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Assessing streamflow modeling using single and multi-site calibration approach on Bharathpuzha catchment, India: a case study

Leelambar Singh[1] · Subbarayan Saravanan[1]

Abstract

A vital challenge of assessing global water resources is to achieve the optimal set of parameters in any hydrological model by simulating streamflow. Simulating single-site hydrological features for a large catchment may not account for regional variation, resulting in unmet watershed needs. The objective of this study was to assess the single-site calibration (SSC) and multi-site calibration (MSC) approaches using the hydrological Soil and Water Assessment Tool (SWAT) model on the Bharathpuzha watershed of India. The multi-site method entails splitting a large catchment into smaller ones and applying MSC criteria to the entire catchment. Monthly streamflow simulations were conducted to verify the model's performance using the coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), percent of bias (PBIAS) and Kling Gupta Efficiency (KGE). Results show that single-site approach values are more meaningful than multi-site. In SSC, the parameter determined by optimizing the model parameters at four different stations delivers a better result than in MSC, and MSC has less uncertainty with lower PBIAS and r-factor values. This case study was assumed to give experience with single and multi-site calibration in a large catchment and reveal the positives and negatives of SSC and MSC estimated parameters.

Keywords Single-site calibration · Multi-site calibration · SWAT · Bharathpuzha catchment · India

Introduction

Simulation of physically oriented and distributed hydrological models is challenging due to limited input information constraints. Hydrological models are frequently used to measure water resources issues, including the climate change impact on water resources, pollution concerns, landuse changes and water resource planning and management across the world (Schellekens et al. 2017; Sharma and Tiwari 2019; Danshgar et al. 2021; Simões et al. 2021). The cautious operation of model calibration and validation includes distributed catchment models and this operating method is needed because every hydrological model is just an accurate reflection of reality. Therefore, parameter values must be adjusted to increase the goodness of fit. Normally, the goodness of fit is determined by applying the data simulated by the model towards the corresponding observed variables (Montanari and Toth 2007; Althoff and Rodrigues 2021). Calibration is essential for developing and representative a reliable model at the river basin scale. It is a well-known approach to simulate any hydrological model at a single site or outlet in a watershed (Desai et al. 2021). The selection of single-site calibration for the entire catchment is not an effective method for investigating hydrology parameter spatial variability and suitable for the smaller watershed. Due to different climatic variations, the selection of single calibration differs in short distances (Leta et al. 2017). It is always important to calibrate the observed data for large catchments at multiple places of the gauge station for improved hydrological system simulation and spatial variability of information (Wang et al. 2012; Song et al. 2021; Ghaffar et al. 2021).

Previous authors proved the importance of multi-site calibration (MSC) approaches against single-site calibration (SSC) on catchment outlet information (Bai et al. 2017; Chen et al. 2019; Pandey et al. 2020; Malik et al. 2021). On the other hand, some authors observed no significant improvement by multi-site changes related to SSC for streamflow (Reed et al. 2004; Shrestha et al. 2016; Franco et al. 2020). An issue arises as to whether the MSC overtakes

✉ Subbarayan Saravanan
  ssaravanan@nitt.edu

  Leelambar Singh
  leeli.singh@gmail.com

[1] Department of Civil Engineering, National Institute of Technology, Tiruchirappalli, Tamilnadu, India

the SSC (Lerat et al. 2012). The multi-objective control of all variable parameters is best to improve model simulation (Rasolomanana et al. 2012; Malik et al. 2021). The capacity to simulate hydrological variables in space and multi-site information is increasingly being utilized to evaluate model performance due to the recent emergence of hydrological distributed models (Peel and McMahon 2020; Zhao et al. 2021). In this study, the hydrological Soil and Water Assessment Tool (SWAT) model was applied to the Bharathpuzha catchment of southern India. SWAT is a semi-distributed hydrological model for large-scale river basins to simulate flow, erosion, and nutrients (Arnold et al. 1998) and it has worldwide applicability for hydrological modeling for different catchments (Ahmadzadeh et al. 2022; Chim et al. 2021; Sirisena et al. 2021; Akoko et al. 2021). Parameter values are needs to adjust throughout the calibration procedure to avoid excessive parameterisation (Beven 1990). According to Anderton et al. 2002, due to the various parameters in modeling the hydrological cycle, the approach of SSC was inadequate in its usefulness. Santhi et al. (2008) demonstrated that SSC cannot account for any variation in the catchment and cannot provide reliable simulation outcomes. This could only be done using several gauges in the measurement and testing processes.

This research selected four gauging stations for multi-site simulation of monthly streamflow data. Piniewski et al. (2011) chose eleven Narew basin gauges for MSC, successfully identified uncertainty parameters, and fine-tuned the model. Previous studies point out that multi-site calibrated parameter values are more appropriate for local situations (Bai et al. 2017; Nkiaka et al. 2018; Mandal et al. 2021). The multi-calibration approach gives good results with sedimentation, nutrient and evaporation simulations. Besides discharge, multi-calibration methods are successfully extended with excellent results for sedimentation models, nutrients and evaporation (Barnhart et al. 2014; Shrestha et al. 2016; Zanin et al. 2018; Odusanya et al. 2019). In India, intensely studies have been done with SSC (Shivhare et al. 2018; Rani and Sreekesh 2019; Sinha et al. 2020; Singh and Jha 2021) and significantly less MSC for hydrological parameter simulation (Hasan et al. 2017; Das et al. 2019). We have adopted 17 streamflow driving parameters considered in previous studies in this study. Previous studies were considered a maximum of 12 to 14 parameters to simulate the streamflow. In addition, we have adopted the satellite-derived precipitation product of Tropical Rainfall Measuring Mission (TRMM) and one to develop the model, which was limited in previous research work. Satellite-derived precipitation products are more meaningful for hydrological modeling and application (Koshuma et al. 2021; Zhang et al. 2022). The research aims to calibrate the SWAT model with the SUFI-2 algorithm using on Bharathpuzha catchment by both single and multi-site calibration approaches and compare the performance of the models. This study will aid the importance of streamflow simulation for large catchments and improve the spatial hydrological components response in future.

Study area

The Bharathpuzha catchment is situated in the Palakkad and Coimbatore district of south India with a geographical area of 5789.47 km^2 and an elevation from 3 to 2493 m (Fig. 1). Bharathpuzha is the longest (251 km) of West flowing rivers from Tadri to Kanyakumari basin, also known as Ponnani in lower reaches. This research was conducted at the Kumbidi, Pulamanthole, Mankara, and Pudur gauging stations. The climate of the catchment is the mostly coastal type and prone to floods and landslides (For example, August 2018 was the heavy flood and August 2019) (Vishnu et al. 2019). Summer and winter are controlled by southeast and northeast rainfall and the annual average rainfall of the catchment is 2340 mm. The geological information of the western catchment consists of permeable Charnockite and less permeable gneiss and schist are underlined in the eastern (CGWB 2012). The soil texture of the lower slope is Dystric. Bharathpuzha, due to its agricultural, forest dominated the land and complex catchment, need proper catchment management, which is possible with the help of calibration and validation of spatial data in hydrological modeling. It is an essential issue in a complex catchment. Therefore, it is crucial for the Bharathpuzha catchment.

Nitosol (clay loam) and Plinthic Acrisol (sandy clay loam), while the higher slope is Pellic Vertisol (clay), Humic Acriso (loam) and Chromic Luvisol (clay loam) (FAO 2003).

Data used

The catchment and topographical characteristics were defined with a resolution of 30 m of the Global ASTER (ASTGTM.003) digital elevation model (DEM) (NASA 2019). Landuse map was derived by Landsat-8 satellite by supervised classification of 2005 was used (Fig. 2) and it was obtained from United States Geological Survey (USGS) web portal (https://earthexplorer.usgs.gov/). Global digital soil map and attribute table extracted from the FAO soil database (Batjes 1997; FAO 2003). Tropical Rainfall Measuring Mission (TRMM-3B42) Multi-satellite precipitation analysis (TMPA) derived product with 0.25° resolution daily rainfall data and Climate prediction centre (CPC) derived 0.50°×0.50 daily global temperature were used. Nine grids have been used for the weather data extraction for both precipitation and temperature. Central Water Commission of India provided monthly streamflow information at four gauge stations (Table 1).
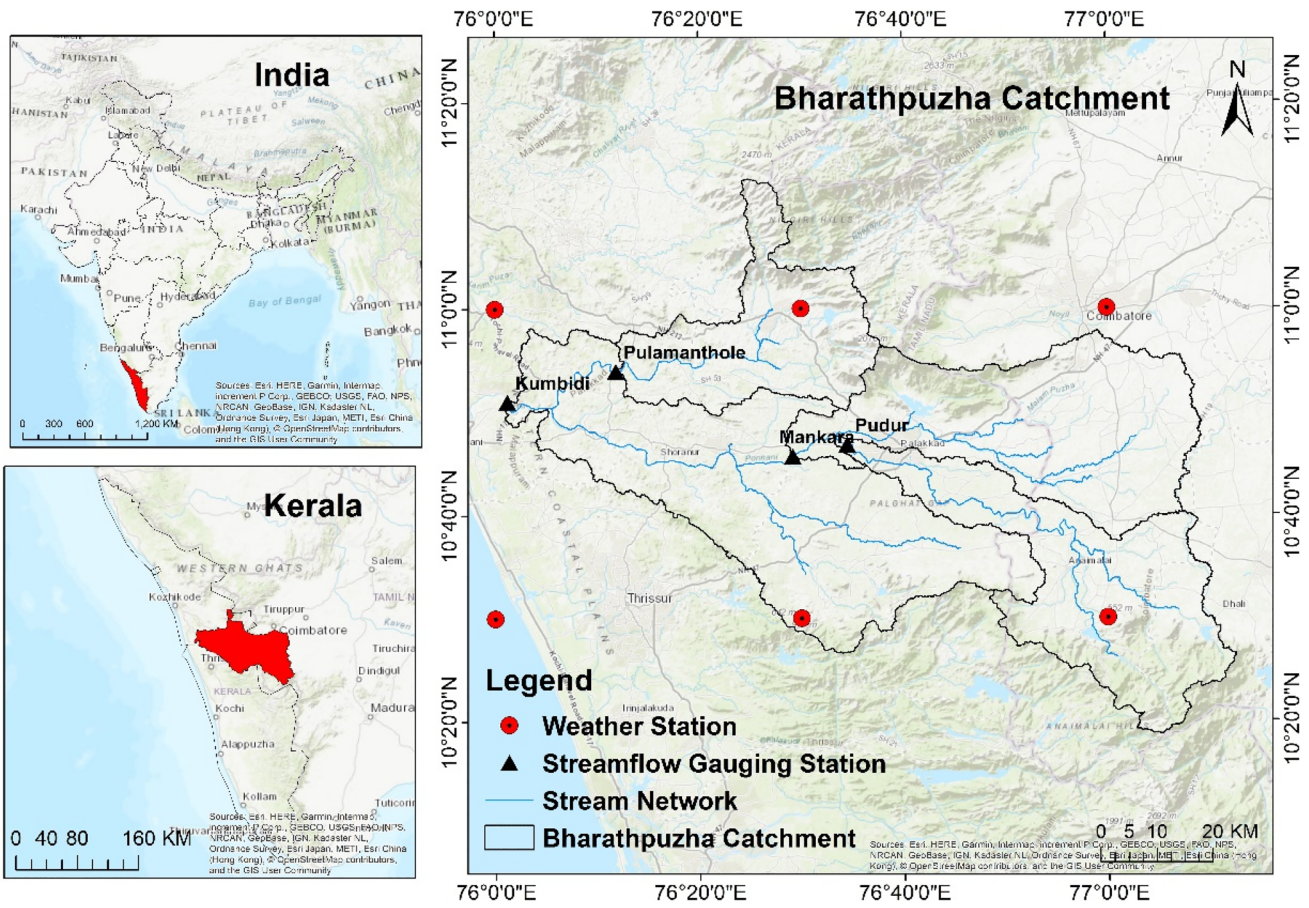
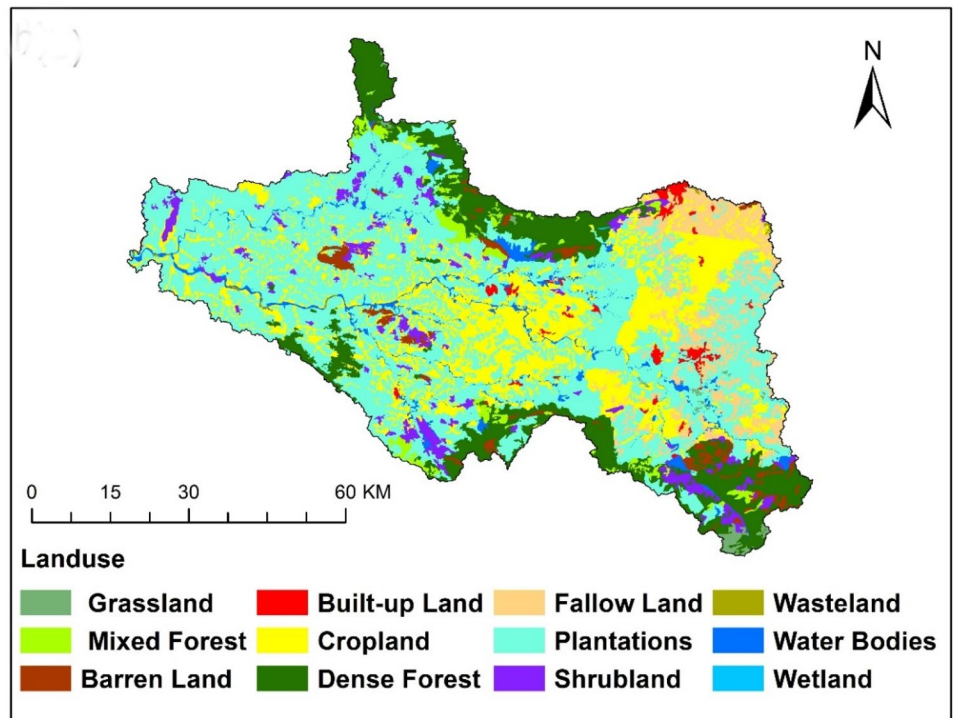**Fig. 1** Study area map of Bharathpuzha catchment

Fig. 2 Landuse of the study area

Table 1 Description of data

Data	References	Date/scale
Landuse and landcover	Landsat TM and ETM satellite imagery (https://earthexplorer.usgs.gov/)	30 m resolution/ acquisition Date:03-FEB-11
Digital elevation model	The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Digital Elevation Model (DEM) (https://gdemdl.aster.jspacesystems.or.jp/)	30 m resolution
Climate data	Rainfall- https://pmm.nasa.gov/data-access/downloads/trmm Temperature-https://www.esrl.noaa.gov/psd/	1998–2016
Discharge (cumec)	Central Water Commission of India	2001–2016
Soil data	Food and Agriculture Organization (FAO) (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/en/)	1:50,000

Methods

SWAT model

SWAT is physical and semi-distributed based hydrological model (Beven 2011). The SWAT model operates daily and is designed for large-scale landuse application, nutrients, and sediment in the watershed and works based on the water balance equation (Arnold et al. 1998; Gassman et al. 2014). The SWAT model divides the entire catchment into small sub-basins and many hydrological response units (HRUs). HRU is the smallest element of the model and it contains landuse, soil and slope. This model uses Soil Conservation Service Curve Number (Boughton et al. 1989), Penman–Monteith method (Monteith 1965) and variable storage routing method to evaluate runoff, evapotranspiration and rout the flow, respectively (Arnold et al. 1998).

## Calibration and validation procedure

In general, the performance of the hydrological model is evaluated using observed data for both calibration and validation. Parameterization of the model is required to achieve the objective function satisfaction criteria. Calibration can usually be defined as approximations of system parameters to closely fit observed data and hydrological behaviour (Abbaspour et al. 2007). Parameters were selected based on streamflow driving parameters (Li et al. 2021; Goudarzi et al. 2021). The developed model was processed from 1998 to 2016 and the first 3 years were given as warm-up time. The entire testing process was divided into two stages, with calibration and validation from 2001 to 2009 and 2010–2016. An SSC and MSC method was used for the monthly streamflow simulation to define a Bharathpuzha catchment model best suited for scenario analysis. The calibration procedure was assessed by comparing observed and simulated flow data. The SSC approach was simulated exclusively by information from the catchment outlet station, i.e., Kumbidi. The strength of a model depends on the type

of model adopted because of the number of variables to be measured differently (Abbaspour et al. 2007).

The corresponding model at four internal stations was further evaluated during the calibration and validation phases. Simulation of observed and simulated data has been done with several iterations (Abbaspour 2011). According to Moussa et al. (2007) and Shrestha et al. (2016), the MSC approach has been implemented to the central and outlet stations of the catchment. Firstly, the model was calibrated separately to obtain the parameter combination $\phi 1$ and $\phi 2$ for the water head catchment for Pudur and Pulamanthole. Subsequently, the model was calibrated to retain the parameter combination $\phi 1$ fixed for Mankara. Lastly, the Kumbidi model was calibrated with all three parameter sets fixed for their corresponding sub-catchment (Fig. 3). Therefore, the MSC approach has benefited from reduced information and enhanced parameter liberty relative to SSC. As such, approaches are common in the hydrological modeling of comparative studies (Molina-Navarro et al. 2017; Franco et al. 2020; He and Molkenthin 2021). The parameters of the SWAT model vary at different spatial stages: basin, sub-basin and HRUs.

Specifying the same catchment parameter value in the entire catchment may restrict the calibration method because sub-catchments can have distinct basin features (Gong et al. 2012; Leta et al. 2017). Simulated flow derived from the parameter given as input for the downstream gauging station rather than setting the parameter collection, as mentioned above. The parameter value of the basin acquired at the upstream gauging station was not subjected to additional revision during the downstream gauging station calibration. The identical amounts of initial parameters ranges were used at each station to initiate the calibration. In this research, calibration and validation of the model parameters have been performed with the Sequential Uncertainty Fitting (SUFI-2) through Latin Hypercube Sampling technique using open-source SWAT-CUP software (Abbaspour et al. 2004). R-factor and p-factor define the uncertainty of the model performance.

Fig. 3 Theoretical chart of single-site and multi-site approaches for modeling the Bharathpuzha catchment
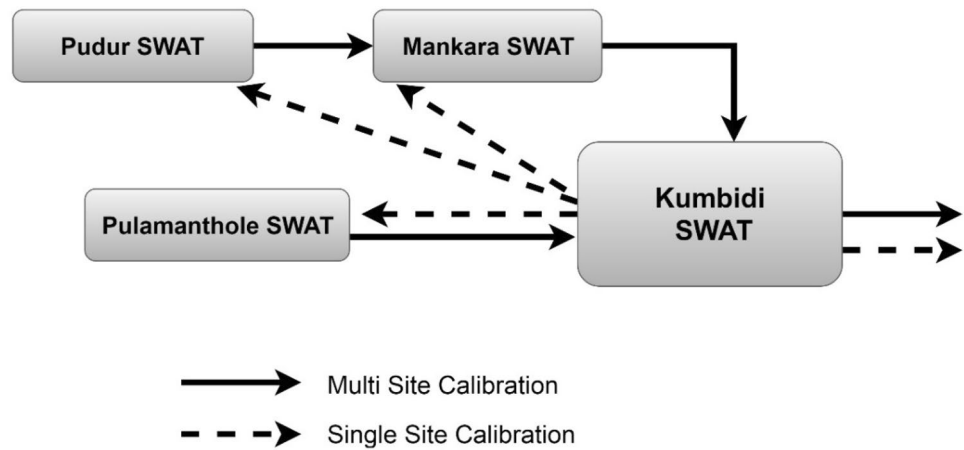
Whereas r-factor indicates the mean width of the 95% prediction band divided by the standard deviation of the respective information, p-factor represents the proportion of observed data bracketed by 95% prediction uncertainty (95PPU) (Abbaspour et al. 2007). The Nash–Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970); coefficient of determination (R^2) (Draper and Smith 1966), bias percentage (PBIAS) (Gupta et al. 1998) and Kling-Gupta coefficient (KGE) (Gupta et al. 2009) have been adopted for valuing the model accuracy as follows:

$$R^2 = \frac{\left[\sum_i \left(X_{o,i} - \overline{X}_o\right)\left(X_{s,i} - \overline{X}_s\right)\right]^2}{\sum_i \left(X_{o,i} - \overline{X}_o\right)^2 \sum_i \left(X_{s,i} - \overline{X}_s\right)^2}. \quad (1)$$

$$\text{NSE} = 1 - \frac{\sum_i \left(X_{o,i} - X_{s,i}\right)^2}{\sum_i \left(X_{o,i} - \overline{X}_o\right)}. \quad (2)$$

$$\text{PBIAS} = 100 \times \frac{\sum_i^N \left(X_{o,i} - X_{s,i}\right)}{\sum_i^n X_{o,i}}. \quad (3)$$

$$\text{KGE} = 1\sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}. \quad (4)$$

$$\alpha = \frac{\sigma_s}{\sigma_o}, \beta = \frac{\mu_s}{\mu_o}, \quad (5)$$

where X is a variable of discharge, and s and o stand for simulated and observed, i is the ith simulated, observed. The r is linear regression coefficient between simulated and observed data, μ_s and μ_s are mean of simulated and observed data, σ_s, σ_o are stand deviation of simulated and observed data.

The efficiency of the model was found to be satisfactory when R^2, NSE and KGE close to 1 (> 0.50) and PBIAS range between $\pm 25\%$ for flow (Moriasi et al. 2007).

Results

This additional detail is presumed to improve models as gauge stations increase in the catchment. Calibration approaches are differentiated for single-site and multi-site to determine whether these approaches are correct.

Single-site performance

SUFI-2 is a highly efficient sampling method and it can reduce uncertainty in a specific space. In this study, around 1000 iterations for each site performance were given for simulation.

The Kumbidi outlet station data were calibrated and validated using a single-site process for the three upstream stations. According to the SWAT-CUP calibration manual, seventeen regulated streamflow parameters were chosen for the flow simulation. The detailed descriptions of selected parameters were available in the SWAT theoretical document (Neitsch et al. 2009). The fitted and initial values of calibrated parameters for all the stations are shown in Table 2. Many differences were found among all stations single and multi-site calibration approaches. For example, soil water capacity was calibrated from 0.3 to − 0.3 relative changes; 2.64% increment was found during single-site calibration, and 0.9%, 2.34%, 1.72% and 2.25% decrement were found respectively for Kumbidi, Pulamanthole, Mankara and Pudur. The CANMX value was calibrated from 0 to 10 mm H_2O. It was fitted with 5.58 mmH2O during single-site that required maximum canopy storage and fitted calibrated

Table 2 Description of Calibrated SWAT parameters value of single-site and multi-site

S.N	Parameter name	Initial range	Single site	Kumbidi	Pulamanthole	Mankara	Pudur
1	Available water capacity of soil, R__SOL_AWC.sol	(− 0.3, 0.3)	0.264	− 0.091	− 0.234	− 0.172	− 0.225
2	Maximum storage of the canopy, V__CANMX.hru	(0, 10)	5.58	3.643	2.19	2.352	4.452
3	Main channel effective hydraulic conductivity, V__CH_K2.rte	(0, 200)	132.392	69.189	7.8	71.32	65.244
4	For return flow, threshold water depth in the shallow aquifer, V__GWQMN.gw	(0, 1500)	553.42	925.73	1108.5	1130.56	910.44
5	Coefficient of deep aquifer percolation, A__RCHRG_DP.gw	(0, 1)	0.001	0.0229	0.015	0.048	0.08
6	Main channel manning's n value, V__CH_N2.rte	(0, 0.3)	0.01	0.086	0.2805	0.023	0.032
7	Delay time of ground water, V__GW_DELAY.gw	(0, 450)	248.57	209.23	6.75	250.39	331.23
8	Mositure condition II Curve number, R__CN2.mgt	(− 0.2, 0.2)	− 0.169	− 0.115	− 0.0164	− 0.177	− 0.098
9	Lag time of Surface runoff, R__SURLAG.bsn	(− 0.5, 0.5)	0.041	0.012	0.015	− 0.021	0.014
10	Soil moist bulk density, R__SOL_BD.sol	(− 0.3, 0.3)	0.11	0.037	0.215	− 0.105	− 0.07
11	For revap to occur, threshold depth of water in the shallow aquifer V_REVAPMN.gw	(0, 500)	343.33	264.7	16.5	410.17	288.8
12	Soil surface to bottom of soil layers depth, R__SOL_Z.sol	(− 0.3, 0.3)	0.22	0.002	− 0.0775	− 0.101	− 0.031
15	Alpha factor of baseflow, V__ALPHA_BF.gw	(0, 1)	0.085	0.088	0.267	0.00042	0.0001
14	Compensation factor of plant water uptake, V__EPCO.hru	(0, 1)	0.599	0.711	0.613	0.722	0.91
15	Compensation factor of Soil evaporation, V__ESCO.hru	(0, 1)	0.294	0.261	0.699	0.0277	0.025
16	'Revap' coefficient of groundwater, V__GW_REVAP.gw	(0.02, 0.2)	0.202	0.094	0.08426	0.031	0.06
17	Saturated hydraulic conductivity of soil, R__SOL_K.sol	(− 0.3, 0.3)	0.118	0.004	− 0.115	0.07	− 0.053

A_ means adds the giving values to existing value; R_ means the present parameter value is multiplied by (1 + a given value) and V_ means the parameter is exchanged by a given value

values were 3.64, 2.19, 2.35 and 4.45 mmH$_2$O respectively for Kumbidi, Pulamanthole, Mankara and Pudur during the multi-site approach. The fitted value of CANMX was less in singles-site than multi-site.

The CH_K2 value was calibrated from 0 to 200 mm/h and it was fitted with 132.39 mm/h during single-site under the very high loss rate of the bed material group. For multi-site, fitted calibrated value of CH_K2 was 69.18, 7.8, 71.32 and 65.24 mm/h, respectively for Kumbidi, Pulamanthole, Mankara and Pudur. The CH_K2 value of Kumbidi, Mankara and Pudur was under the High loss rate of bed material group and moderate loss rate for Pulamanthole. The fitted value of CH_K2 was less in singles-site than multi-site. The GWQMN value was calibrated from 0 to 1500 mm and it was fitted with 553.42 mm during single-site required for return flow in the shallow aquifer. For multi-site, the fitted value of 925.73 mm, 1108.5 mm, 1130.56 mm and 910.44 mm, respectively, for Kumbidi, Pulamanthole,

Mankara and Pudur. Required return flow depth was very less compared in single-site than multi-site approach. The RCHRG_DP value was calibrated from 0 to 1 and it was fitted with 0.001 during single-site that indicating higher percolation to the deep aquifer. For multi-site, fitted values of RCHRG_DP were 0.029, 0.015, 0.048 and 0.08, respectively for Kumbidi, Pulamanthole, Mankara and Pudur. The CH_N2 value was calibrated from 0 to 0.3 and it was fitted with 0.01 during single-site that indicate earth, straight and uniform channel characteristics. For multi-site, fitted values of CH_N2 were 0.086, 0.280, 0.023 and 0.032, respectively for Kumbidi, Pulamanthole, Mankara and Pudur. The GW_DELAY value was calibrated from 0 to 450 days and it was found 248.57 days during single-site that indicate delay to reach shallow aquifer range through the vadose zone. For multi-site, the fitted value of GW_DELAY were 209.23, 6.75, 250.39 and 331.23 days, respectively, for Kumbidi, Pulamanthole, Mankara and Pudur and it indicates

groundwater delay was very good for Mankara. The Curve Number (CN) was calibrated from − 20 to 20% relative value and it was fitted at − 16% relative value during single-site that indicate low flow and discharge will decrease. For multi-site, fitted values of CN were at − 11.5%, − 1.64%, − 17.7% and − 9.8% relative value, respectively for Kumbidi, Pulamanthole, Mankara and Pudur. Both single-site and multi-site showed decreasing flow. The SURLAG was calibrated from − 20 to 20% relative value and it was fitted at 4.19% relative value during single-site, indicating surface runoff lag time was more to reach the mainstream. For multi-site, fitted values of CN2 were at 1.25%, 1.55%, − 2.1% and 1.44% relative value, respectively for Kumbidi, Pulamanthole, Mankara and Pudur. These values indicate that the lag time of surface runoff at Mankara was less than other and decreased value of SURLAG more water is held in storage. The SOL_BD was calibrated from − 30 to 30% relative value and it was fitted at 11% relative value during single-site that indicate the increased value of soil moist bulk density. For multi-site, fitted values of SOL_BD were at 3.7%, 21.5%, − 10.5% and − 7%, respectively for Kumbidi, Pulamanthole, Mankara and Pudur and here negative value indicate the decreased value of soil moist bulk density. The REVAPMN was calibrated from 0 to 500 mm and it was found fitted at 343.33 mm during single-site, indicating a high threshold depth of water in the shallow aquifer to percolate to the deep aquifer. For multi-site, fitted values of REVAPMN were at 264.7 mm, 16.5 mm, 410.17 mm and 288.8 mm, respectively, for Kumbidi, Pulamanthole, Mankara and Pudur and here the lower value of indicating a high rate of percolation of water to the deep aquifer. The SOL_Z was calibrated from -30% to 30% relative value and it was found fitted at 22% relative value during a single-site approach that indicated the increased depth of soil surface to the bottom of the layer. For multi-site, fitted values of REVAPMN were at 0.2%, − 7.7%, − 10.1% and -3.1% mm, respectively, for Kumbidi, Pulamanthole, Mankara and Pudur here negative relative value indicates the decreased value of depth of soil surface. The ALPHA_BF value was calibrated from 0 to 1 day and it was found fitted at 0.085 days during a single-site approach that indicates very less baseflow alpha factor. For multi-site, fitted values of ALPHA_BF were at 0.088, 0.267, 0.0004, 0.0001 days respectively for Kumbidi, Pulamanthole, Mankara and Pudur, and these results indicate slow response to recharge. The EPCO value was calibrated from 0 to 1. It was found to be fitted at 0.59 during the single-site approach, indicating that the model allows a moderate amount of water uptake demand to be met by a lower layer in the soil. For multi-site, fitted values of EPCO were at 0.71, 0.61, 0.72 and 0.91 respectively for Kumbidi, Pulamanthole, Mankara and Pudur, and here model allows more amount of water uptake demand to be met by lower layer in the soil. The ESCO value was calibrated from 0 to 1. It

was fitted at 0.294 during the single-site approach, indicating the model can extract a moderate amount of evaporative demand from lower levels. For multi-site, the fitted value of ESCO was at 0.26, 0.69, 0.027 and 0.025, respectively for Kumbidi, Pulamanthole, Mankara and Pudur. Results indicate that the evaporative demand from lower layers is highest at Pulamanthole station, whereas it is lowest at Mankara and Pudur stations. The GW_REVAP value was varied from 0.02 to 0.2 mm. It was calibrated at 0.20 during single-site, indicating a moderate restriction of water movement from the shallow aquifer to the root zone. For multi-site, fitted values of GW_REVAP were at 0.094, 0.084, 0.03 and 0.06 respectively for Kumbidi, Pulamanthole, Mankara and Pudur. These results indicate a very high restriction of water movement from the shallow aquifer to the root zone. The SOL_K value was calibrated from − 30 to 30% relative value and it was fitted at 11.8% during single-site approach that indicates the increased value of saturated hydraulic conductivity of soil (ease movement of water through soil). For multi-site, fitted values of SOL_K were at 4%, − 11.5%, 7% and − 5.3%, respectively for Kumbidi, Pulamanthole, Mankara and Pudur and here negative results indicate decreased saturated hydraulic conductivity. These values were evaluated separately for both approaches, essential for watershed management.

Table 3 provides the performance statistics for this model during the calibration and validation period for monthly streamflow. NSE values were expanded from 0.53 to 0.78 and 0.54–0.81 from the catchment outlet and downstream flow stations, well beyond the adequate requirement during both periods of simulation, respectively (Moriasi et al. 2007).

The performance of the validation period and simulated graph are shown in Fig. 4a–d. The performance statistics of calibration are shown in Table 3.

Multi-site performance

Calibrated parameters of each station have been displayed in Table 2, which shows each parameter's ranges and fitted values. For MSC, all interior and outlet were taken into account and its efficiency statistics are shown in Table 3. The streamflow effects were slightly reduced throughout the simulation phase, with R^2 and NSE values increasing from 0.52 to 0.76 and 0.53–0.83, respectively. Except for Mankara, streamflow modelling proved adequate for both approaches. However, the model showed overestimation and underestimating for most of the sub-catchments over the flow time series (Fig. 4e–h). R^2, PBIAS and KGE were also well above the value of 0.50 for good performance. The comparison of NSE in Fig. 4 and Table 3 shows that the validation phase was performed better in both approaches. Pudur station suggests that the same amount of rainfall did

Table 3 Summary of both SSC and MSC

Gauge station	Area(sqkm)	Performance criteria	Calibration approach		Validation approach	
			Single-site	Multi-site	Single-site	Multi-site
Kumbidi	2138.36	R^2	0.75	0.68	0.72	0.65
		NSE	0.54	0.53	0.60	0.62
		PBAIS	− 28.4	− 21.2	− 21.6	17.4
		KGE	0.60	0.64	0.58	0.61
Pulamanthole	913.15	R^2	0.78	0.76	0.81	0.83
		NSE	0.77	0.65	0.81	0.68
		PBAIS	17.9	24.4	17.9	− 22.3
		KGE	0.70	0.72	0.72	0.73
Mankara	1502.22	R^2	0.53	0.52	0.58	0.56
		NSE	0.54	0.53	0.58	0.54
		PBAIS	5.5	− 22.6	5.5	− 21.6
		KGE	0.65	0.68	0.67	0.70
Pudur	1235.74	R^2	0.53	0.52	0.54	0.57
		NSE	0.53	0.52	0.55	0.56
		PBAIS	− 19.9	− 13.96	9.9	− 18.9
		KGE	0.58	0.62	0.60	0.64

not result in the same level of streamflow as in 2007 and it was a La Niña year (Fig. 5a and b). Overall, multi-site calibrated parameters for each station will help the proper understanding of catchment spatial behaviour. Out of seventeen parameters, SOL_AWC, CANMAX, GW_DELAY, CN2, SURLAG, SOL_BD, ALPHA_BF, SOL_Z, SOL_K and EPCO were the dominant parameters due to significant differences of fitted parameters ranges in SSC and MSC. The fundamental explanation for the difference was the sensitivity of the catchment's characteristics.

Model uncertainty analysis

Total uncertainty was measured using the SUFI-2 algorithm by calculating p-factor and r-factor statistics. For each station, these values were calculated using the final measured set of calibrated parameters for the SSC and MSC approaches during the validation period, as shown in Table 4. A p-factor should be near to one and r-factor < 1.5 (Abbaspour et al. 2015). A p-factor should be close to 1, which indicates all observations are incorporated in prediction uncertainty. An r-factor should be less than 1.5 for desirable performance (Abbaspour et al. 2007).

The p-factor values during the single-site (for validation period) approach were 0.62, 0.68, 0.72 and 0.90, and r-factor was 1.40, 0.57, 1.2 and 1.32 for Kumbidi, Pulamanthole, Mankara and Pudur station, respectively. The Pudur station performed better than other stations during the single-site approach with able to account for 90% of the observed streamflow narrow uncertainty band and The Kumbidi station had higher uncertainty with a larger r-factor (1.40).

The p-factor values during multi-site approach were 0.48, 0.61, 0.34 and 0.45 and r-factor were 0.65, 0.87, 0.76 and 0.72 for Kumbidi, Pulamanthole, Mankara and Pudur station, respectively. The Mankara had broader coverage, accounting for 34% of observed streamflow in a larger uncertainty band. The large r-factor (0.87) indicates the higher uncertainty for the station of Pulamanthole. Overall, the p-factors were higher as per the satisfying criteria in the single-site approach than the multi-site approach as per the guideline (Abbaspour et al. 2007). The p-factor was greater than 0.70 in Mankara and Pudur, indicating the acceptable range for better simulation during validation phases. The lower uncertainty was able to observe during MSC.

Performance criteria for all parameters are shown in Table 5. The p-factor values during single-site (for calibration) approach were 0.68, 0.72, 0.67 and 0.56 and r-factor were 0.77, 1.14, 0.72 and 0.68 for Kumbidi, Pulamanthole, Mankara and Pudur station, respectively. The p-factor values during multi-site (calibration) approach were 0.55, 0.64, 0.54 and 0.49 and r-factor were 0.67, 1.07, 0.65 and 0.64 for Kumbidi, Pulamanthole, Mankara and Pudur station, respectively. The r-factor of SSC and MSC varied 0.68–1.14 and 0.64–1.07, respectively. Higher uncertainty was also observed during the validation phase of SSC. The r-factor was also represented as a box plot in Fig. 6. The larger r-factors were observed during SSC than MSC.

Except for Pulamanthole, all stations in the SSC had minimal uncertainty in the validation period compared to calibration. It indicates no depreciation from the calibration to the validation period. Except for Pulamanthole, all stations were under considerable r-factor uncertainty
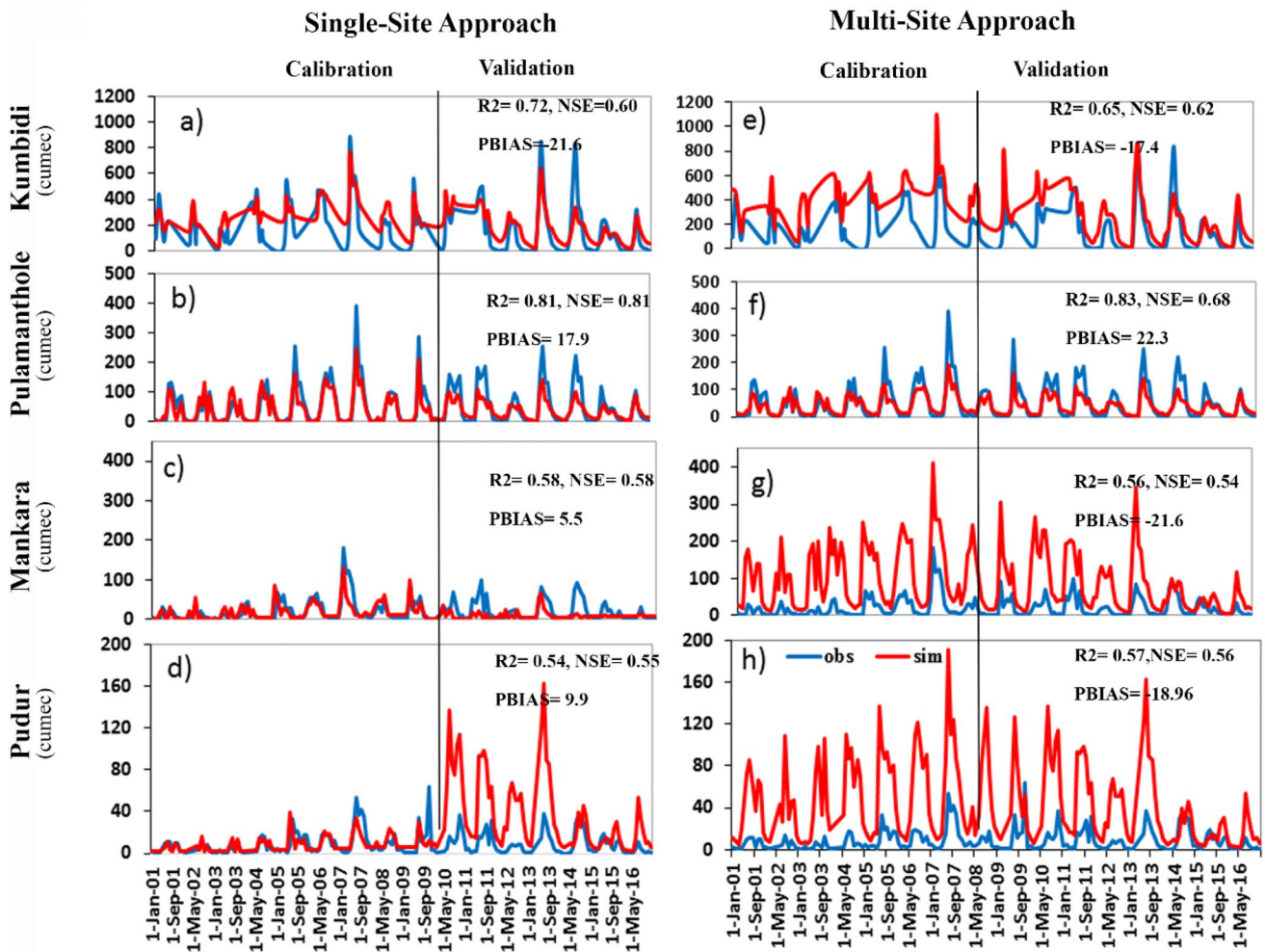
Fig. 4 Assessment of monthly streamflow simulation of calibration period (2001–2009) and validation period (2010–2016) for both single-site (**a**–**d**) and multi-site approach (**e**–**h**)
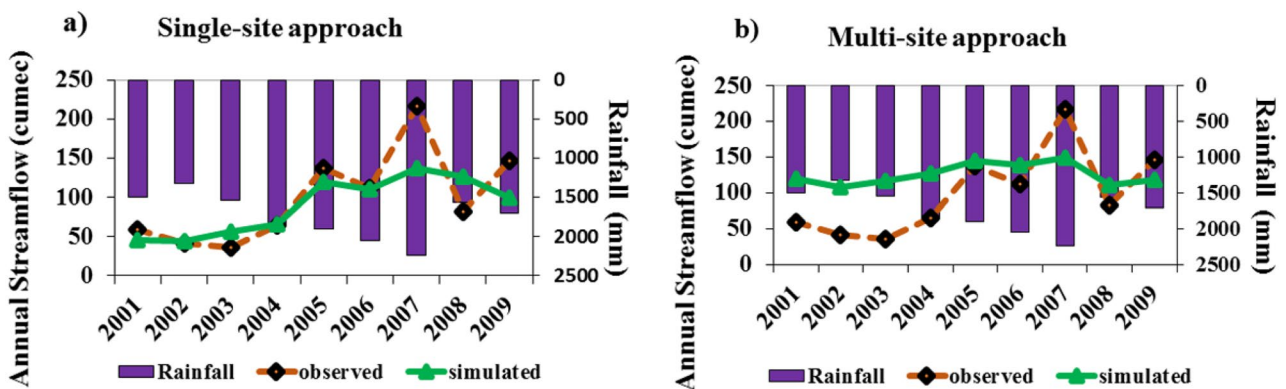

Fig. 5 Rainfall and streamflow for Pudur. **a** SSC approach. **b** MSC approach

Table 4 Uncertainty analysis for both approaches for validation period

Gauge Station	Approach	Performance criteria	
		p-factor	r-factor
Kumbidi	Single-site	0.62	1.4
	Multi-site	0.48	0.65
Pulamanthole	Single-site	0.68	0.57
	Multi-site	0.61	0.87
Mankara	Single-site	0.72	1.2
	Multi-site	0.34	0.76
Pudur	Single-site	0.9	1.32
	Multi-site	0.45	0.72

during the MSC (Abbaspour et al. 2007). In modeling, the r-factor results were significant to satisfactory. With a decreased PBIAS value and an excellent r-factor range, the uncertainty of the Pudur station was reduced in MSC (Fig. 7).

Discussions

The developed model simulated monthly streamflow data at each streamflow gauge station with SSC and MSC. R^2, PBIAS and KGE were also well above the 0.50 for good performance during simulation, but it had uncertainty (Moriasi et al. 2007). Although the criteria for adequate model results were satisfied, most peak flows were underestimated, whereas the low flow was marginally overestimated for all stations except the outlet. The statistical values of the SSC approach showed better results than the MSC approach. The variations in parameters between SSC and MSC suggest that SSC belongs to a single outlet calibrated parameter set, whereas MSC belongs to spatially varying station calibrated parameters. Calibrated parameters of MSC were more essential due to spatial variability.

The peak flow and low flow were discussed based on the fitting curve of the hydrograph. The peak flow was performed better in both SSC and MSC approaches except for low flow in Kumbidi. Both peak and low flow were performed better in both SSC and MSC in Pulamanthole. In

Table 5 Performance criteria for all parameter

Gauge Station	Performance criteria							
	Calibration				Validation			
	Single-site		Multi-site		Single-site		Multi-site	
	p-factor	r-factor	p-factor	r-factor	p-factor	r-factor	p-factor	r-factor
Kumbidi	0.68	0.77	0.55	0.67	0.62	1.4	0.48	0.65
Pulamanthole	0.72	1.14	0.64	1.07	0.68	0.57	0.61	0.87
Mankara	0.67	0.72	0.54	0.65	0.72	1.2	0.34	0.76
Pudur	0.56	0.68	0.49	0.64	0.90	1.32	0.45	0.72

Fig. 6 Box plot of r-factor of SSC and MSC (calibration and validation combined) for all stations
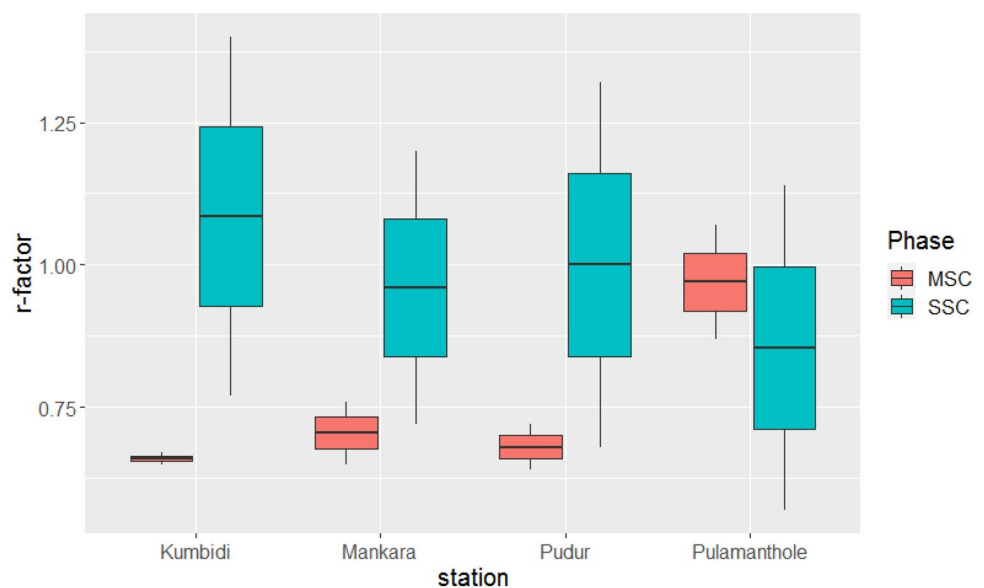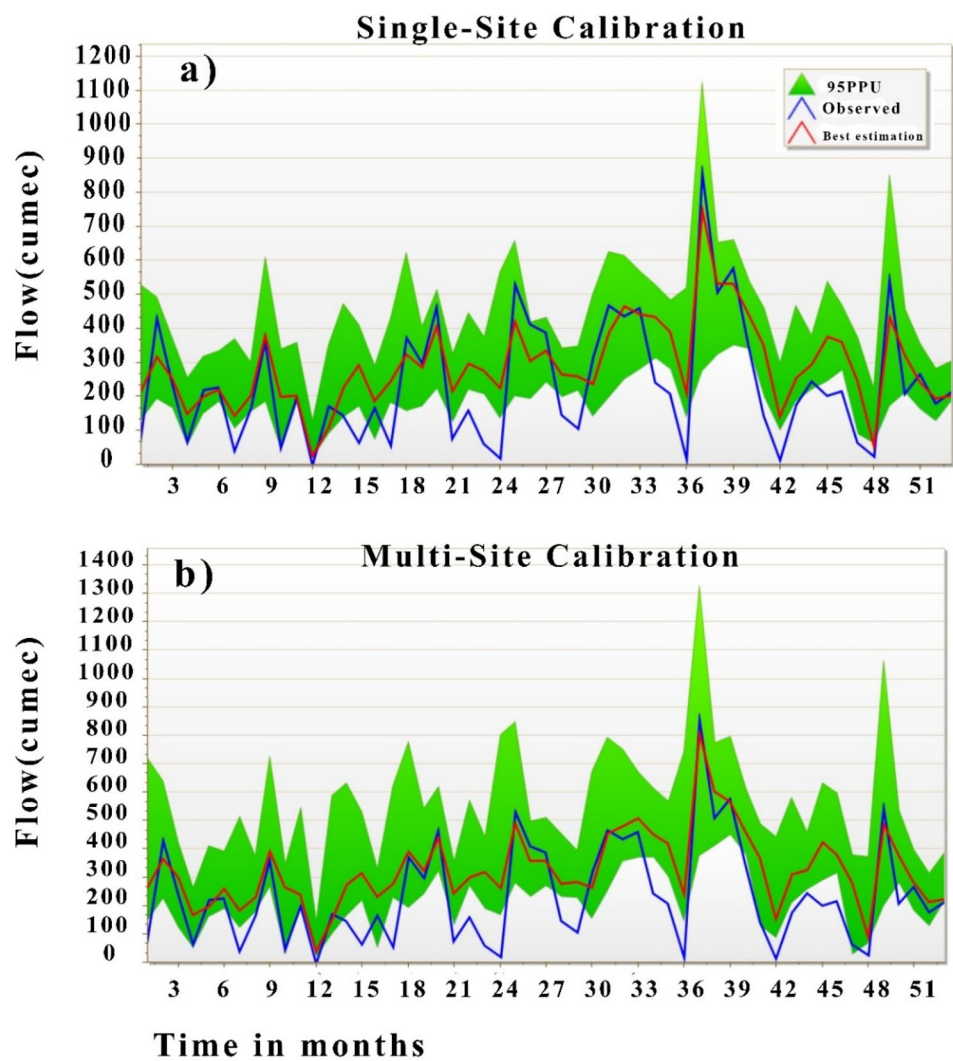
Fig. 7 Observed, Simulated and 95 PPU for validation period at Kumbidi

Mankara, peak flow was performed better in calibration except for validation in SSC and both the peak flow and low flow were not performing better in both SSC and MSC. Pudur was also following the same model performance behaviour as Mankara. According to Abbaspour et al. (2007), peak flow match is a good indicator of the better simulation of the model.

Sahu et al. (2016) used the SUFI-2 algorithm with NSE as the objective function to simulate the streamflow using the multi-site data in the Mahi river basin of India. They reported the p-factor and r-factor ranging from 0.13 to 0.42 and 0.17–0.44, respectively. The author suggested that the small value of p-factor and r-factor despite R^2 and NSE were due to situated dams on the upstream side.

In our study, single-site and multi-site accounted for 62–90% in narrow uncertainty band and 34–61% in larger uncertainty band observed streamflow, respectively. Except for Pulamanthole, all stations indicated larger uncertainty with r-factor > 1.0 during the validation phase of SSC than MSC. Pulamanthole station showed larger uncertainty with higher r-factor during calibration of both SSC and MSC. However, the largest uncertainty with SSC. Lower uncertainty stations cover larger drainage areas. As per Sahu et al. (2016), larger coverage drainage has higher uncertainty during simulation. In addition, such variation could be due to temporal and spatial variability of rainfall (Islam et al. 2012).

Overall, the catchment showed that the streamflow simulation of SSC performance was similar to MSC. According to Shrestha et al. (2016), MSC provides a better catchment management response. However, the predicting uncertainty of MSC was lower (lower r-factor). When a model is calibrated simply at the basin outflow, it overestimates its performance compared to calibrated at the sub-basin scale and reduces heterogeneity (Daggupati et al. 2015). According to statistical performance results, SSC was performed better than MSC. Franco et al. (2020) also observed that single-site calibration is executed better than multi-site, but multi-site

had lower uncertainty in the Iguazu River catchment. However, its statistical results of SSC were slightly lower performance than MSC and with the lower performance of MSC; it could be the better response for the catchment. The uncertainty for all sub-basins was more reliable by multi-site calibration than with single-site calibration and MSC reduced the uncertainty of the developed model. This reduction in performance is thought to be caused by a disruption in the rainfall-runoff interaction.

The MSC was particularly beneficial for parameter transferability over time (i.e. regular time stage simulation with monthly-calibrated parameters). The MSC assuredly affects the upstream sub-basins performance, revealing poor performance and higher uncertainty. Comparatively, the MSC approach has narrow uncertainty for flow simulation as indicated by lower r-factor and higher p-factor. MSC model parameters could be a better option for spatial hydrological study application with less uncertainty and implemented the approach in the catchment should be considered for integrated watershed management. These findings significantly influence the calibration and validation of large-area watershed models.

Conclusion

Because of the increased availability of geographical data and the complexity of hydrological models, spatial data to calibrate and validate hydrological models is becoming increasingly important. For the Bharathpuzha watershed, this study was evaluated using single-site and multi-site calibration approaches, and it was built up for the four gauging stations using monthly streamflow data. Model results showed that both single-site and multi-site performed well. However, the uncertainty of the model is lower on multi-site with less PBIAS than single-site. Kumbidi and Pudur show overestimation during calibration and validation and Pulamanthole show underestimation. However, Mankara shifts overestimation. Parameter estimated by optimizing the model parameters at four different stations produces a better result in SSC than MSC (i.e. R^2, NSE and KGE are well above).

However, the calibration phase was performed better. Similar study results were reflected on Iguaçu River Basin (Franco et al. 2020). Therefore, these calibrated parameters, calibration and validation approaches can play a better role in watershed management. The SWAT model proved suitable for simulating streamflow using both SSC and MSC. However, the multi-site performance does not reflect the performance statistics and lower uncertainty could be a better sign for spatial application of calibrated parameters for future study. MSC approach had narrow uncertainty for flow simulation and MSC simulated parameter can be used to

minimize the spatial variability in the future. Model performance could be considered in future using landuse change scenarios for spatial application. Other streamflow driving characteristics and the high precision of the soil and meteorological databases might help overcome the study's limitations. This study demonstrates the significance of spatially dispersed hydrological measurements. It is the essence of any progress in interpreting, modeling and planning hydrological procedures.

Author contributions LS: conceptualization, methodology, model development, writing—original draft preparation. SS: resources, supervision, writing—reviewing and editing.

Declarations

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