Environmental Earth Sciences (2019) 78:282
https://doi.org/10.1007/s12665-019-8281-5

ORIGINAL ARTICLE

Towards the use of conceptual models for water resource assessment in Indian tropical watersheds under monsoon-driven climatic conditions

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Received: 22 July 2018 / Accepted: 20 April 2019 / Published online: 30 April 2019

Abstract
Water resource assessment is important for integrated water resources management of a basin to which rainfall is a vital component. Generally, semi-distributed to distributed models are used for water resource management studies. Higher data requirement and simulation time restrict the use of these models. Lumped conceptual models are drawing attention these days owing to their simplicity and minimum data requirement. In the present study, the performance of conceptual models Génie Rural à 4 paramètres Journalie (GR4J) and Australian Water Balance Model (AWBM) was evaluated in comparison with semi-distributed Soil and Water Analysis Tool (SWAT) model. The selected study area, Upper Godavari River Basin, is in the windward side of Western Ghats in India, which receives heavy rainfall during south-west monsoon season. However, this region faces water scarcity issues in non-monsoon period due to lack of proper water management scenarios. Five catchments in upper Godavari basin are used for the analysis. Spatiotemporal analysis of rainfall is done to understand its effect on streamflow at the catchment outlet. The efficacy of model predictions has been analysed statistically in terms of Nash–Sutcliffe Efficiency, coefficient of determination (R^2) and percentage bias. Flow duration curves and time series diagram of streamflow predictions are also compared to better understand the results. All three models predicted streamflow with reasonable accuracy. Considering structural simplicity, less data requirement and simplicity in calibration process, this study proposes conceptual models over SWAT in the regions facing data scarcity.

Keywords Hydrological modelling · Conceptual models · GR4J · AWBM · SWAT · Spatiotemporal analysis of rainfall

Introduction

Most of the Indian subcontinent experiences tropical and sub-tropical climate, which is driven by the monsoon winds. Indian summer monsoon extending from June–September is of great significance as the annual agricultural, urban and industrial water requirement mainly relies on it (Ladejinsky 1973). However, the volume of monsoon-driven rainfall varies vastly across the country (Parthasarathy et al. 1993). Due to orographic nature of this monsoon rainfall, abundant rainfall receives in the windward side of Western Ghats and North-East India (Subramanya 2013). The catchments present in the leeward side to the monsoon winds get comparatively lesser rainfall and proper water resource management is important for these regions to meet increase in agriculture, urban and vegetation water demand. Bisht et al. (2018) analysed the spatiotemporal trends of rainfall for all major river basins in India using 100 years of (1901–2015) Indian Meteorological Department (IMD) gridded data. From their study, it was concluded that the monsoonal rainfall has decreased during 1951–2015 as compared to that of 1901–1950. As per another study in Kerala, which is located along western coast of India by Nair et al. (2014) using 100 years (1901–2000) of IMD data observed that the rainfall during monsoon season has a decreasing trend. These decreasing trends in rainfall pattern and increasing water demands in every sector call for better water management practices.

Hydrological models have been used for water resource management studies across the world (Sorooshian et al. 1993; Jayakrishnan et al. 2005; Pechlivanidis et al. 2011).

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Hydrologic models can be distributed or lumped (Beven 2001). Distributed models predict the spatially varying hydrologic components of the watershed based on the distributed catchment characteristics, inputs and parameters to some extent. Lumped models consider catchments as a single unit and predicts the hydrologic variables at the outlet of the catchments. In India, heterogeneous condition exists with spatially varying climatic and topographic conditions. Distributed to semi-distributed models such as Variable Infiltration Capacity (VIC) (Liang et al. 1994) and Soil Water Assessment Tool (SWAT) models are commonly used in Indian River basins for streamflow assessment and sediment studies, and for understanding the impacts of changes in climate and land use/land cover (Mishra et al. 2007; Wagner et al. 2011, 2013; Narsimlu et al. 2013; Hasan and Pradhanang 2017; Himanshu et al. 2017; Hengade et al. 2017; Madhusoodhanan et al. 2017; Garg et al. 2017; Sinha and Eldho 2018). However, distributed models require many meteorological and non-meteorological data to simulate results and that limits its application in data-scarce regions. Complexity of these models increases its modelling time. Instead of depending on these distributed models, many countries are using lumped conceptual models for their water resource management studies (Boughton and Chiew 2007; Vaze et al. 2011; Yu and Zhu 2015). Lumped models simulate hydrologic components with minimum input data and with less time. However, application of these models may not be a good choice when spatial variation of hydrologic data is a concern.

Numerous conceptual hydrologic models were developed in the past for runoff generation across the globe including Génie Rural à 4 paramètres Journalie (GR4J) (Perrin et al. 2003), Australian Water Balance Model (AWBM) (Boughton 2004), IHACRES (Croke et al. 2006), Sacramento (Burnash et al. 1973), etc. GR4J and AWBM are two simple models among them with only 4 and 8 free parameters, respectively. Further, GR4J was successfully applied in many water resource assessment (WRA) studies worldwide (Tian et al. 2013; Traore et al. 2014; Hublart et al. 2015; Nepal et al. 2015). Similarly, AWBM was broadly applied for runoff generation at ungauged catchments in Australia (Boughton and Chiew 2007; Kumar et al. 2015). However, there are not many studies reported by intercomparing these conceptual models for streamflow assessment. Therefore, the current study will evaluate the performance of these selected conceptual models, against that of the semi-distributed model SWAT, which is commonly used for streamflow estimation in of river basins. Advantages and disadvantages of each model are discussed in detail. The study is conducted in five catchments in Upper Godavari River Basin (UGRB). To support the predictions of different models, the spatiotemporal analysis of rainfall for entire UGRB is also carried out in his study.

Study area and data

Study area

Godavari is the second largest river basin in India after Ganges. It flows through seven states in India towards Bay of Bengal meeting various agricultural, domestic and industrial water demands. Catchments in upstream of Godavari region draining to Jayakwadi reservoir were selected for the present study. The selected sub-basins are located entirely in Maharashtra state. The geographical extent of UGRB is approximately 21,000 km^2 located between 73°29′30″E to 75°29′6″E and 19°2′25″N to 20°24′58″N. The elevation of the study area varies from 460 m to 1486 m sloping from west to east (Fig. 1). Five catchments, namely Adhala, Alandi, Bhandardhara, Kadwa and Mula in UGRB are selected based on data availability. Some general information about the catchments is presented in Table 1.

There are 32 dams, 102 rain gauging stations (Fig. 2) and 13 PET stations (see Fig. 1) in UGRB. The catchments selected in this study were delineated by taking corresponding dams as outlet points. The discharge at these outlet points was calculated using storage level-volume-area curve of the reservoirs and outflow from the dam (Redpath and Daamen 2018).

Data

The selected conceptual models mainly require rainfall and potential evapotranspiration (PET) for streamflow simulation. The rain gauges in UGRB basin are non-uniformly distributed (Fig. 2). The missing data estimation and calculation of rainfall at all catchments were done by eWater, Australia (Redpath and Daamen 2018). The rain gauge density is high near Western Ghats and lower in the plane areas. The missing data of the rain gauges were filled using data of linearly correlated rain gauges within a certain radius. Missing data in dry periods were taken as zero, assuming zero rainfall in summer. After estimation of missing data, Theissen polygon method is used to determine the rainfall for each catchment. PET data for each catchment were obtained from PET stations in Fig. 1.

Along with rainfall, the SWAT model needs land use, soil, elevation, temperature and wind speed records (Table 2). In SWAT, PET for the catchments is generated using Penman-Monteith method. Dominant land use type for Adhala, Alandi, Bhandardhara and Kadwa watersheds is agricultural land with 48.13%, 38.39%, 34.01% and 53.21% coverage, respectively, as per LULC data of year 2004. In Mula catchment, barren land acquires majority of

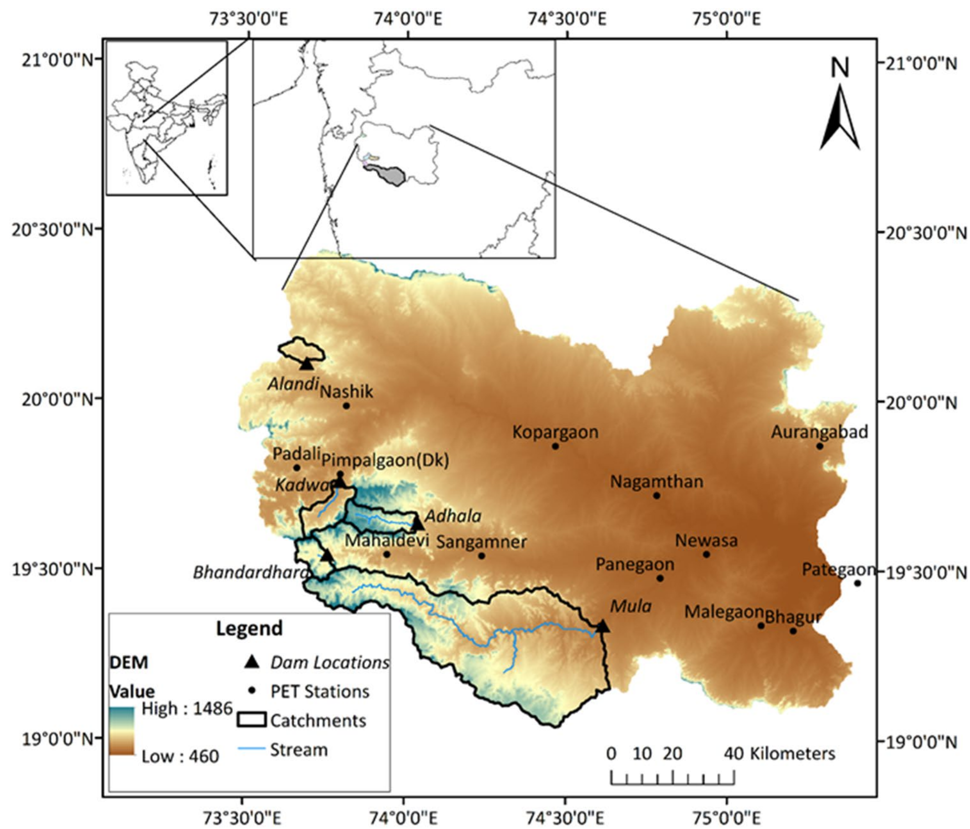

Fig. 1 Study area with catchments selected for hydrological modelling

Table 1 Details of the catchments selected for the study

Catchment name	Area (km^2)	Annual average rainfall (mm)	Elevation min/max	Major land use
Adhala	134	778	660/1358	Agriculture
Alandi	69	1298	630/1026	Agriculture
Bhandardhara	98	2619	747/1486	Agriculture
Kadwa	162	1263	578/1486	Agriculture
Mula	2292	607.73	515/1460	Barren

the area (42.93%). In the selected catchments, major soil class is loamy soil. The digital elevation model (DEM) from USGS's SRTM was filled and used for stream generation in the models.

Spatiotemporal analysis of rainfall

Rainfall intensity varies significantly across UGRB basin. Upstream catchments, which fall in Western Ghats region, receive very heavy rainfall during monsoon season and the intensity of rainfall varies significantly in east ward direction. The drastic changes in rainfall intensity across the basin and improper water resource management led to drought in the sub-basin during past few years (Oughton 1982; Udmale et al. 2014a, b). Understanding the rainfall pattern of study area is an important prerequisite for planning water management scenarios. Owing to its importance in UGRB, we performed a spatiotemporal analysis of rainfall using the available rain gauge station data.

In this study, the non-parametric Mann–Kendall test (Nair et al. 2014; Bisht et al. 2018; Zamani et al. 2018) was used to understand annual and seasonal trends in rainfall at UGRB. The slope of the trend is measured using Sen slope technique. The rainfall data for the period 1984–2015 from 102 rain gauge stations (Fig. 2) in UGRB basin have been used for this study.

Mean annual, monsoon and non-monsoon distribution of rainfall over UGRB basin are presented in Fig. 3. From the figure, it is evident that catchments in UGRB basin receive most of its rainfall during monsoon season. The western part of UGRB obtains high rainfall being windward side to the south-west monsoon. The catchments Adhala, Alandi,

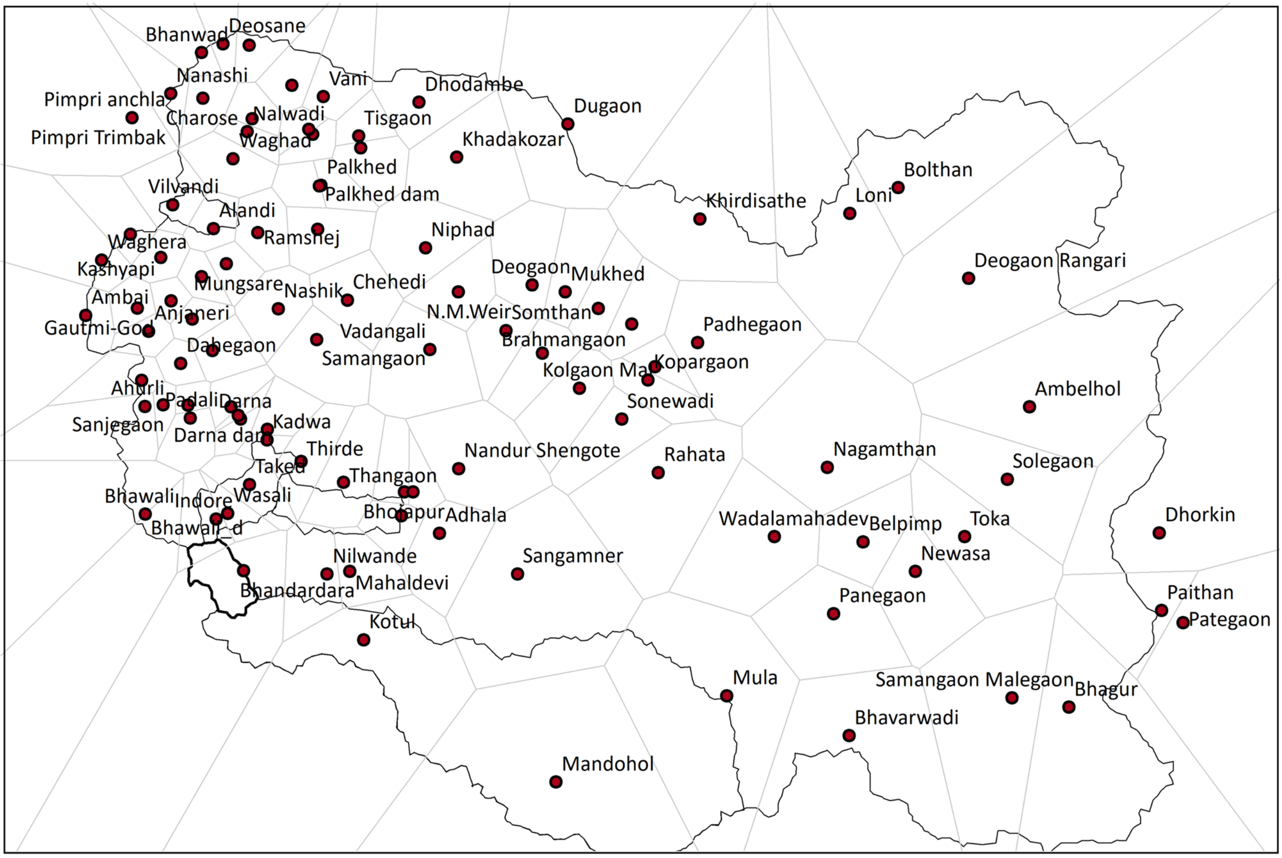

Fig. 2 Rain gauge stations in UGRB and the Theissen polygons

Table 2 Details of data used

Sl. no.	Data type	Scale/time period	Source
1	DEM	30 m	SRTM digital elevation data produced by NASA (https://earthexplorer.usgs.gov/)
2	Land use/land cover (LULC)	30 m	NRSC, ISRO Hyderabad
3	Soil type	1:5,000,000	Food and Agricultural Organization (FAO)
4	Rainfall	1984–2011	WALMI (Water and Land Management Institute), Aurangabad
5	PET	2000–2011	WALMI (Water and Land Management Institute), Aurangabad
6	Temperature	2000–2011	IMD (Indian Meteorological Department)
7	Wind speed	2000–2011	IMD (Indian Meteorological Department)
8	Streamflow	2000–2011	WALMI(Water and Land Management Institute), Aurangabad

Bhandardhara, Kadwa and Mula received 89.8%, 93.2%, 97.1%, 93.5% and 88.15% of annual rainfall in the monsoon season. The central region of UGRB received least amount of rainfall during monsoon when compared to western and eastern regions. It was also observed that the central and eastern regions received more rainfall than western region from retreating monsoon during October–November, which comes in the north-east direction. Among the different catchments selected in this study, Bhandardara is the most and Mula is the least rain fed catchment.

The Sen slope was used to measure the rate increase or, decrease of the trend of a time series (Bisht et al. 2018; Zamani et al. 2018). From the trend analysis of annual mean rainfall, it was observed that rainfall at all stations have statistically significant trend. Out of 102 rain gauge stations, 94 stations showed increasing and 8 stations showed decreasing trends (see Fig. 4). The Sen Slope estimates show that

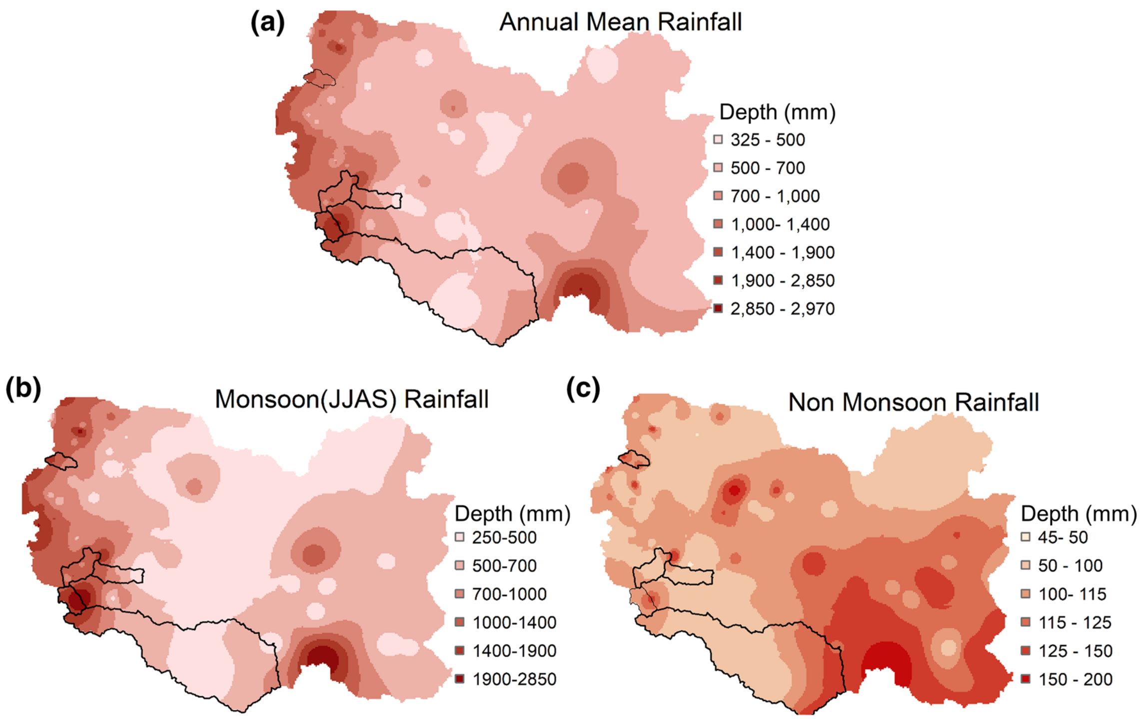

Fig. 3 Spatial distribution of **a** mean annual rainfall, **b** monsoonal rainfall and **c** non-monsoonal rainfall

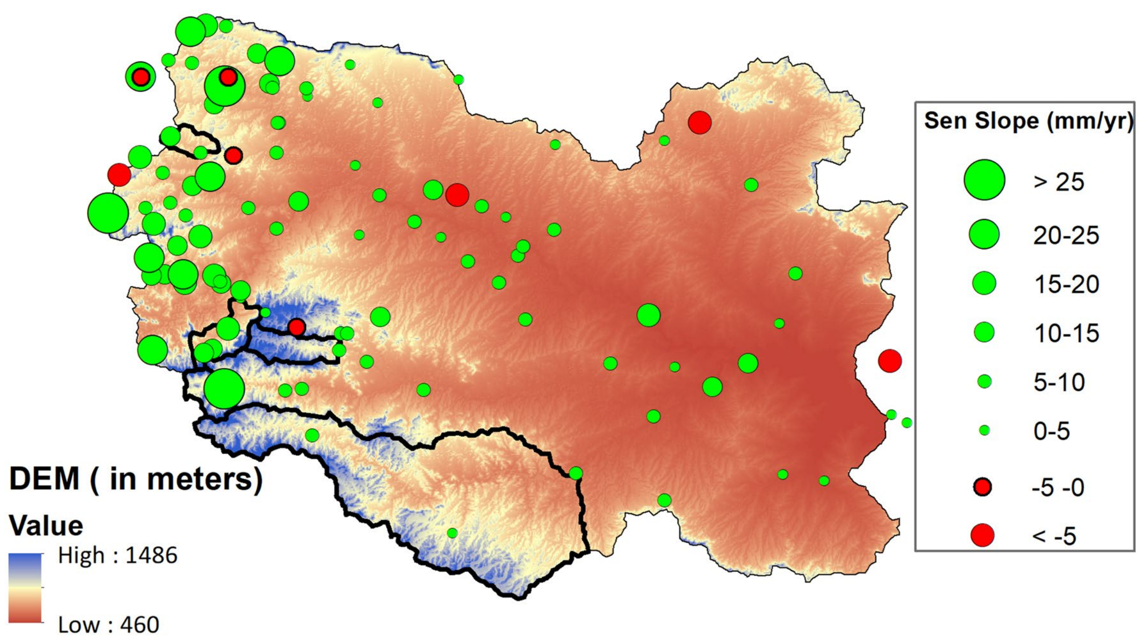

Fig. 4 Rain gauges with trend analysis results

the increase in depth of rainfall per year is most in the stations nearer to the Western Ghats. The maximum values of increments were observed at Bhandardhara and Ambai which were 57.6 mm/year and 33.27 mm/year, respectively. The stations in central region had increments lesser than 10 mm/year with most of the stations being in the 0–5 mm/year range.

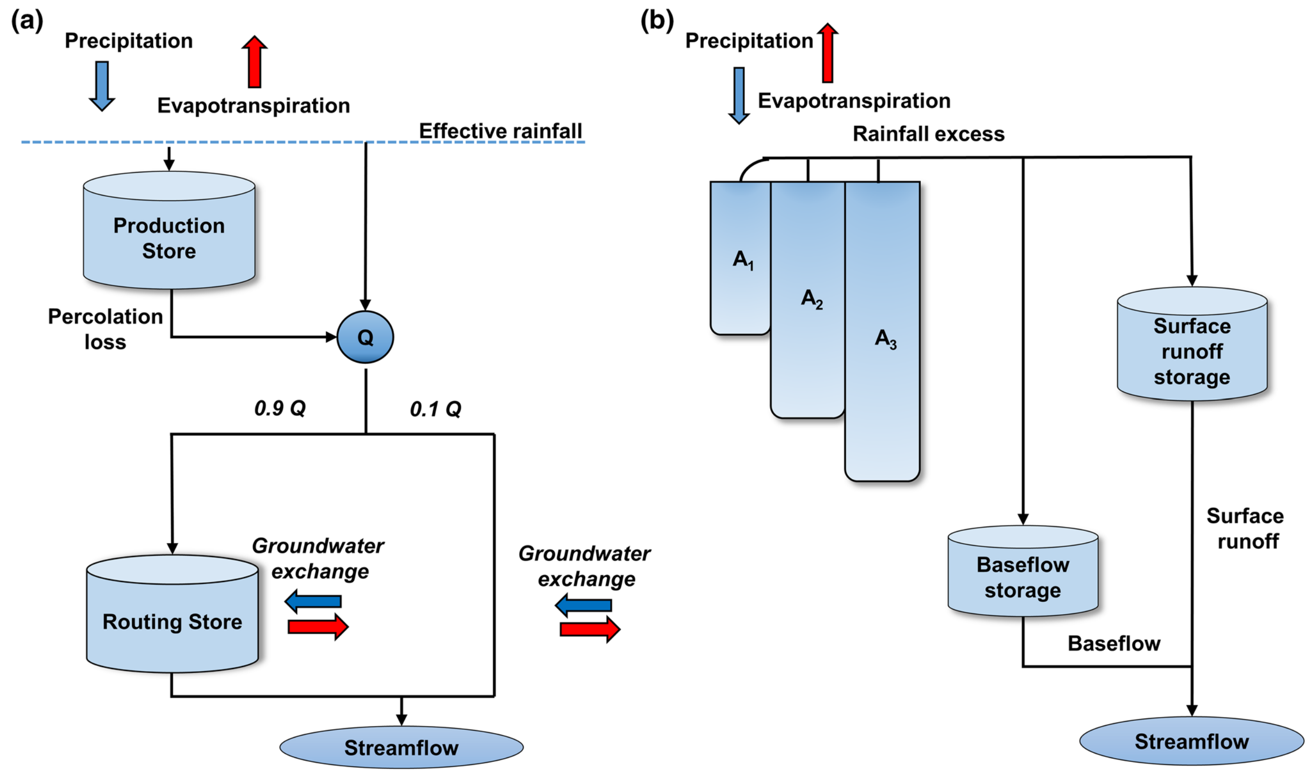

Fig. 5 Schematic diagram of **a** GR4J and **b** AWBM

Methodology

Rainfall runoff models

Three hydrologic models compared in this study include (1) SWAT, (2) GR4J and (3) AWBM. The conceptual models are set up in SOURCE modelling platform developed by Co-operative Research Centre, eWater Australia (Carr and Podger 2012) (https://wiki.ewater.org.au/). The structural details of each model used in this study are briefly described in the following sections.

SWAT model

SWAT (Arnold et al. 1998) is a semi-distributed hydrological model including many physical parameters to approximate most hydrological processes in a catchment. ArcSWAT platform is used for model setup and simulation in this study. Rainfall, temperature, relative humidity, wind speed and solar radiation are the major meteorological inputs to SWAT model. Rainfall data from the gauging stations (Fig. 2) and gridded windspeed and temperature data from IMD are used for this study. For other meteorological inputs, weather generator tool in SWAT is used for each catchment.

In SWAT, catchments are subdivided in to smaller unique hydrologic response units (HRU) using DEM, soil and landuse/landcover data. On occurrence of a rainfall event, the excess water is drained from each HRU and routed along the flow direction paths to obtain streamflow at the catchment outlet. The water content in each HRU (SW) is computed using components of hydrologic cycle such as rainfall (P), evapotranspiration (E_a), surface runoff (Q_{surf}), loses to vadose zone (W_{seep}) and groundwater (Q_{gw}) based on the mass balance equation (Arnold et al. 1998).

$$\mathrm{SW}_t = \mathrm{SW}_0 + \sum_{i=1}^{t} (P - Q_{\mathrm{surf}} - E_{\mathrm{a}} - W_{\mathrm{seep}} - Q_{\mathrm{gw}}). \tag{1}$$

For the present study, SCS-CN (USDA Soil Conservation Service 1972) is applied for the estimation of surface runoff. Penman–Monteith (Monteith 1965) method is used for calculation of evapotranspiration in SWAT.

GR4J

GR4J (see Fig. 5) belongs to the group of soil moisture accounting models. Four-parameter (Table 3) GR4J model by Perrin et al. (2003) is modified from GR3J (Edijatno et al. 1999) which had three free parameters. In the model, the soil mass is conceptualized as two stores, namely production

Table 3 Parameters of GR4J and AWBM model

Parameters	Description of parameters	Units	Range
GR4J			
x_1	Maximum capacity of the production store	mm	1 to 1500
x_2	Water exchange coefficient	mm	− 10 to 5
x_3	Maximum capacity of the routing store	mm	1 to 500
x_4	Time parameter for unit hydrographs	day	0.5 to 4
AWBM			
A_1	Partial area of store 1		0 to 1
A_2	Partial area of store 2		0 to 1
C_1	Capacity of partial area store 1	mm	0 to 50
C_2	Capacity of partial area store 2	mm	0 to 200
C_3	Capacity of partial area store 3	mm	0 to 500
BFI	Base flow index		0 to 1
Kbase	Base flow recession constant		0 to 1
Ksurf	Surface flow recession constant		0 to 1

store and routing store. A part of effective rainfall (P_n) after being subjected to initial losses enters into production store. The maximum water holding capacity of this store is denoted by the parameter x_1. Evapotranspiration and percolation losses occur from the production store. The percolation from the production store joins the surplus effective rainfall. 90% of this accumulated water is routed as *slow flow* through routing store and the rest is routed as *fast flow*. The parameter x_3 denotes the maximum capacity of the routing store. The parameter x_4 is used for denoting the time lag in hydrographs of these flows. The exchange of water between groundwater and fast and slow flows is represented by parameter x_2. A detailed explanation of parameters is presented in Perrin et al. (2003).

Australian Water Balance Model (AWBM)

AWBM is a conceptual model-based multiple capacities (Boughton 2004). It represents the soil mass into three partial areas having three different moisture holding capacities. These partial areas are named as A_1, A_2 and A_3 based on the increasing order of capacities (C_1, C_2 and C_3) (see Fig. 5). The precipitation after evapotranspiration loss enters and fills up these partial areas. On exceeding the capacity, water is first discharged from area having least capacity (C_1) and from larger capacities afterwards. A fraction of this rainfall excess is converted to baseflow recharge and stored in baseflow storage, whereas the remaining is drained as surface runoff. The parameter baseflow index governs the fraction of rainfall excess shared between baseflow and surface runoff storage. From these storages, water reaching the outlet is computed using the parameters K_{surf} and K_{base}. The model has eight free parameters which are presented in Table 3. It should be noted that only the partial areas A_1 and A_2 are calibrated. A_3 is estimated by deducting sum of A_1 and A_2 from 1. The model is presented in detail by Boughton (2004).

Calibration procedure

SWAT simulates the components of hydrologic cycle with the help of numerous physical parameters. In the present study, SWAT-Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour 2007) platform is used for the sensitivity analysis and calibration. Among the available optimization algorithms in SWAT-CUP, Sequential Uncertainty Fitting-2 (SUFI-2) is chosen for calibrating the parameters due to its superior performance (Khoi and Hang 2015). The sensitivity of each parameter is estimated after a designated number of simulations using *p* value and *t* stat. The parameters used for model calibration are presented in Table 4.

The parameters of GR4J and AWBM model are optimized using shuffled complex evolution (SCE) (Duan et al. 1993) global optimization algorithm in calibration wizard of SOURCE. The parameter sets in the model are divided into a few complexes in SCE. The calibration starts with some default values of the model parameters. Based on the fitness values of the complexes, they are shuffled and evolved after each iteration. The model runs for designated number of simulations. Monthly Nash–Sutcliffe Efficiency (NSE) is used as the objective function for the calibration process in all three models. The calibration period for the models is 2000–2007 and the validation period is 2008–2011. Detailed flowcharts representing model set up and calibration in SWAT and conceptual models are presented in Fig. 6.

Performance assessment of hydrological models

Performance of each model should be analysed statistically and visually. NSE, coefficient of determination (R^2) and percentage bias (PBIAS) are used as the efficiency criteria for understanding the capability of models statistically. NSE indicates how well the simulations match the observations. NSE varies between $-\infty$ to 1 and a value of 1 indicates perfect match between observations (Q_{o}) and simulations (Q_{m}). NSE is computed using the following Eq. (2) (Nash and Sutcliffe 1970).

$$\mathrm{NSE} = 1 - \frac{\sum_i \left(Q_{\mathrm{o}} - Q_{\mathrm{m}}\right)_i^2}{\sum_i \left(Q_{\mathrm{o},i} - \overline{Q_{\mathrm{o}}}\right)^2}, \tag{2}$$

$$R^2 = \frac{\left[\sum_i \left(Q_{\mathrm{o},i} - \overline{Q_{\mathrm{o}}}\right)\left(Q_{\mathrm{m},i} - \overline{Q_{\mathrm{m}}}\right)\right]^2}{\sum_i \left(Q_{\mathrm{o},i} - \overline{Q_{\mathrm{o}}}\right)^2 \sum_i \left(Q_{\mathrm{m},i} - \overline{Q_{\mathrm{m}}}\right)^2}, \tag{3}$$

Table 4 Parameters of SWAT used for calibration

Name of parameter	Description	Min.	Max.
CN2.mgt	Initial SCS curve number corresponding to moisture condition II	35	98
SOL_AWC.sol	Soil available water capacity (mm of water/mm of soil)	0	1
SOL_K.sol	Saturated hydraulic conductivity of soil (mm/h)	0	2000
SOL_CLAY.sol	Percentage clay content	0	100
ESCO.hru	Soil evaporation compensation factor	0	1
SLSUBBSN.hru	Average slope length (m)	10	150
HRU_SLP.hru	Average slope steepness (m/m)	0	1
GWQMN.gw	Threshold depth of water for return flow to occur (mm)	0	5000
REVAPMN.gw	Threshold depth of water in shallow aquifer in order to percolation to deep aquifer to occur (mm)	0	500
GW_REVAP.gw	Groundwater 'revap' coefficient	0.02	0.2
ALPHA_BF.gw	Base flow Alfa factor (1/day)	0	1
RCHRG_DP.gw	Deep water percolation fraction	0	1
ALPHA_BNK.rte	Base flow alpha factor for bank storage	0	1
CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/h)	−0.01	500
CH_N2.rte	Average manning's 'n' for main channel	−0.01	0.3

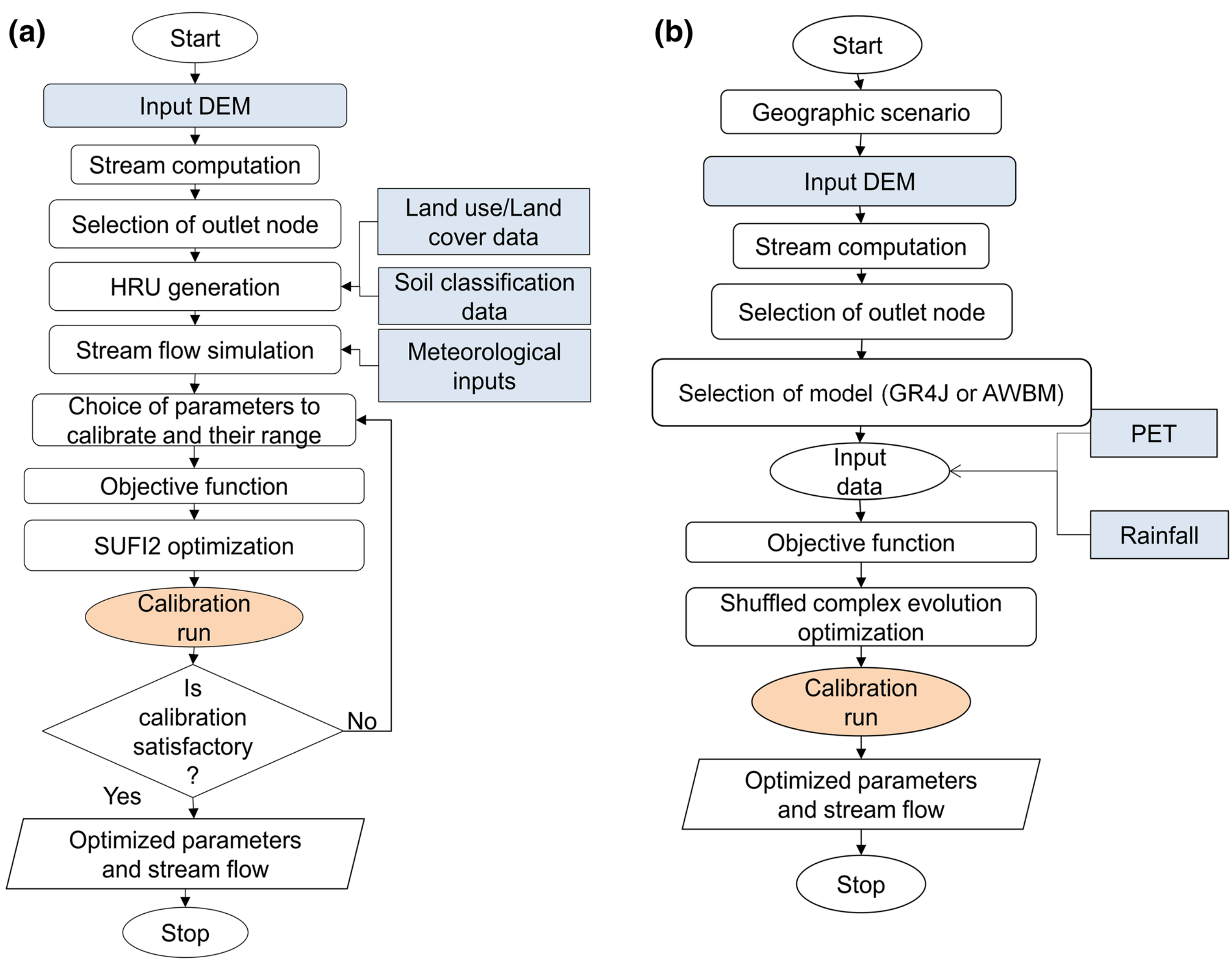

Fig. 6 Model setup and calibration procedure for **a** SWAT, **b** conceptual models (GR4J and AWBM)

Table 5 Sensitive parameters for each catchment and their respective t stat and p values

Parameters	Adhala		Alandi		Bhandardhara		Kadwa		Mula	
	t stat	p value	t stat	p value	t stat	p value	t stat	p value	t stat	p value
ALPHA_BF	–	–	2.23	0.03	0.54	0.59	−0.48	0.63	−0.25	0.81
ALPHA_BNK	5.28	0.10	−0.91	0.37	15.37	0.00	5.60	0.00	0.18	0.86
CH_K2	−1.47	0.66	0.36	0.72	−3.47	0.01	2.53	0.01	9.86	0.00
CH_N2	−1.45	0.30	1.48	0.14	−2.25	0.02	0.20	0.84	14.24	0.00
CN2	0.27	0.00	6.38	0.00	48.12	0.00	21.13	0.00	0.31	0.76
ESCO	−0.96	0.89	10.96	0.00	0.61	0.54	1.67	0.10	0.56	0.57
GW_REVAP	13.63	0.00	−15.22	0.00	−1.20	0.23	−3.92	0.00	−0.21	0.83
GWQMN	–	–	−5.65	0.00	0.77	0.44	−1.63	0.10	–	–
REVAPMN	–	–	1.56	0.12	0.29	0.77	0.28	0.78	–	–
SOL_AWC	−1.60	0.75	−48.18	0.00	−3.05	0.00	−4.00	0.00	2.37	0.02
SOL_CLAY	–	–	1.97	0.05	−1.66	0.10	1.72	0.09	–	–
SOL_K	−4.53	0.00	12.21	0.00	21.18	0.00	12.57	0.00	−1.26	0.21
RCHRG_DP	–	–	–	–	–	–	–	–	−1.57	0.12
HRU_SLP	–	–	–	–	–	–	–	–	−3.42	0.00

R^2 also determines how well the observations match with simulations based on the total variance of dataset explained by the model (Eq. 3). PBIAS computes the percentage of simulated results which lie above or below observed values. A value of zero represents perfect fit. Positive value depicts underestimation and negative value represents overestimation of simulation.

$$\mathrm{PBIAS} = 100 \times \frac{\sum_i \left(Q_\mathrm{o} - Q_\mathrm{m}\right)_i}{Q_{\mathrm{o},i}}. \quad (4)$$

Along with the statistical analysis of model performance, the model efficacy has been tested in quantile domain using flow duration curves. These curves are divided into five groups, such as high flows (0–10%), moist flows (10–40%), mid-range flows (40–60%), dry flows (60–90%) and low flows (90–100%) (Kannan and Jeong 2011; Tegegne et al. 2017). In each group, efficacy of model predictions is tested in this study.

Results

Sensitivity and uncertainty analysis in SWAT

To avoid over-parameterization in SWAT calibration, sensitivity analysis is done to obtain the sensitive parameters. The parameters present in Table 1 are used for first iteration and the parameters showing little impact on model performance are removed for subsequent iterations. The list of parameters and their sensitivities from the best calibration for each catchment are shown in Table 5. The parameters having p value less than 0.05 are referred to as sensitive and the magnitude of t stat denotes the sensitivity. Out of the 15 parameters for sensitivity test, 8 parameters in Adhala, 12 parameters in Alandi, Bhandardara and Kadwa and 11 in Mula were chosen for calibration.

Calibration with most-sensitive parameters in each catchment was performed. The ensemble of parameters obtained for each catchment was then used to generate 95 PPU bands of streamflow predictions. The fraction of observed streamflow captured within this band is denoted by p-factor, whereas the width of the band is referred to as r-factor. SWAT-CUP Manual (Abbaspour 2007) suggests that p-factor of 0.7 and r-factor of nearly 1 is ideal for streamflow simulations. A comparison of 95 PPU streamflow band with observed streamflow is shown in Fig. 7. The black dotted line in the Fig. 7 represents the simulations with best objective function values, which is largely in line with observations. It is observed that the measured streamflows were well bracketed by the 95 PPU band for Adhala, Alandi, Kadwa and Mula. It is also observed that the 95 PPU band does not capture most of the measured streamflow values for Bhandardhara catchment.

In all catchments except Bhandardhara, the p-factor values obtained for study catchments range from 0.7 to 0.81 for calibration period and 0.25 to 0.69 for validation period (Table 6). The model shows poor value of p-factor in validation period as it is unable to encapsulate the peak flows. The r-factor values for both calibration and validation for all catchments, except Adhala, are less than 1, representing narrow uncertainty range. For Adhala, it is slightly above one for calibration period. As expected, poor values of p-factor and r-factor are observed in Bhandardhara. After successful completion of sensitivity and uncertainty analysis, the simulation which gives the best value for the objective function NSE is compared with results from conceptual models.

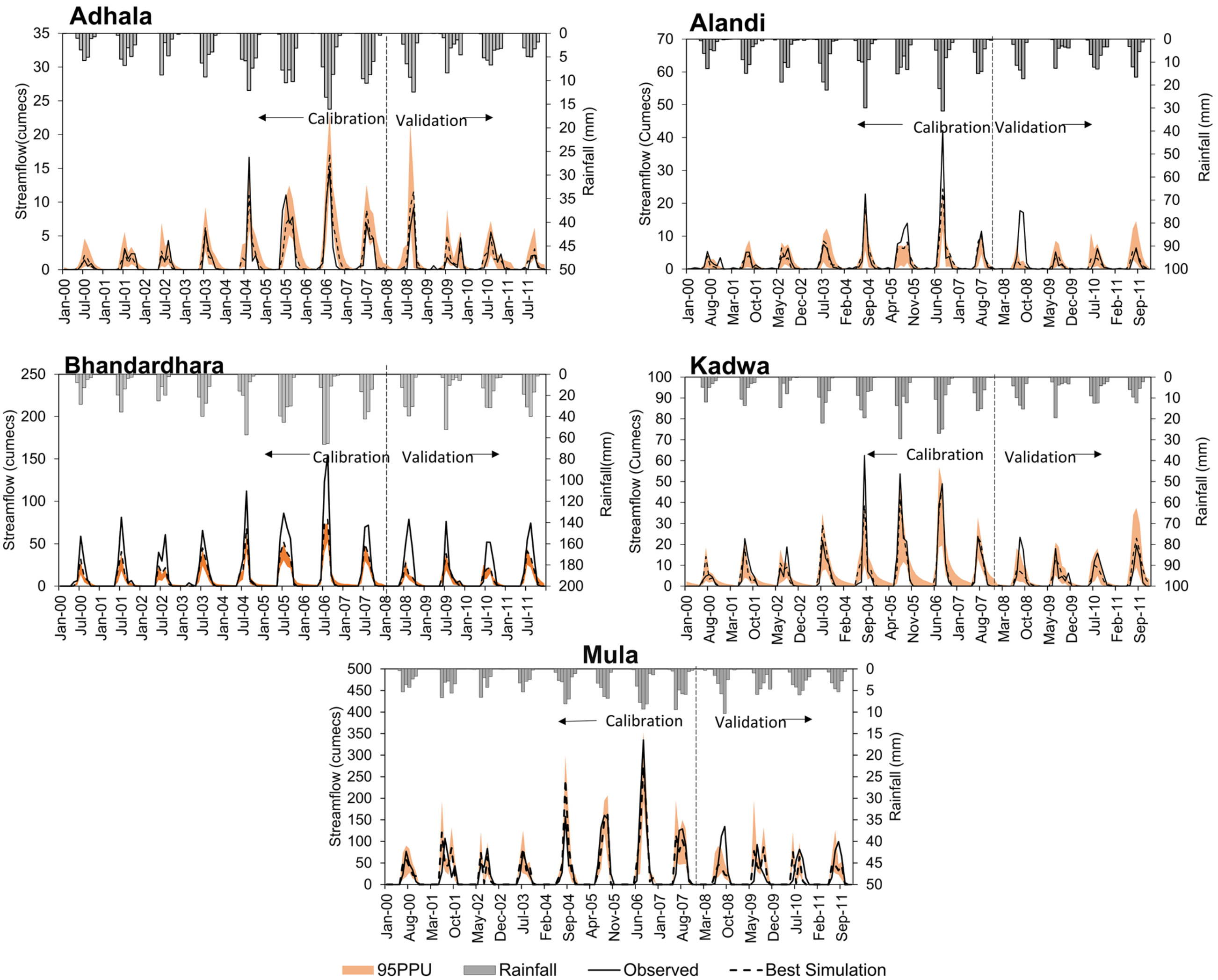

Fig. 7 Comparison of observed streamflow with 95 PPU plots of streamflow from SWAT for all catchments

Table 6 *p*-factor and *r*-factor of streamflow uncertainty range simulated by SWAT for each catchment

Name of catchment	Calibration period		Validation period	
	p-factor	*r*-factor	*p*-factor	*r*-factor
Adhala	0.81	1.09	0.69	1.00
Alandi	0.70	0.45	0.46	0.63
Bhandardhara	0.18	0.21	0.17	0.22
Kadwa	0.72	0.59	0.25	0.68
Mula	0.77	0.49	0.59	0.55

Comparison between SWAT, GR4J and AWBM

GR4J and AWBM models were calibrated for the same period as SWAT (2000–2007) and validated for 2008–2011. It is observed that all three models gave reasonable streamflow predictions, whereas in Bhandardhara, no models are able to capture the peak flows properly.

NSE for GR4J, AWBM and SWAT varies between 0.57–0.82, 0.58–0.85 and 0.42–0.88 respectively in all the catchments (see Table 7). The best performance obtained by the models for each catchment in terms of NSE, R2 and PBIAS are shown in italics. In Adhala, all three models performed well except for the peaks in the years 2002 and 2004. For the year 2002, catchment showed delayed response to rainfall while both the conceptual models gave immediate response. It may be noted that these uncertainties are captured in 95 PPU band in SWAT (see Fig. 7). In Alandi, streamflow predictions are not as good as Adhala. The conceptual models overestimated streamflow during the years 2000–2003 and it is highly underestimated for the year 2006. Nonetheless, the performance of SWAT model is better for this catchment. It may be noticed from Table 5 that the soil and groundwater-related parameters are highly sensitive for

Table 7 Summary statistics of model performance

Catchments	NSE		R^2		PBIAS (%)	
	Cal	Val	Cal	Val	Cal	Val
Adhala						
SWAT	*0.81*	0.56	*0.82*	0.63	*−5.12*	−52.9
GR4J	0.79	*0.61*	*0.82*	0.71	−13.31	−25.47
AWBM	0.78	0.58	0.80	0.69	−16.00	*−12.24*
Alandi						
SWAT	*0.82*	0.57	*0.88*	0.71	13.4	35.8
GR4J	0.72	*0.76*	0.81	*0.81*	*−1.30*	*−5.68*
AWBM	0.68	0.69	0.79	0.75	5.25	−7.49
Bhandardhara						
SWAT	*0.75*	0.52	*0.97*	0.75	*38.8*	48.6
GR4J	0.60	*0.75*	0.65	*0.81*	50.69	*28.83*
AWBM	0.56	0.73	0.62	0.75	59.13	44.64
Kadwa						
SWAT	*0.88*	0.59	*0.89*	0.60	*1.3*	*0.61*
GR4J	0.79	0.72	0.82	0.75	−2.07	−12.31
AWBM	0.84	*0.92*	0.87	*0.92*	6.52	−14.17
Mula						
SWAT	0.78	0.42	0.78	0.43	−1.7	25.6
GR4J	0.82	0.57	0.84	0.61	*−1.22*	37.85
AWBM	*0.85*	*0.73*	*0.86*	*0.74*	3.59	*2.45*

Alandi. It denotes that the surface and groundwater interactions are significant for the catchment and it is well captured by SWAT. In Kadwa, predictions by all models are satisfactory in the calibration period except for the years 2002 and 2004. It is observed that SWAT model under predicts streamflow in the validation period. Model predictions were matching well with observations for Mula catchment in calibration period. However, SWAT model yields poor results in validation period. It is observed that in some years, Mula catchment gives delayed response similar to Adhala and Kadwa which results in multiple peak flow values in that particular year. These peaks occur due to rainfall pattern of that year and high length-to-width ratio of the catchments giving an elongated shape. It can be observed that the rainfall during these years is more uniform. Further, due to elongated shape of the catchment, the time of concentration at the catchment outlet increases giving a delayed response. This phenomenon is more prominent at Mula catchment as it is larger in size compared to Adhala and Kadwa. Moreover, this catchment receives more rainfall in non-monsoon period (see "Spatiotemporal analysis of rainfall"). This delayed response is not captured satisfactorily by all models which give immediate response to the rainfall. Such delayed response is observed in notable number of years in the validation period. Hence, models give poor NSE and R^2 values in validation period for these catchments. The performance of the conceptual models is better compared to SWAT model which give closer values to observed discharge. In contrast, such delayed responses are not that significant in Alandi which has low length-to-width ratio.

SWAT, AWBM and GR4J provided monthly NSE greater than 0.7 during calibration period in all study catchments except Bhandardhara. NSE values during validation are better for conceptual models than SWAT. Similarly, best correlation between observed and simulated streamflow was observed for SWAT in calibration period and conceptual models in validation period. R^2 between monthly streamflow observations and simulations was around or greater than 0.8 for most cases. PBIAS was ranging from 1% to a maximum of 16% in calibration period except for Bhandardhara. It is observed that all three models gave reasonable streamflow predictions, whereas in Bhandardhara, no models are able to capture the peak flows properly (Fig. 8).

Flow duration curves of streamflow predictions from different models are compared with observed flow duration curve in quantile domain as in Fig. 9. The discharge is represented in *y*-axis (log scale) while the *x*-axis represents the percentage times the corresponding discharge is exceeded. This analysis is done to investigate the performance of the models in different flow ranges. It is observed that all three models simulated the high flows (0–10%) and moist flows (10–40%) with reasonable accuracy for all catchments except Bhandardhara. The performance of GR4J and SWAT is better during mid-range flows and dry flows for Adhala and Alandi. However, SWAT and AWBM were better for

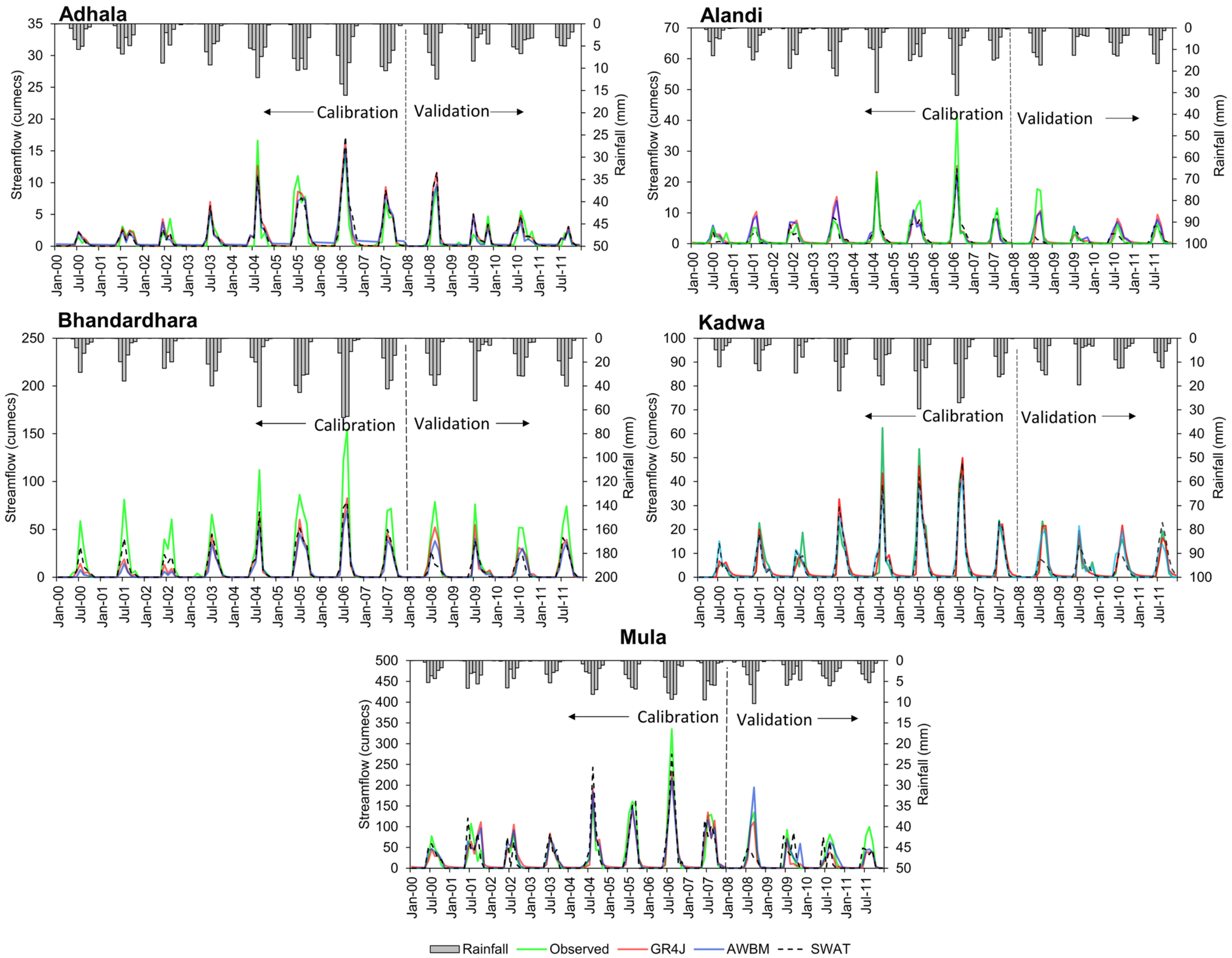

Fig. 8 Comparison of streamflow predictions from different models with observations

Kadwa and Mula for the same. Since most of the observed streamflow are zero in non-monsoon period, there is no observed runoff in the flow duration curve for low flows. Conceptual models and SWAT simulate insignificant values of runoff during non-monsoon period; therefore, the flow duration curve extends till low flows as in Fig. 9.

Discussion

In this study, comparison of two conceptual models GR4J and AWBM is done with a complex semi-distributed model SWAT for streamflow estimation. The conceptual models are simple in structure and have very few lumped parameters compared to SWAT. Due to this, these models require only rainfall and PET data for generating streamflow at catchment outlet unlike SWAT, which necessitates various meteorological and non- meteorological data for simulation. Apart from that, the calibration procedure for conceptual models is straightforward, which is performed in SOURCE platform. On the other hand, in SWAT parameters influencing the streamflow are identified and calibrated stochastically which is more complex and time-consuming.

The models are applied to five catchments, namely Adhala, Alandi, Bhandardhara, Kadwa and Mula located in UGRB for estimation of streamflow at the catchment outlet. These catchments receive high amount of rainfall during monsoon period. However, the rainfall sharply decreases in non-monsoon period during which it occurs mostly on the central and eastern part of UGRB. A few catchments having elongated shape yield two distinct peak flows during monsoon in some years due to high time of concentration. It is observed that models considered in this study do not predict the delayed response of these catchments satisfactorily. Apart from that, conceptual models are weak in predicting streamflow–groundwater interaction as observed in Alandi catchment, where the streamflow during calibration period is overpredicted. On the other hand, the SWAT model

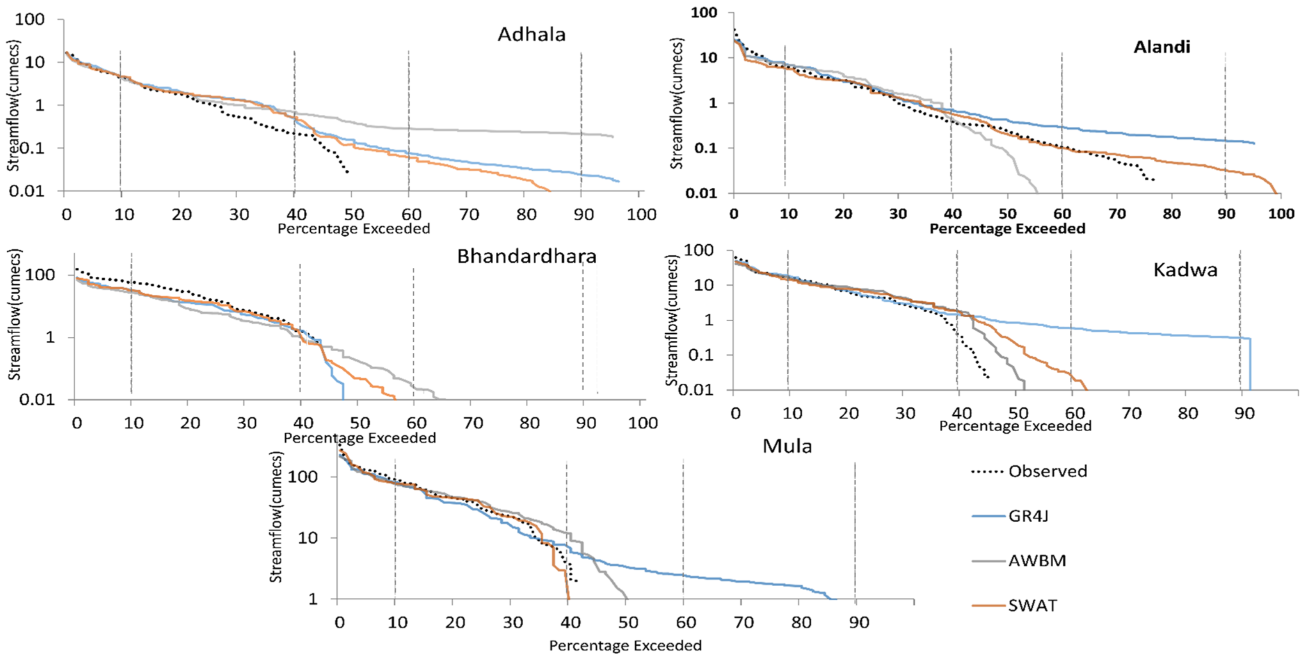

Fig. 9 Comparison of flow duration curves of streamflow predictions from different models with observations

satisfactorily models this process giving high values of NSE and R^2.

In quantile domain, all models are performing well in high and moist flows (see Fig. 9). However, during mid-range and dry flows, performance of all models is equally poor. Since rainfall during non-monsoon period, especially during November–April, is negligible, streamflow at the catchment outlet is almost zero. Nevertheless, the models produce some insignificant values of streamflow during non-monsoon period, which is responsible for poor results in these domains. This is particularly observed in Adhala catchment where AWBM produces *some* streamflow values during non-monsoon period in the years 2006, 2007 and 2008 (see Fig. 8).

As discussed, all models have under predicted the high and moist flows for Bhandardhara catchment. This catchment is located in windward side of Western Ghats. From spatiotemporal analysis of rainfall ("Spatiotemporal analysis of rainfall"), it is observed that this region receives very high amount of rainfall during monsoon. The trend analysis at the rain gauge located at Bhandardhara dam also shows highly increasing rainfall with Sen slope of 57.6 mm/year. Apart from that, it is observed that the number of rain gauge stations near Bhandardhara is limited. The difference between volume of rain recorded at the Bhandardhara dam and that of downstream is considerably high. Due to this reason, the representative rainfall computed for the catchment using Theissen polygon method may have been underestimated. Hence for accurate estimation of streamflow for this catchment, there is a requirement of more number of rain gauges in the upstream of Bhandardhara dam. Due to such variability of rainfall in space and time, a proper management of water resources is paramount in UGRB. Although the rain water is stored by several small and medium dams, poor water resource management has led to droughts in the past.

All three hydrological models considered for the study performed well for the selected catchments in terms of NSE, R^2 and PBIAS. Since the conceptual models GR4J and AWBM are able to simulate streamflow using only rainfall and PET data, these models can replace data intensive semi-distributed model, for example: SWAT or, VIC, which are generally applied in Indian catchments for watershed management studies due to the heterogeneous terrain and climatic conditions. Lack of data in many parts of the world limits the application of these semi-distributed models. Conceptual models like GR4J or, AWBM can be a replacement to those models where only streamflow is required to be modelled. Simple conceptual models will be a good option for river basin management, flood and drought forecasting and reservoir management studies (Yang et al. 1995; Cameron et al. 1999).

Conclusions

The present study compares the performance of the conceptual models GR4J and AWBM with complex semi-distributed model SWAT for streamflow prediction in five catchments at Upper Godavari River Basin. Owing to high variability of rainfall in the region, spatiotemporal analysis is performed to understand its effect on streamflow at the selected catchments. All three models perform satisfactorily and provide similar results for the concerned study area. Amongst the conceptual models studied, GR4J is more robust and provides better streamflow predictions than AWBM. Moreover, GR4J has only four parameters. It is observed that the SWAT model fails to predict multiple peaks in some years caused due to elongated shape of catchments and more uniform temporal distribution of rainfall. SWAT model captures catchment surface–subsurface interaction satisfactorily compared to conceptual models, which overpredict the streamflow in many occasions. Nevertheless, due to structural simplicity, faster calibration and lesser data requirement, GR4J and AWBM can be considered as viable options for streamflow prediction at data-scarce areas and for water resource management studies where modelling streamflow is of prime importance.

Acknowledgements The authors of the paper thank Godavari Marathwada Irrigation Development Corporation (GMIDC), Aurangabad, Water And Land Management Institute (WALMI), Aurangabad and eWater, Australia for providing necessary data for this study. The authors are thankful for the valuable suggestions of the reviewers which helped us to improve the manuscript.

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