



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2025): 5.20
www.agronomyjournals.com
2025; SP-8(12): 637-643
Received: 25-10-2025
Accepted: 26-11-2025

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Optimal data series length for calibration using SIMHYD model: Insights from Bhima basin

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DOI: <https://www.doi.org/10.33545/2618060X.2025.v8.i12Sh.4612>

Abstract

The Simple Hydrology (SimHYD) model, a lumped conceptual daily rainfall-runoff model suitable for runoff model available in the Rainfall-Runoff Library (RRL), is suitable for runoff simulation under data-scarce conditions. The present study aims to evaluate the optimal data series length required for effective rainfall-runoff modeling using SimHYD. The impact of the calibration data series length was evaluated by conducting an analysis on two basins: the Pulgaon-Bhima upper basin and the Jeewangi-Bhima lower basin. A total of nine schemes, five from Pulgaon and 4 from Jeewangi basin, were selected for the study. The data series lengths of the Pulgaon catchment were three, four, five, six and seven years, while for the Jeewangi catchment, they were three, six, ten and sixteen years. After conducting hundreds of random samples across the two basins, it was determined that a minimum data length of 6 years yielded favorable results for both the Pulgaon and Jeewangi catchments. In the Pulgaon of Bhima upper basin, analysis of different data lengths showed significant NSE values for Scheme S₄, with 0.56 and 0.55 during the calibration and validation periods for daily data and 0.86 and 0.78 for monthly stream flows, respectively. Similarly, the Jeewangi catchment of the Bhima lower basin exhibited higher NSE values for Scheme S₇, with 0.66 and 0.52 during the calibration and validation periods. Our results show that minimum six years of gauge data can be used to simulate and assess the runoff of ungauged stations.

Keywords: Runoff prediction, optimal data series length, calibration, SIMHYD, ungauged stations

1. Introduction

A rainfall runoff model is a mathematical representation used to simulate the process of rainfall turning into surface runoff. This process is vital in hydrology and is essential for understanding water resource management, flood forecasting and environmental impact assessment as every component is interconnected (Kokkonen *et al.*, 2001; Sitterson *et al.*, 2017) ^[13, 17]. Rainfall runoff models typically depends on various factors such as rainfall intensity, duration, antecedent soil moisture conditions, topography, land use, soil properties and soil type to predict how much rainfall will become surface runoff and how it will flow through the drainage network (Yang *et al.*, 2015) ^[20]. Rainfall-runoff models are essential tools in hydrology for predicting the transformation of rainfall into runoff within a watershed. They are employed in various applications such as flood forecasting and mitigation, water resources management, infrastructure design, erosion control and environmental impact assessments. These models can be categorized into two main types, namely, empirical models and process-based models. Empirical models are based on observed data and statistical relationships between rainfall and runoff. They are relatively simple and require less computational effort. Examples include the rational method, which estimates peak runoff rates based on rainfall intensity and the SCS (Soil Conservation Service) Curve Number method, which considers soil moisture and land use to estimate runoff (Dawson & Wilby, 2001) ^[12]. Process-based models simulate the physical processes involved in rainfall-runoff generation, such as infiltration, surface runoff and channel routing. They are more complex and require detailed input data but provide a more comprehensive understanding of the hydrological system. Examples include the Soil and Water Assessment Tool (SWAT) (USDA, 1986; Di Luzio *et al.* 2002) ^[10, 11], Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) (Scharffenberg *et al.* 2000) ^[8] and the Variable

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Infiltration Capacity (VIC) model (Lohmann *et al.* 1998) [9].

Rainfall runoff models can be further classified based on spatial scale (e.g., lumped or distributed) and temporal scale (e.g., event-based or continuous). Lumped models represent the entire watershed as a single unit and are suitable for small watersheds or quick assessments, while distributed models divide the watershed into smaller spatial units and simulate runoff processes at each unit, providing more detailed results but requiring more data and computational resources. Overall, rainfall runoff models are essential tools for hydrologists, engineers and policymakers to understand and manage water resources effectively, especially in regions prone to flooding or water scarcity. They play a crucial role in flood forecasting, water supply management and ecosystem conservation (Liu *et al.*, 2015) [19].

Simple hydrology (SIMHYD) is one of the conceptual lumped daily rainfall-runoff models are widely used for surface runoff predictions in poorly gauged or ungauged catchments. Model was developed in the 1970s (Porter and McMahon 1975) [27] which is simple, easy to calibrate and relatively accurate in runoff predictions with inputs precipitation and potential evapotranspiration (Siriwardena, 2005) [7]. The SIMHYD model, ignores the spatial diversity of watershed attributes, may require less extensive input data compared to other models like SWAT, which can be advantageous in situations where data availability is limited or uncertain on the other hand potentially reducing the time and effort required to obtain satisfactory model performance provided the output data depends on the quality of observed data.

Present study focused on the importance of calibration data length required to estimate the performance of model. This can help improve application of conceptual rainfall-runoff model in poorly gauged and ungauged catchments. The impact of length of data series in generation the runoff for which we have selected different lengths of data series depending on the availability of the observed data over the catchment of two basins viz, Bhima upper and Bhima lower basin. Four schemes were selected for the Pulgaon catchment of Bhima upper basin and 4 schemes were selected for the Jeewangi catchment of the Bhima lower basin. Li *et al.*, 2010 studied on different lengths of data series ranging from one to ten years and found that eight years of data are sufficient to obtain steady estimates. Studies were conducted by other researches with five, seven (Buzacott, *et al.*, 2019 Rao, *et al.*, 2024) [23, 24], eight and ten years of data period showed reliable results depending on the selection of parameter range, wet period of data than the dry period (Peel *et al.* 2000) [25] and humid catchments compared to arid catchment.

2. Materials and Methods

2.1 Model description

The SimHYD (Simulation model for Hydrology and Development) is a lumped rainfall-runoff model is a widely used hydrological model designed for simulating runoff processes in watershed systems and is developed by Donohue *et al.* (2001). It has been tested and used extensively across Australia (Chiew *et al.* 2002) [7]. The lumped model considers the catchment as a single unit disregarding the spatial variability in the catchment parameters. Model used in this study has 9 parameters as shown in the Table1 with minimum and maximum parameter range and Fig. 1 showing the Structure of lumped rainfall runoff model SIMHYD.

Moisture infiltration is channeled through various pathways including interflow, groundwater recharge and retention within

the soil moisture store. Interflow is determined by a linear relationship with soil wetness, representing the ratio of soil moisture level to capacity and reflecting areas of potential saturation excess runoff within the catchment. Groundwater recharge follows a similar linear function with soil wetness. Any remaining moisture is stored in the soil moisture store, with evapotranspiration from this store modeled linearly constrained by the maximum rate of potential evapotranspiration. The soil moisture store's finite capacity leads to overflow into the groundwater store, from which base flow is simulated as a linear recession (Podger, 2004) [22]. This model delineates runoff generation from three main sources: infiltration excess runoff, interflow (including saturation excess runoff) and base flow. Study uses a version of the SIMHYD model with nine parameters whose ranges are taken from Podger (2004) [22].

The fundamental equations of the model are

Impervious ET = min (pet, (1-pervious Fraction) * pervious Threshold, impervious Incident)

Interception ET = min (pervious Incident, pet, rainfall Interception Store Capacity)

Infiltration Capacity = Pervious Fraction x Infiltration Coefficient*exp (Infiltration Shape* Soil Moisture Fraction)

Infiltration = min (throughfall, infiltration Capacity)

Interflow Runoff = Interflow Coefficient* Soil Moisture Fraction*Infiltration

Infiltration after interflow = Infiltration - Interflow Runoff;

Recharge = Recharge Coefficient * Soil Moisture Fraction* Infiltration After Interflow

Soil Input = Infiltration After Interflow - Recharge

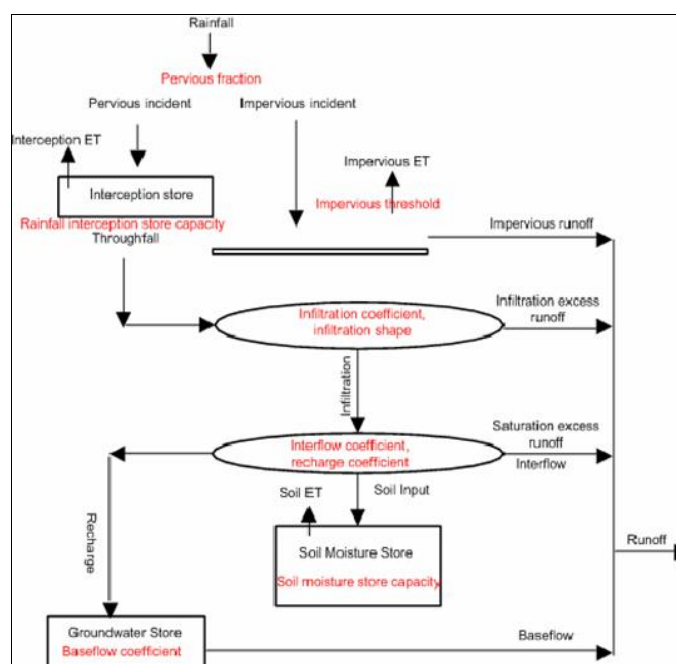


Fig 1: Structure of lumped rainfall runoff model SIMHYD (Podger, 2004) [22]

Table 1: Description and ranges of parameters in SIMHYD model

Description	Unit	Default value	Minimum Value	Maximum Value
Baseflow coefficient	na	0.3	0	1
Impervious Threshold	mm	1	0	5
Infiltration Coefficient	na	200	0	400
Infiltration shape	na	2	0	10
Interflow coefficient	na	0.1	0	1
Pervious fraction	na	0.9	0	1
Rainfall interception store capacity	mm	1.5	0	5
Recharge Coefficient	na	0.2	0	1
Soil moisture store capacity	mm	320	1	500

2.2 Catchment data

The Bhima River Basin, comprising the upper and lower sections, is vital for the socio-economic development and ecological sustainability of the region. Understanding the runoff dynamics, identifying key influencing factors and implementing appropriate water management measures are essential to address the challenges posed by variability in runoff patterns, ensure equitable water distribution and enhance resilience to climate change impacts in both the upper and lower basin areas. It travels through the states of Maharashtra, Karnataka and Telangana, serving as a crucial source of water for irrigation, drinking and industrial purposes in the region. The basin of the Bhima River is divided into two main sections: the Bhima Upper Basin and the Bhima Lower Basin, an important sub-basin of Krishna river basin, the second largest eastward draining river of India (Biggs *et al.* 2007; Rai *et al.* 2017; Devappa, 2013; Devappa *et al.* 2011; Singh *et al.* 2019) ^[1, 2, 3, 4, 14]. Each section has distinct characteristics regarding runoff patterns, contributing factors and water management challenges. Few researches suggests flooding in some watersheds of Bhima lower basin (DDMA, 2019; Swarnakar and Channabasappa, 2022) ^[6] requires proper planning of watershed management techniques. Two catchments selected for the study are part of Krishna basin viz. Pulgaon of Bhima upper basin and Jeewangi of Bhima lower basin. The catchment area of Pulgaon is 2205

km² and Jeewangi is 1920 km².

The source of the data used in the study are daily rainfall data at grid interval of 0.25° X 0.25° and maximum and minimum temperatures at grid interval of 1° X 1° are obtained from Indian meteorological department website for the study period. Stream flow data on daily time steps was downloaded from Indian water resource information system website for the study period which is used for calibration and validation of the model output. This paper aims to assess the effect of data series length on the runoff calibration of catchments. The maximum length of study period for the two catchments is based on the available stream flow data which is used for calibration and validation. Calibration and validation runs for Pulgaon catchment were conducted for three, four, five, six and seven years. Based on model performance of the Pulgaon basin, indicators such as stability of calibrated parameters and consistency between calibration and validation results, four representative data series lengths were chosen for Jeewangi catchment. These selected lengths provided a balance between data availability and reliable model performance and were therefore considered suitable for further analysis. Thus for Jeewangi catchment calibration and validation runs were conducted for three, six, ten and sixteen years data length (Table 2). The total length of selected time series data was divided into three parts: model warm up period, calibration and validation (Swain and Patra, 2017) ^[18] which are detailed in table 2.

This method is more suitable for catchments where hydrological data are limited and fragmentary because it is based on a conceptual lumped rainfall-runoff modelling framework that requires relatively few input variables while maintaining reliable predictive capability. Lumped conceptual models such as SIMHYD utilize basin-averaged rainfall and potential evapotranspiration, thereby reducing dependence on detailed spatial datasets that are often unavailable in poorly gauged or ungauged catchments (Siriwardena, 2005) ^[7]. Several studies have shown that acceptable model performance and stable parameter estimation can be achieved using relatively short calibration data lengths, typically ranging from five to eight years (Li *et al.*, 2010; Peel *et al.*, 2000) ^[21, 25].

Table 2: Showing the study region, period, various schemes, calibration and validation periods

Basin	Catchment	Length of data series	Schemes	Calibration		Validation period	
				Warmup period	Calibration period	Warmup period	Validation period
Bhima Upper	Pulgaon (2012-18)	2012-14	S ₁ : 3 years recorded data	6 Months	1Year	6 Months	1Year
		2012-15	S ₂ : 4 years recorded data	6 Months	2Year	6 Months	1Year
		2012-16	S ₃ : 5 years recorded data	6 Months	3 Year	6 Months	1Year
		2012-17	S ₄ : 6 years recorded data	1 Year	3 Year	1 Year	1Year
		2012-18	S ₅ : 7 years recorded data	1 Year	3Year	1Year	2 Years
Bhima Lower	Jeewangi (1991-2006)	1991-95	S ₆ : 3 years recorded data	6 Months	1Year	6 Months	1Year
		1991-97	S ₇ : 6 years recorded data	1 Year	3Year	1Year	2 Years
		1990-99	S ₈ : 10 years recorded data years recorded data	1 Year	5 Year	1Year	3Year
		1991-2006	S ₉ : 16 years recorded data years recorded data	2 Year	8Year	1Year	5Year

2.3 Parameter optimization

The objective function measures the over goodness-of-fit between the simulated flow and observed flow; thus, it produces the calibration accuracy value of rainfall-runoff models. It also interprets the observed and modelled outputs into a single number (Vaze *et al.*, 2011) ^[16] For this study, from the available objective functions Nash Sutcliffe Efficiency (NSE), Coefficient of Determination (R²) used during the calibration process. The performance of the model was analyzed during calibration and validation with statistical indices such as Nash Sutcliffe Efficiency (NSE) and Coefficient of Determination (R²). The

details of the model performance indices are given below.

Nash Sutcliffe Efficiency (NSE)

Nash Sutcliffe Efficiency (NSE) is a statistical measure used to evaluate the performance of hydrological or environmental models. It is the normalized statistic and ranges from one to infinity. It is used to estimate the magnitude of variance in comparison to observed data variance (Nash and Sutcliffe, 1970) ^[15]. This parameter depicts better idea of how the observed and simulated values perfectly fit linearly. The NSE ranges from negative infinity to 1, where 1 indicates perfect model

performance, 0 indicates the model performance is as good as the mean of the observed data and negative values indicate the model performs worse than simply using the mean of the observed data. The NSE was calculated with following equation.

$$\text{Nash - Sutcliffe Efficiencies (NSE)} = 1 - \frac{\sum_{i=1}^n ((Q_i)_{obs} - (\bar{Q})_{obs})^2}{\sum_{i=1}^n ((Q_i)_{obs} - (\bar{Q})_{obs})^2}$$

Where

$(Q_i)_{obs}$ = observed discharge at time i, m^3s^{-1}

$(Q_i)_{sim}$ = Simulated discharge at time i, m^3s^{-1}

$(\bar{Q})_{obs}$ = Mean observed discharge at time i, m^3s^{-1}

n = Is the total number of data points

Coefficient of Determination (R^2)

Is a parameter used to check the goodness of fit between observed and simulated data. The coefficient of determination is commonly called r-squared (or r^2) for the statistical value it represents. This measure is represented as a value between 0.0 and 1.0, where a value of 1.0 indicates a perfect correlation. R^2 is calculated using the following formula

$$R^2 = \frac{[\sum_{i=1}^n ((Q_i)_{obs} - (\bar{Q})_{obs}) ((Q_i)_{sim} - (\bar{Q})_{sim})]^2}{\sum_{i=1}^n ((Q_i)_{obs} - (\bar{Q})_{obs})^2 \sum_{i=1}^n ((Q_i)_{sim} - (\bar{Q})_{sim})^2}$$

Where,

Mean simulated discharge at time i, m^3s^{-1} , observed and simulated discharges respectively are in m^3s^{-1} mean observed and mean simulated discharges respectively are in m^3s^{-1}

The performance of each calibration was evaluated for the different selected period, using Nash-Sutcliffe efficiency and then validated for the varied time series from the available observed data for the selected catchments one from each of the

two basins.

3. Results and Discussion

Application of SIMHYD model for evaluation of minimal data length required for optimal estimation of discharges were taken up with nine schemes. Five on Pulgaon catchments of Bhima upper basin and four for Jeewangi of Bhima lower basin. NSE was chosen as the primary objective function as it is sensitive to high flows (Smith *et al.*, 2019) [26] and then by applying a genetic algorithm in defining the objective function NSE. Parameters are further evaluated within the limits.

Calibration runs were conducted using data lengths shown in table2, and was applied for five different calibration schemes to Pulgaon catchments of Bhima upper basin and two distinct catchments, utilizing the available observation data. For the Pulgaon catchment in the Bhima Upper Basin, performed 100 random samples with data series lengths of three, four, five, six and seven years. Similarly, for the Jeewangi catchment in the Bhima Lower Basin, data series lengths of three, six, ten and sixteen years were used. For the three-year data series, data from each year were sampled independently across the entire observation dataset. We did not impose any constraints on the random sampling process, allowing calibration years to be selected freely from any part of the record, whether they were dry, normal, or wet years. This method ensured that the calibration data included a wide range of hydrological conditions, thus providing more variability and independent hydrological characteristics compared to using continuous year periods. This approach is particularly advantageous for catchments with limited data availability. In each case, the data from the first year were used to warm up the hydrological model, which helps to minimize initialization errors and improve the reliability of the calibration. The performance of each calibration was evaluated over the entire period using the Nash-Sutcliffe efficiency metric, a standard measure for assessing the predictive power of hydrological models.

Table 3: Scheme wise calibration and validation values for daily and monthly stream flow data

S. No.	Catchment/Basin	Scheme No.	NSE for calibration period		NSE for validation period	
			Daily	Monthly	Daily	Monthly
1	Pulgaon-Bhima upper basin	S ₁	0.45	0.59	0.44	0.55
2		S ₂	0.45	0.61	0.41	0.56
3		S ₃	0.41	0.54	0.42	0.51
4		S ₄	0.56	0.86	0.55	0.78
5		S ₅	0.49	0.64	0.45	0.53
6	Jeewangi-Bhima lower basin	S ₆	0.44	0.56	0.42	0.56
7		S ₇	0.66	0.96	0.52	0.95
8		S ₈	0.49	0.60	0.53	0.61
9		S ₉	0.43	0.59	0.45	0.61

3.1 Pulgaon, Bhima upper basin

Basin area comprising of 2205km² with discharge data available for 7 years from 2012 to 2018. Among the 5 schemes of different time period i.e. 3, 4, 5, 6 and 7 years. Out of 5 schemes for S₁ which is 3 years S₂ 4 years and S₃ 5 years, 6 months of data used for warmup during calibration and validation and for the other two schemes S₄ and S₅, 1 year data is used for warmup for calibration and validation. In the Pulgaon-Bhima upper basin, Scheme S₁ exhibited NSE values of 0.45 for daily and 0.59 for monthly during the calibration period and 0.44 for daily and 0.55 for monthly during the validation period. Scheme S₂ has NSE values of 0.44 (daily) and 0.61 (monthly) for the calibration period and 0.41 (daily) and 0.56 (monthly) for the validation period S₃ has NSE values of 0.41 (daily) and 0.54 (monthly) for the calibration period and 0.42 (daily) and 0.51 (monthly) for the validation period. Scheme S₄ shows higher NSE values, with 0.56 for daily and 0.86 for monthly during the

calibration period and 0.55 for daily and 0.78 for monthly during the validation period. Scheme S₅ presents NSE values of 0.49 (daily) and 0.64 (monthly) for the calibration period and 0.45 (daily) and 0.53 (monthly) for the validation period. Screen shots of the model input data selection (Fig.2) of calibration and validation periods with warmup period (Fig.3). The NSE value is achieved at 0 for the base flow coefficient, 3.588 for impervious threshold, 343.529 for infiltration coefficient, 0.274 for infiltration shape, 0 for interflow coefficient's, 0.956 for previous fraction, 4.980 for rainfall interception store capacity, 0.737 for recharge coefficient and 462.819 for soil moisture store capacity (Fig.4). Calibration values of the 9 parameters (Fig.4) scatter plots for daily and monthly stream flows (Fig. 4). The coefficient of determination (R^2) shown in Fig.4, indicate that there is a good agreement between observed and simulated daily flows.

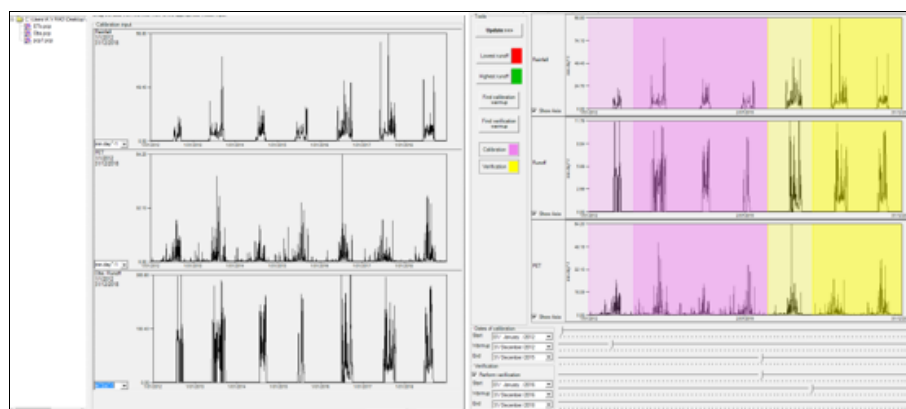


Fig 2: Showing input data with calibration and validation period

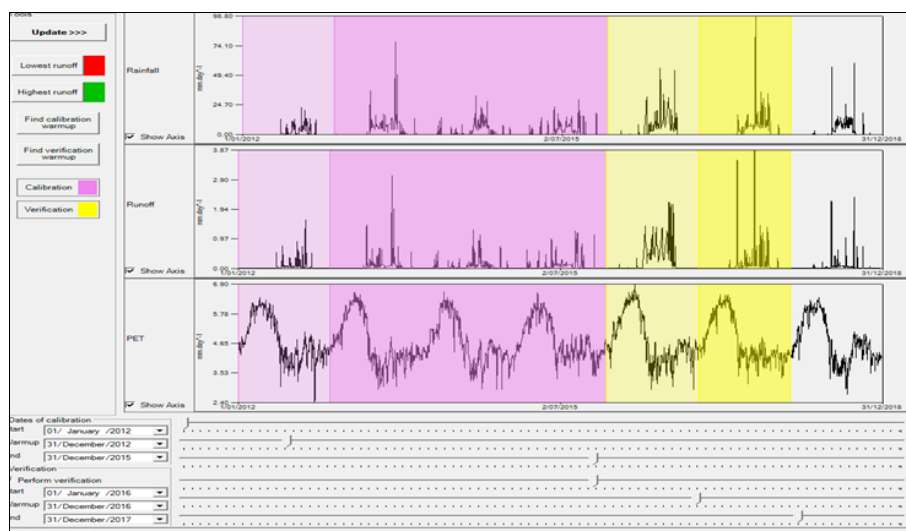


Fig 3: Calibration and validation period along with model warmup periods of scheme S₃

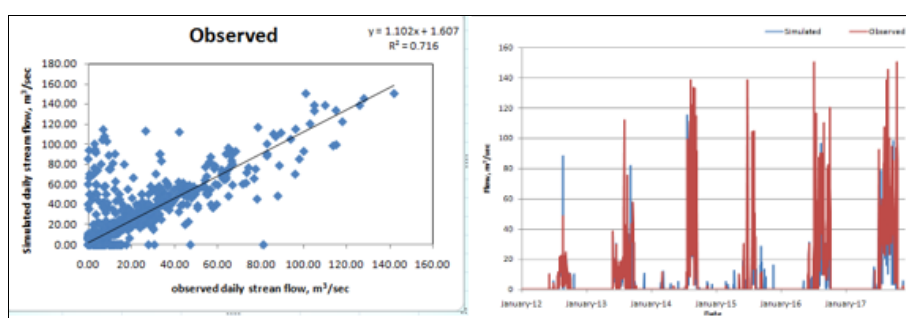


Fig 4: Scatter plot between observed and simulated for daily and monthly data

3.2 Jeewangi of Bhima lower basin

Jeewangi basin area comprising of 1920 km² with available discharge data from 1991 to 2006 i.e. for 16 years. Among the 4 schemes of different time period i.e. 3, 6, 10 and 16 years. For S₆ scheme 6 months of warmup period was fixed for calibration and validation periods and for the remaining schemes S₇, S₈ and S₉, 1 year data was fixed for calibration and validation. Scheme S₆ records NSE values of 0.44 for daily and 0.56 for monthly during the calibration period and 0.42 for daily and 0.56 for monthly during the validation period. Scheme S₇ achieves NSE values of 0.66 (daily) and 0.96 (monthly) for the calibration period and 0.52 (daily) and 0.95 (monthly) for the validation period. Scheme S₈ shows NSE values of 0.49 for daily and 0.60 for monthly during the calibration period and 0.53 for daily and 0.61 for monthly during the validation period. Lastly, Scheme S₉ has NSE values of 0.43 (daily) and 0.59 (monthly) for the calibration period and 0.45 (daily) and 0.61 (monthly) for the

validation period. Thus calibration results of S₇ data has shown better values of NSE for calibration and validation period for daily and monthly stream flows. Screen shots of the model input data selection (Fig.5) of calibration and validation periods with warmup period, calibration values of the 9 parameters (Fig.6) scatter plots for daily and monthly stream flows provided by the model (Fig.6&7).

The NSE value is achieved at 0.066 for the base flow coefficient, 4.745 for impervious threshold, 186.66 for infiltration coefficient, 0.039 for infiltration shape, 0 for interflow coefficient's, 1 for previous fraction, 4.862 for rainfall interception store capacity, 0.623 for recharge coefficient and 478.474 for soil moisture store capacity (Fig.5). Finally, the Fig. 7 shows that the coefficient of determination (R²) for daily and monthly stream flow are in good agreement with R² 0.821 and 0.899 for daily and monthly flows respectively.

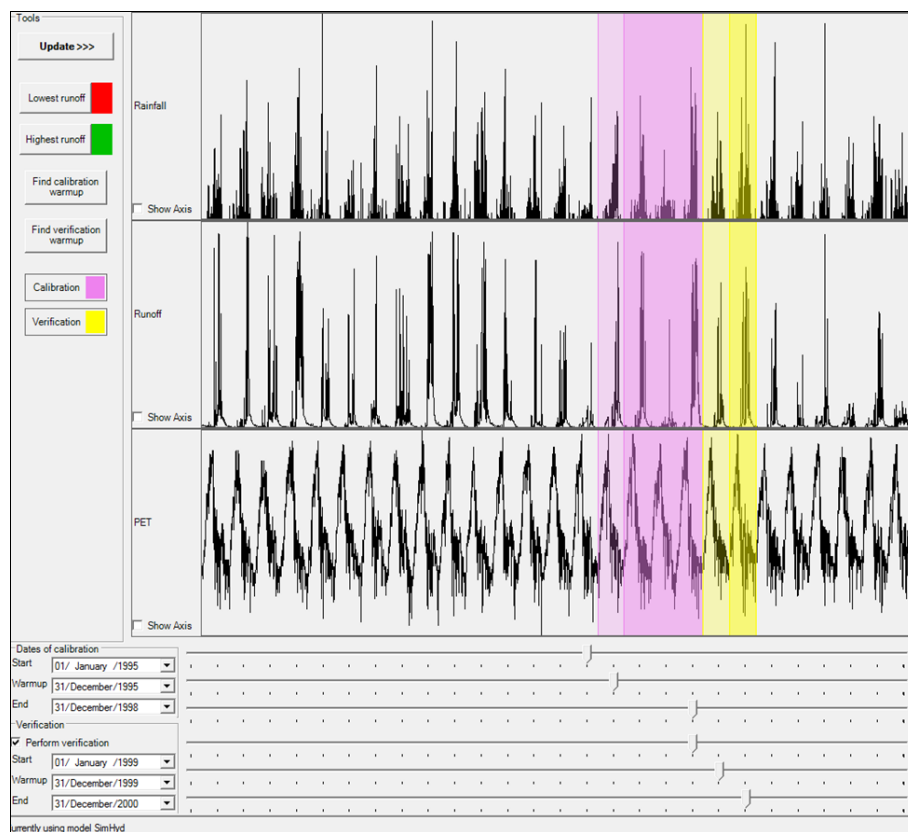


Fig 5: Calibration and validation period along with model warmup periods of scheme S₆

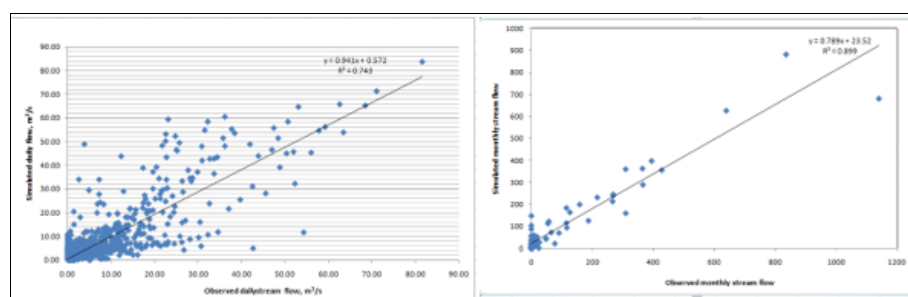


Fig 6: Scatter plot between observed and simulated for daily and monthly data

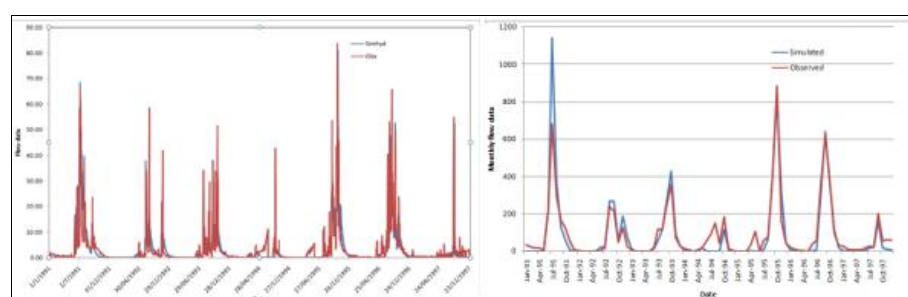


Fig 7: Comparison of observed and simulated daily and monthly stream flow discharge

4. Conclusion

The study evaluates the suitability of the rainfall-runoff model (SIMHYD) used to generate streamflow in an ungauged catchment by analyzing the different length of data series. Analysis conducted over the two basins has shown that with minimum 6 years of data length can be used to generate the stream flows of ungauged catchments by considering the parameter values of the assessed gauge station. Pulgaon of Bhima upper basin analyzed for different data lengths, has shown significant NSE values among the four schemes with 0.56 and 0.55 during calibration and validation period for daily

data and 0.86 and 0.78 for monthly stream flows respectively for Scheme S₄. Similarly, Jeewangi catchment of Bhima lower basin has shown higher NSE values for scheme S₇ with 0.66 and 0.52 during calibration and validation period for daily data and 0.96 and 0.95 respectively for monthly stream flow data. Among different length of data series 6 years data is giving better values compared to less and more i.e. from 3 years up to 16 years data length for the particular basins with the available data. The SIMHYD simulations was finally verified for goodness of fit between observed and simulated data by assessing the R² for daily flows, which was 0.716 and 0.821 for Pulgaon and

Jeewangi catchments respectively. Thus it can be concluded that minimum of six years for gauge data can be used to simulate and assess the runoff of nearby ungauged station.

Further Research

Acknowledgements

Research was supported by the Indian Council of Agricultural Research, Department of Agricultural Research and Education, Government of India. The authors thank ICAR - Central Research Institute for Dryland Agriculture for supporting this research work and providing facilities for undertaking the research.

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