1. Location of study area

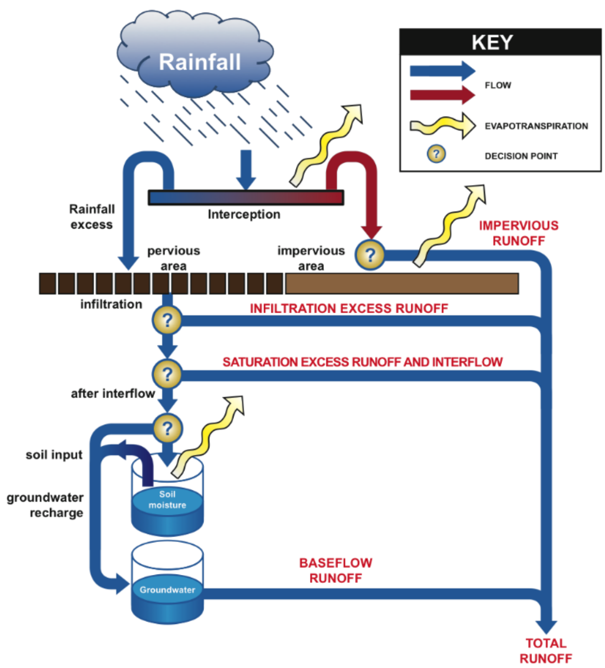

Fig. 2. Structure of SIMHYD model

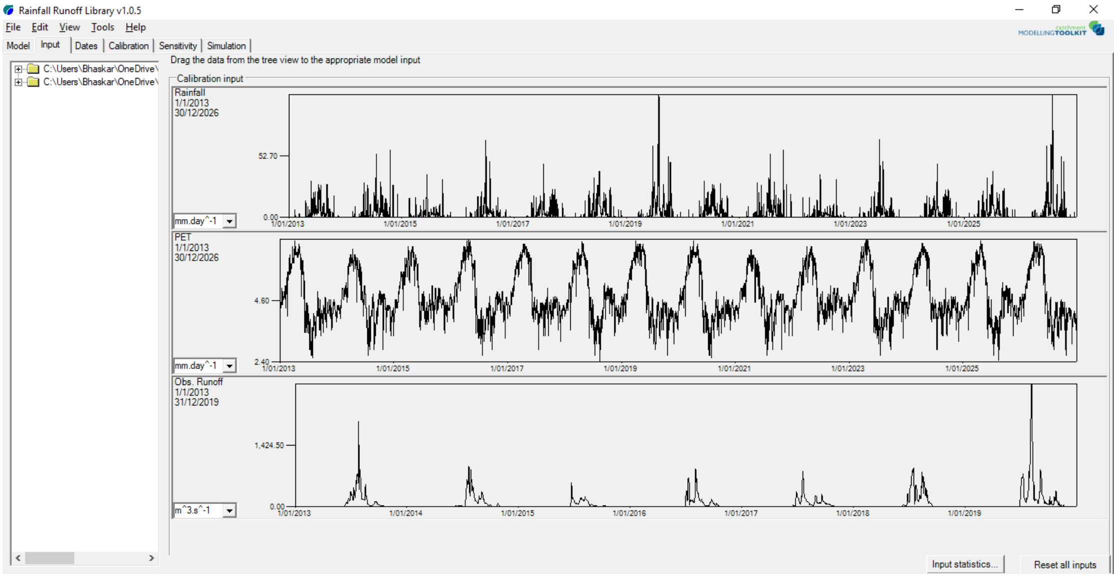

Fig. 3. Screenshot of model input data setup

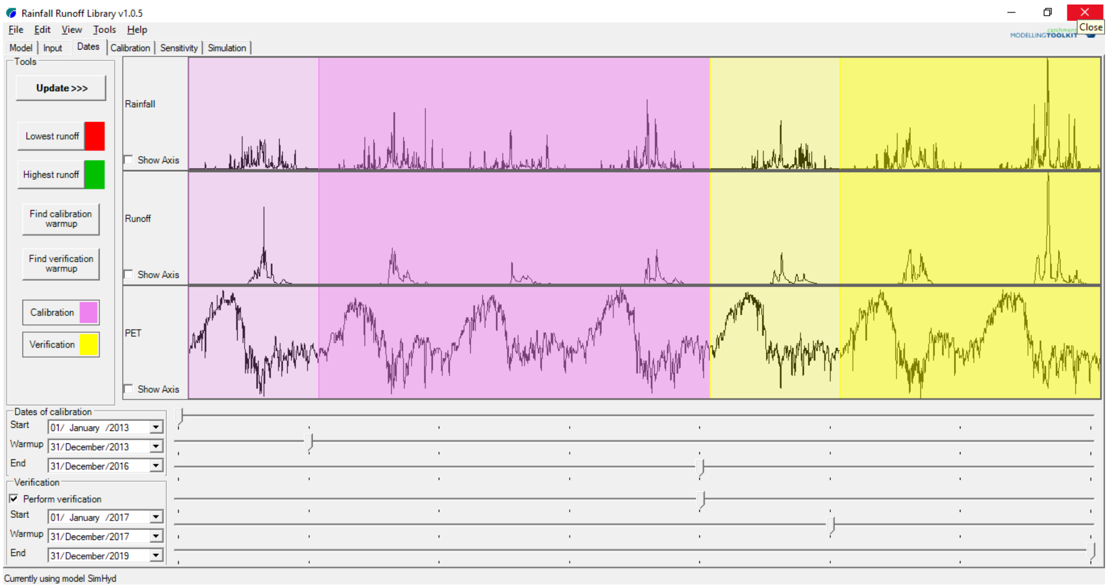

Fig. 4 Screenshot of selection of model warmup, calibration and validation periods

Table 1. SIMHYD Parameters and their ranges

Parameter	Description	Units	Min.	Max.
Baseflow coeff.	Base flow Coefficient	na	0	1
Impervious Threshold	Impervious Threshold	mm	0	5
Infiltration Coeff.	Infiltration Coefficient	na	0	400
Infiltration shape	Infiltration Shape	na	0	10
Interflow Coeff.	Interflow Coefficient	na	0	1
Perv. Fraction	Pervious Fraction	na	0	1
Recharge coefficient	Recharge Coefficient	na	0	1
RISC	Rainfall Interception Store Capacity	mm	0	5
SMSC	Soil Moisture Store Capacity	mm	1	500

Sensitivity analysis of the model parameters was also done. It is important to understand how sensitive a model is to certain parameters. This is very important to identify the most influential parameters that influence the model output. If the model is significantly affected by a particular parameter, then the focus of calibration should be on that parameter. The sensitivity of parameters against different values of their assigned range was also plotted and analysed. The simulation was run after setting up model input, calibration, validation, and sensitivity analysis. The model results (graphs and time series data) were saved in the folder at daily and monthly time steps and the stream flow in mm/day and m^3/s was also saved.

3. RESULTS AND DISCUSSION

SIMHYD model was set up for the simulation of stream flow for a catchment area of Hidkal comprising an area of 1370 km^2. The parameters sensitivity, range and model were calibrated with a genetic algorithm using auto-calibration option. The objective function of model was fine-tuned with manual adjustment of parameter ranges based on the sensitivity graphs. The results are presented in below sections.

3.1 Parameter Sensitivity

Sensitivity analysis was carried out using genetic algorithm of auto-calibration model. The sensitivity graphs between parameter values against the objective function values are presented Fig. 5 to Fig. 13. The parameter values against the maximum values of objective function were selected as fitted value of the model. The new set of minimum and maximum values were selected as new range of model parameters. The sensitivity graphs for all nine parameters are presented below.

3.1.1 Sensitivity of baseflow coefficient

The parameters in question have a default range of 0 to 1. A graph in Fig. 5 shows that the baseflow coefficient is highly sensitive. It was found that the best NSE value is achieved when the coefficient value is set to 0.1. As the parameter value increases, the NSE value decreases in a monotonic fashion.

3.1.2 Sensitivity of impervious threshold

The default range of impervious threshold is 0 to 5. The sensitivity of impervious threshold is presented in Fig. 6. It was observed that the parameter is not sensitive and highest NSE was found when value was fixed at 4.5. The NSE value didn’t follow certain trends with increase in the parameter value.

3.1.3 Sensitivity of infiltration coefficient

The infiltration capacity range typically spans from 0 to 400. Fig. 7 illustrates the sensitivity of the infiltration coefficient. The graph indicates that the optimal NSE is achieved when the impervious value is set at 190. As the infiltration coefficient value increases up to 190, the NSE value progressively improves. However, beyond this point, the NSE value begins to decline as the infiltration coefficient value increases.

3.1.4 Sensitivity of infiltration shape

The default range of infiltration shape is 0 to 10. The sensitivity of infiltration shape is presented in Fig. 8. It was observed from the graph that infiltration shape parameter was not sensitive. The value of this factor was taken as 1.096.

3.1.5 Sensitivity of interflow coefficient

The interflow coefficient's standard range spans from 0 to 1, as demonstrated in Figure 9 which outlines its sensitivity. The graph revealed that the optimal NSE was achieved with an impervious value of 0.076. Furthermore, a decrease in the interflow coefficient value led to an increase in the NSE value.The interflow coefficient's standard range spans from 0 to 1, as demonstrated in Figure 9 which outlines its sensitivity. The graph revealed that the optimal NSE was achieved with an impervious value of 0.076. Furthermore, a decrease in the interflow coefficient value led to an increase in the NSE value.

3.1.6 Sensitivity of pervious fraction

By default, the previous fraction range is from 0 to 1. The sensitivity analysis of the previous fraction is depicted in Fig. 10. The graph indicates that the optimal NSE was obtained at a previous fraction value of 0.7. As the previous fraction increased, the NSE value also increased. By default, the previous fraction range is from 0 to 1. The sensitivity analysis of the previous fraction is depicted in Fig. 10. The graph indicates that the optimal NSE was obtained at a previous fraction value of 0.7. As the previous fraction increased, the NSE value also increased.

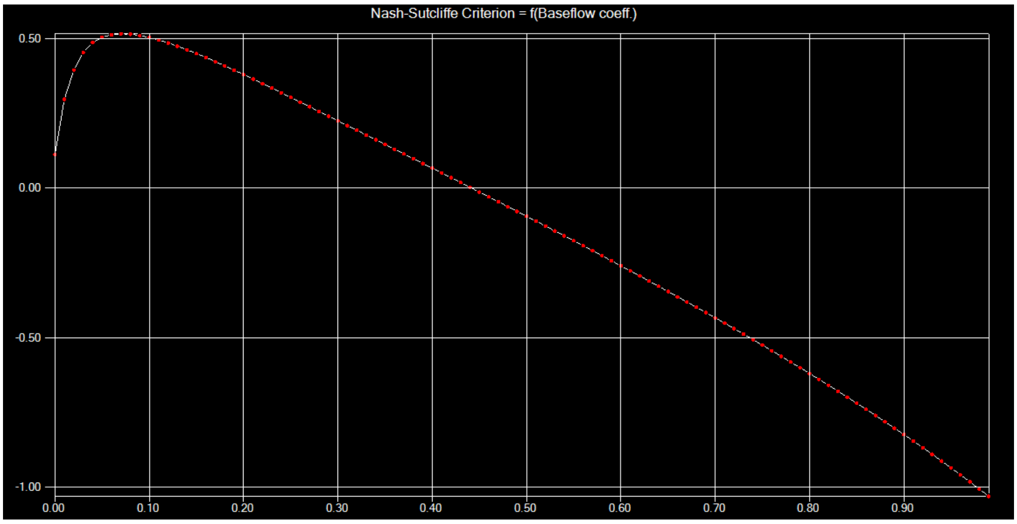

Fig. 5. Sensitivity of baseflow coefficient (x axis – parameter value; y axis – NSE value)

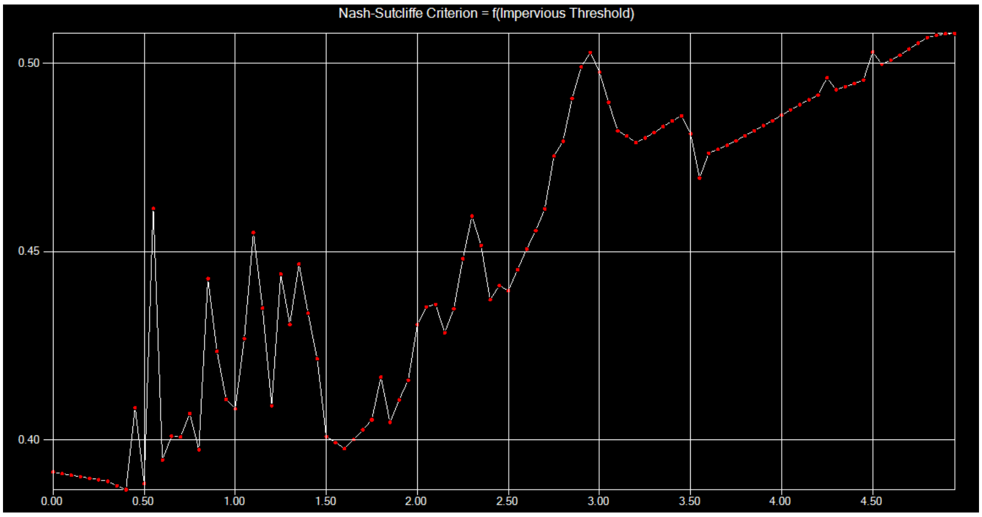

Fig. 6. Sensitivity of impervious threshold (x axis – parameter value; y axis – NSE value)

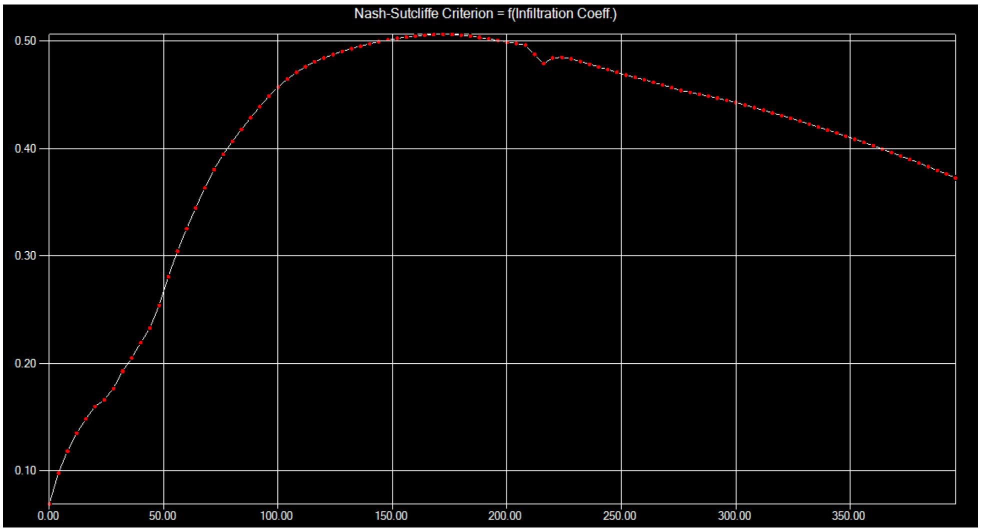

Fig. 7. Sensitivity of infiltration coefficient (x axis – parameter value; y axis – NSE value)

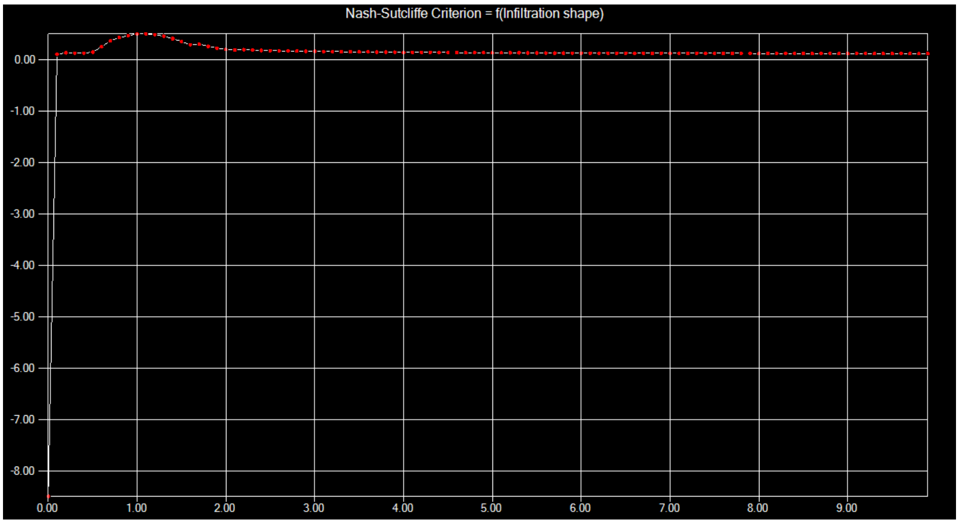

Fig. 8. Sensitivity of infiltration shape (x axis – parameter value; y axis – NSE value)

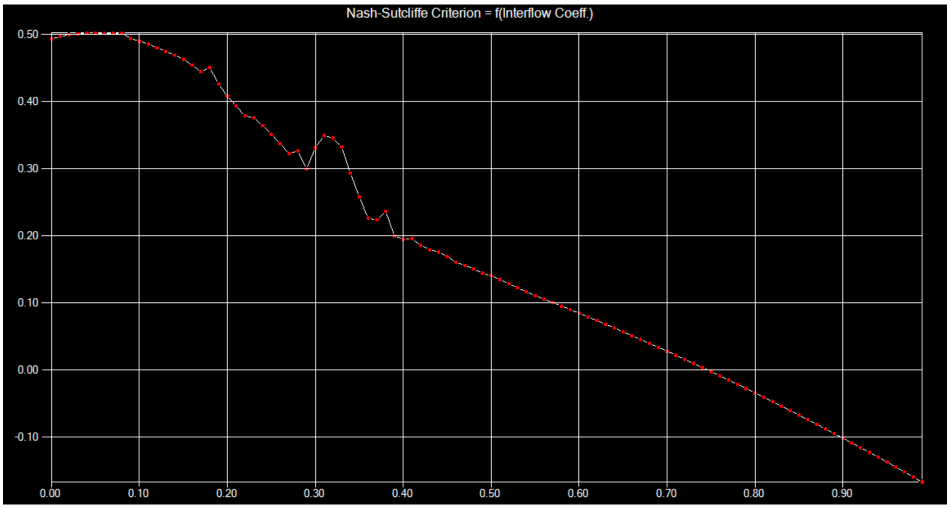

Fig. 9. Sensitivity of Interflow coefficient (x axis – parameter value; y axis – NSE value)

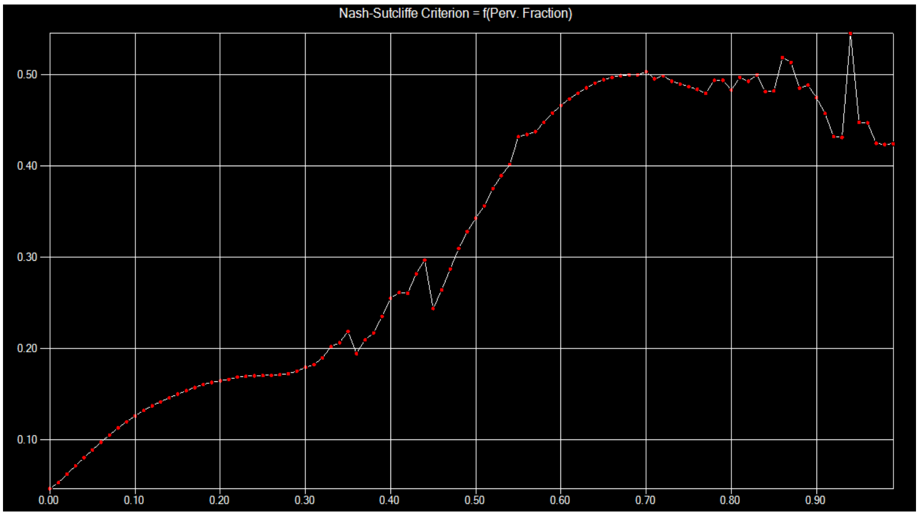

Fig. 10. Sensitivity of Interflow coefficient (x axis – parameter value; y axis – N

3.1.7 Sensitivity of rainfall interception store capacity (RISC)

The default range of rainfall interception store capacity is 0 to 5. The sensitivity of rainfall interception store capacity is presented in Fig. 11. It is observed from the graph that the highest NSE is found when impervious value is fixed at 3.43.

3.1.8 Sensitivity of recharge coefficient

The default range of recharge coefficient is 0 to 1. The sensitivity of interflow coefficient is presented in Fig. 12. It was observed from the graph that recharge coefficient was one of the sensitive parameters and the highest NSE is found when recharge coefficient value is fixed at 0.92. The NSE value increased with increasing value of recharge coefficient.

3.1.9 Sensitivity of soil moisture store capacity

The default range of soil moisture storage capacity is 1 to 500. The sensitivity of soil moisture store capacity interflow is presented in Fig. 13. It was observed from the graph that soil moisture storage capacity was one of the sensitive parameters and the highest NSE is found when soil moisture storage capacity value is fixed at 1. The NSE value increased with decreasing value of soil moisture storage capacity.

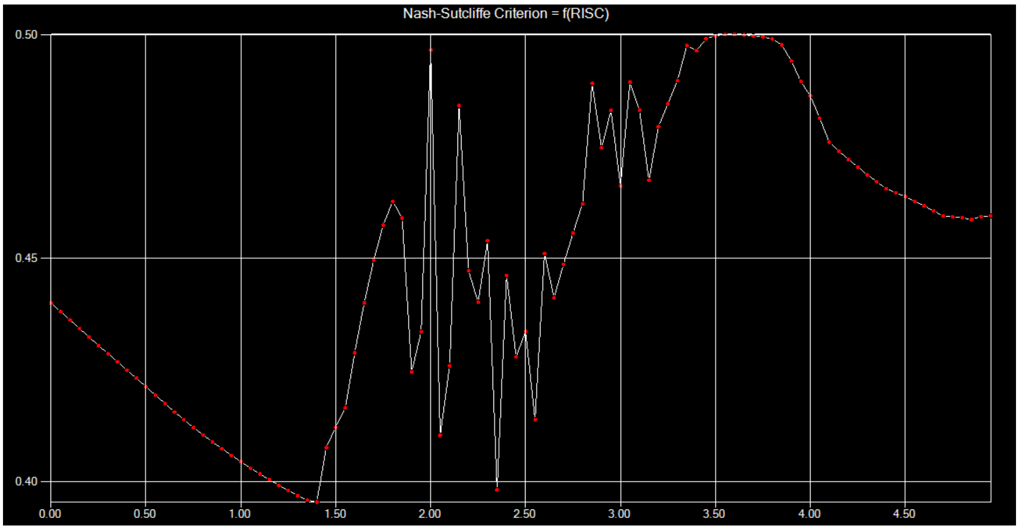

Fig. 11. Sensitivity of rainfall interception store capacity (x axis – parameter value; y axis – NSE value)

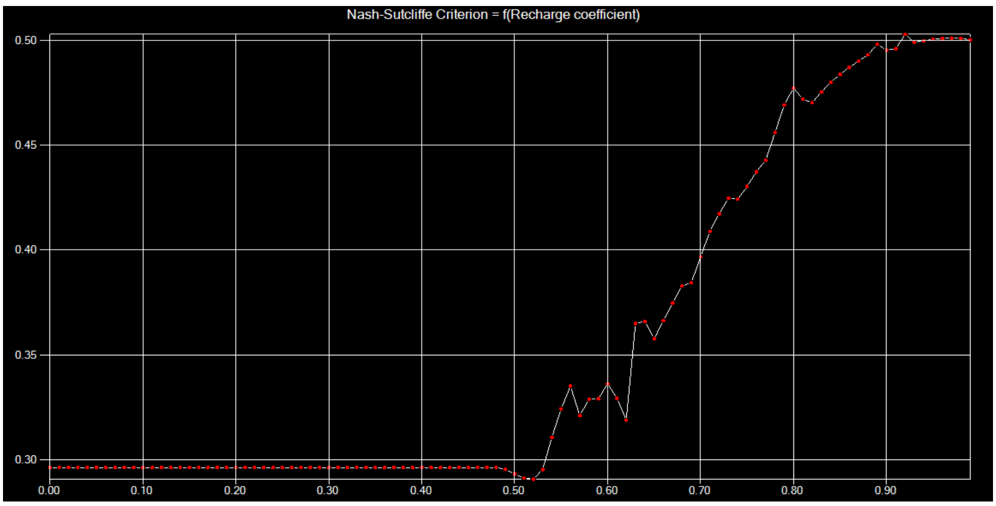

Fig. 12. Sensitivity of rainfall storage (x axis – parameter value; y axis – NSE value)

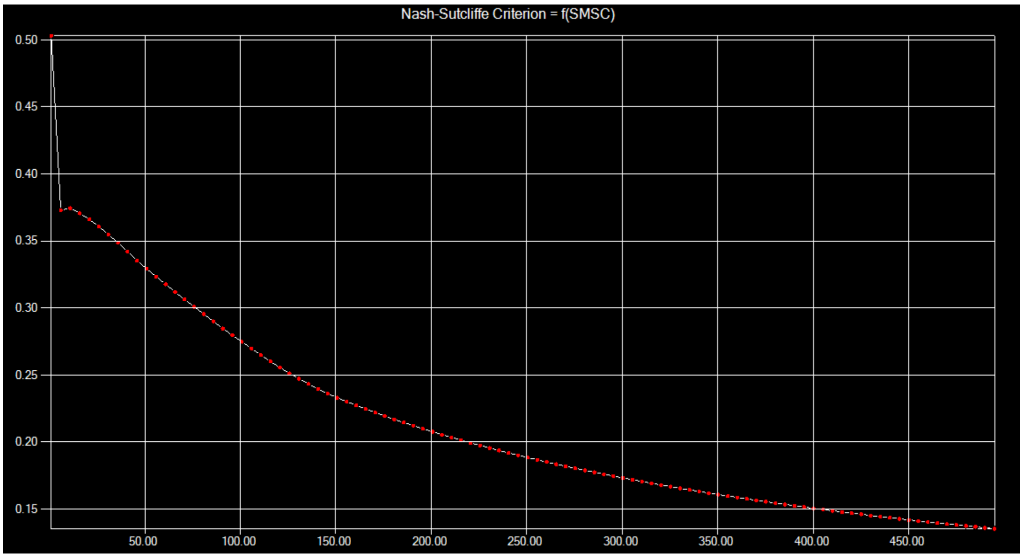

Fig. 13. Sensitivity of soil moisture storage capacity (x axis – parameter value; y axis – NSE value)

3.2 Calibration and Validation of SIMHYD Model

The model calibration and validation setup were done for Ghataprabha (Hidkal) dam with a catchment area of 1370 km^2 for the years 2014-2019. Warm up period for the model was adjusted from 1/1/2013 to 31/12/2013, calibration period was taken from 1/1/2014 to 31/12/2016 and performance verification (validation) period was adjusted from 1/1/2017 to 31/12/2019 in which 1/1/2017 to 31/12/2017 period was taken as warm period.

The model was calibrated with observed stream flow and was run with genetic optimizer. The fitted parameters which were obtained in parameter sensitivity process were used for calibration of model (Table 2), the NSE was selected as primary objective function for both calibration and validation period. The first step in applying a genetic algorithm is defining an objective function NSE. This function is used to evaluate the performance of a particular set of parameters. The next step in applying the genetic algorithm to the SIMHYD model is defining the range of values that each respective parameter can take. This is done to ensure that the parameters stay within physically plausible limits. Once the range of each parameter is defined, the next step of the genetic algorithm is the initialization. The initialization assigns random values to each of the parameters (within its limits) to each of the individuals of the population. After the initialization, the initial population passes through the general loop of the genetic algorithm.

The model provided a scatter graph between daily observed and simulated runoff of the study area for both calibrated and validated periods (Fig. 14). The scatter plot between monthly observed and simulated runoff are also presented in Fig. 15. During the calibration and validation process of model, it compared the daily and monthly simulated data with comparative statistics and univariate statistics.

The model's monthly calibration and validation performance was analyzed and presented in Table 3. Daily calibration and validation were conducted using runoff (mm), while monthly calibration and validation were performed using monthly stream flow data (m3/s). The Nash Sutcliffe value during the calibration period with daily runoff was satisfactory at 0.51, with a correlation coefficient of 0.74. During the validation period using daily data, the NSE and correlation coefficient were 0.80 and 0.9, respectively, indicating an improvement over the calibration period. The model's warmup period was limited to one year due to data constraints, but a longer warmup period would have improved the calibration period results. The model's performance during calibration and validation with monthly stream flow was excellent, with NSE and correlation coefficient values of 0.77 and 0.93 during calibration and 0.90 and 0.95 during validation, respectively (Table 3). The high correlation coefficient during both calibration and validation indicates a strong agreement between observed and simulated stream flows. Graphs illustrating the model-generated daily observed and calculated runoff during the calibration and validation periods are presented in Fig. 16 and Fig. 17.

3.3 Prediction of Stream Flow

The simulation model was applied daily and monthly over the entire period from 2013 to 2019, including calibration and validation stages. As shown in Fig. 18, the model effectively simulated low and medium flow, although it failed to capture the extreme events of 2019. Nonetheless, the model performed well in terms of matching the observed stream flow, with an R2 value of 0.72. Fig. 19 displays a scatter plot comparing monthly discharges, which shows a high level of agreement between the simulated and observed discharges, with an R2 value of 0.73. However, the model underestimated high flow events exceeding 1000 m3/s. The monthly stream flow data from 2013 to 2019, as seen in Fig. 20, show a similar trend between the observed and simulated values. Finally, the scatter plot in Fig. 21 confirms the good agreement between observed and simulated monthly stream flow, with an R2 value of 0.89.

Table 2. Parameters fitted values of SIMHYD

Parameter	Units	Min.	Max.	Fitted values
Baseflow coeff.	na	0	1	0.1
Impervious Threshold	mm	0	5	4.5
Infiltration Coeff.	na	0	400	190
Infiltration shape	na	0	10	0.0196
Interflow Coeff.	na	0	1	0.0762
Perv. Fraction	na	0	1	0.7
Recharge coefficient	na	0	1	3.431
RISC	mm	0	5	0.92
SMSC	mm	1	500	1.0

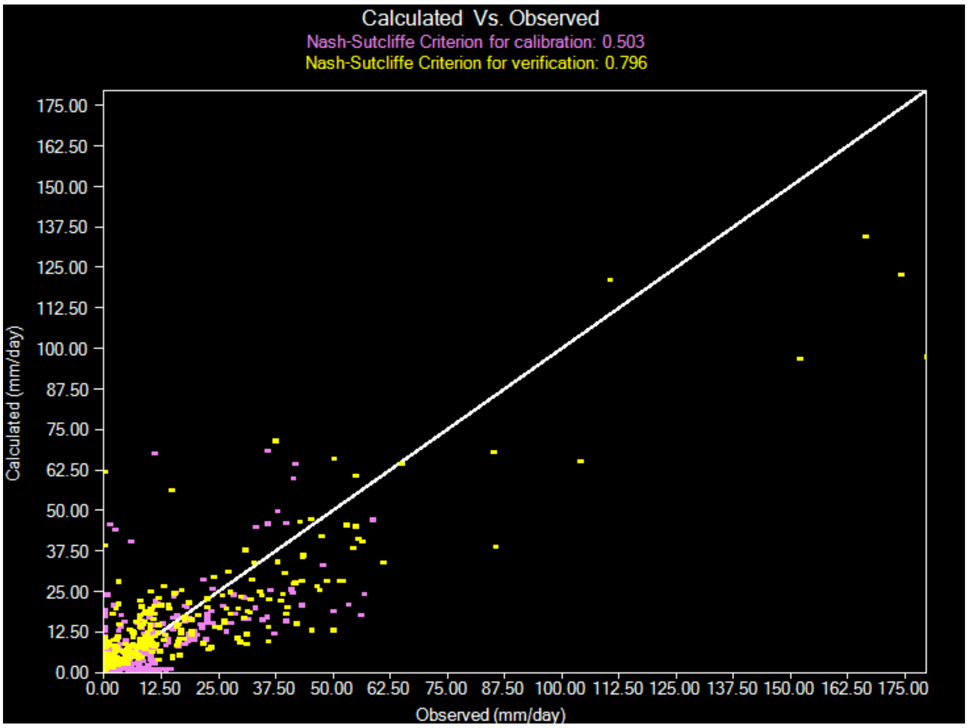

Fig. 14. Scatter plot between daily observed and simulated runoff – Ghataprabha (Hidkal) dam during calibration and verification period

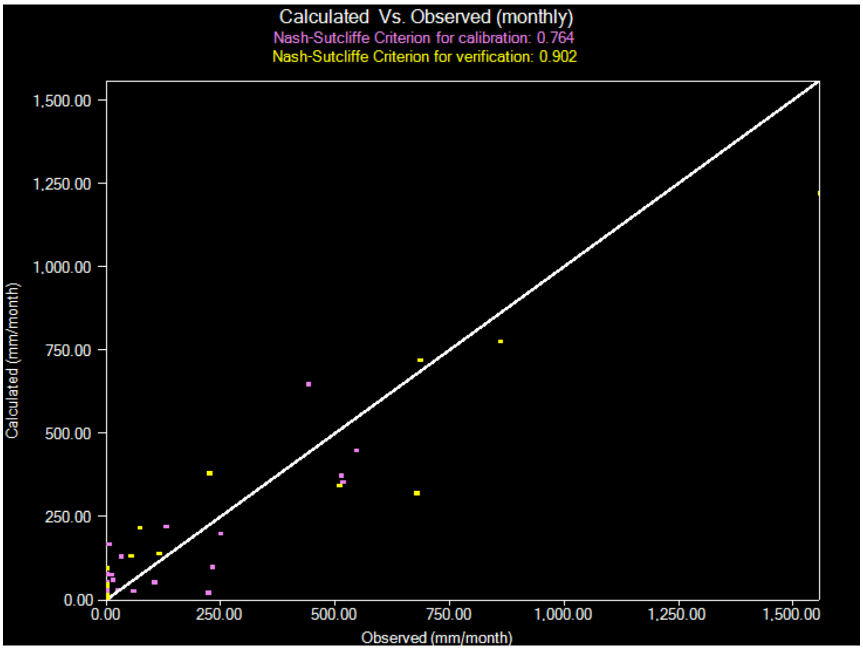

Fig. 15 Scatter plot between monthly observed and simulated runoff – Ghataprabha (Hidkal) dam during calibration and verification period

Table 3. Results of model performance indices during calibration and validation periods

Sl. No.	Parameter	Calibration		Validation	
		Daily	Monthly	Daily	Monthly
1	NSE	0.51	0.77	0.80	0.90
2	Coefficient of correlation	0.74	0.93	0.90	0.95
3	Coefficient of determination	0.56	0.86	0.81	0.91

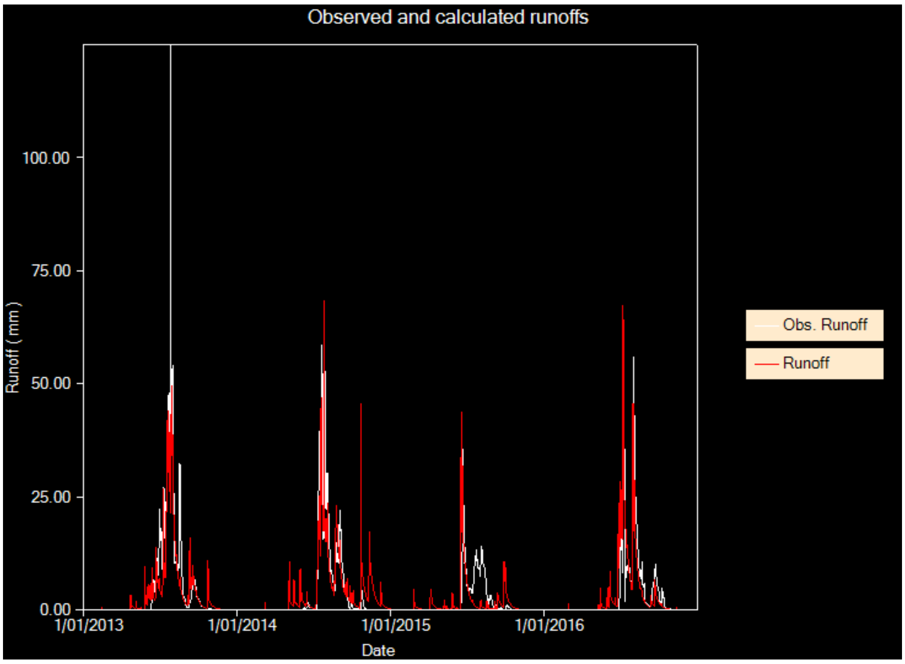

Fig. 16. Comparison between simulated and observed runoff for calibration period from 2013 to 2016

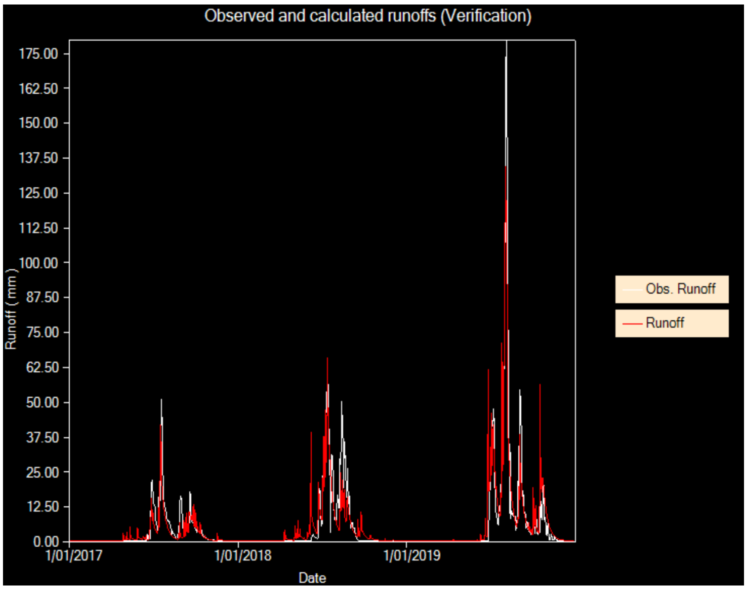

Fig. 17. Comparison between simulated and observed runoff for validation period from 2017 to 2019

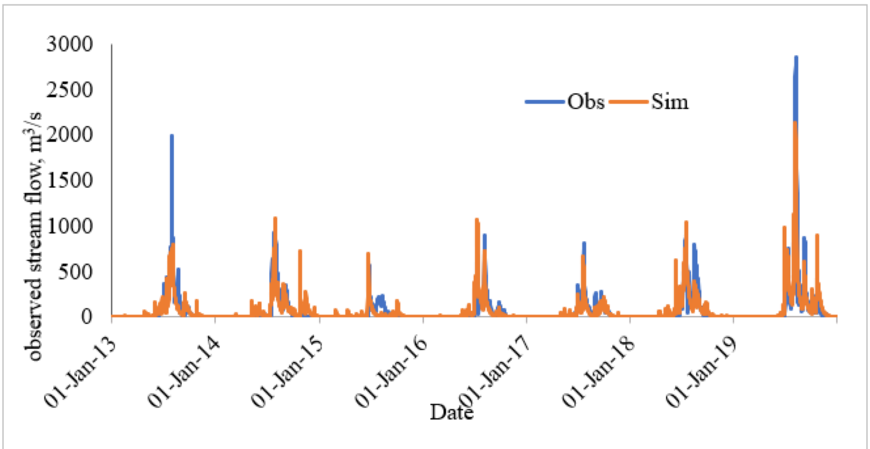

Fig. 18. Comparison of observed and simulated daily stream flow discharge from 2013-2019

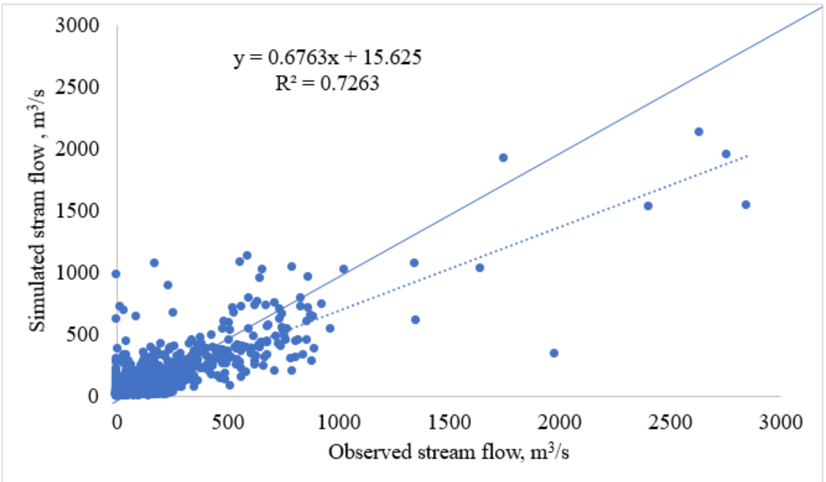

Fig. 19. Scatter plot between observed and simulated daily stream flow from 2013-2019

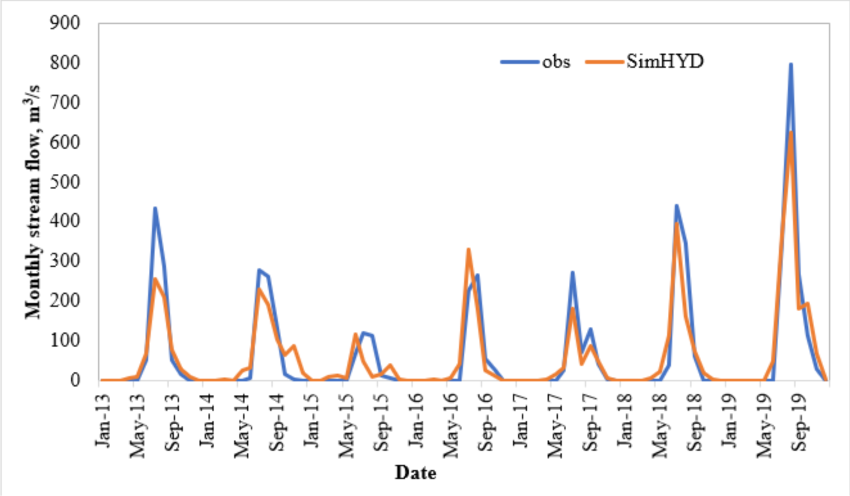

Fig. 20. Comparison of observed and simulated monthly stream flow discharge from 2013-2019

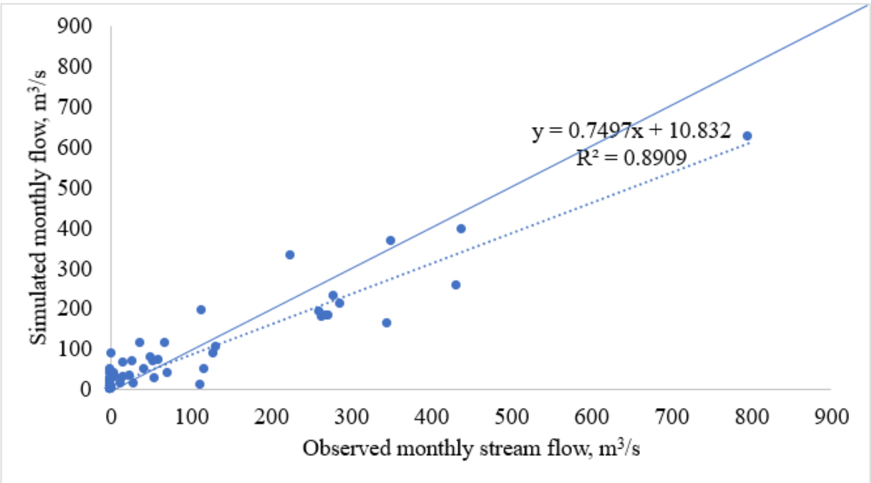

Fig. 21. Scatter plot between observed and simulated monthly stream flow discharge from 2013-2019

4. CONCLUSION

The SIMHYD conceptual lumped model underwent calibration and validation using autocalibration's genetic algorithm for the Hidkal dam catchment area in the Krishna Basin of Karnataka, India. This model successfully simulated both daily and monthly stream flows with results closely matching observed stream flows. Statistical indices, including NSE and R2, were used to measure the model's performance during both calibration and validation periods. The study found a significant agreement between observed and monthly stream flows in the Hidkal dam catchment area. Moreover, the SIMHYD model proved its capability to simulate stream flows even under limited data conditions.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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