

Model Performance Evaluation using Streamflow and Potential Evapotranspiration over Middle Tapi Basin, India



Prabhat Dwivedi, Lalit Kumar Gehlot, and P. L. Patel

Abstract Integrated watershed planning, management and decision-making are important for the efficient utilization of available water resources. The physics-based hydrological models enable quantitative and qualitative evaluation of water at different spatial and temporal scales. The current study aims to ascertain the reliability of hydrologic simulations using the SWAT hydrologic model. The model was developed for a climate-sensitive and agriculturally dominated catchment, i.e., the Middle Tapi basin (MTB), between Hatnur and Ukai reservoirs. The monthly inflows of the Ukai reservoir were utilized to calibrate and validate the SWAT model for 1998–2007 and 2008–2013, respectively. The simulated potential evapotranspiration (PET) at the basin scale was compared with CRU-PET data to ascertain the reliability of the simulated variable. The global sensitivity analysis shows that *GWQMN.gw*, *REVAPMN.gw*, *GW_REVAP.gw*, *SOL_K.sol*, *CNCOEF.bsn*, *SOL_AWC.sol* are the most sensitive parameters at 5% significance level. The model performance metrics, namely *KGE*, *NSE*, R^2 and *PBIAS* with respect to observed streamflow during calibration (validation) period are 0.98 (0.98), 0.98 (0.97), 0.98 (0.97) and 0.6% (–1.2%), respectively. The similar statistics for PET during simulation period (1998–2013) are 0.73, 0.84, 0.94 and –4.36%, respectively. The model performance metrics show that the hydrologic model reliably simulates monthly inflows into the Ukai reservoir and PET in MTB. Thus, the developed model can accurately forecast hydrologic changes in response to climate instability in the study area, allowing for better water management practices.

Keywords Potential evapotranspiration (PET) · Soil and water assessment tool (SWAT) · Sequential uncertainty fitting version-2 (SUFI-2) · SWAT-calibration and uncertainty prediction (SWAT-CUP) · Middle Tapi basin

P. Dwivedi (✉) · L. K. Gehlot · P. L. Patel
Department of Civil Engineering, Sardar Vallabhbhai National Institute of Technology Surat,
Surat 395007, India
e-mail: prabhat20011996@gmail.com

P. L. Patel
e-mail: plpatel@ced.svnit.ac.in

1 Introduction

The physics-based spatially distributed watershed models can predict the integrated response of the changing climatic conditions and anthropogenic activities in the watershed. These models/tools can effectively address the potential environmental and water management threats pertaining to climate variability, land-use change, reservoir operation, water yield, soil erosion, etc. The degree of accuracy and uncertainty of hydrologic model simulations is primarily a function of model inputs, model structure, calibrating variables, etc., affecting the decision-making. The researchers utilize remote sensing (RS) and geographic information systems (GIS) products, available at various spatiotemporal scales, for modeling uncertainty due to different data sources [1]. The quantification of uncertainties in hydrological simulations helps hydrologists and government authorities make decisions for long-term water resource planning and management.

The Soil Water Assessment Tool (SWAT), a hydrologic response unit (HRU)-based watershed model, evaluates the effects of topography, land development activities, climate variability and alternative watershed management strategies on water, sediment and nutrient yields from the basin [2, 3]. The SWAT model is globally accepted to simulate various water balance components and processes in the watershed. The Sequential Uncertainty Fitting (SUFI-2) in SWAT-CUP (calibration and uncertainty program) is widely used to account for parametric sensitivity and uncertainty in hydrologic simulations [4, 5]. However, calibration of the hydrologic model using a single variable, particularly in heterogeneous catchments, may lead to unrealistic hydrologic model predictions due to the non-uniqueness of the model parameters and uncertainty associated with parameters range [5–8]. This requires a thorough evaluation of the model's goodness using multivariable/multisite calibration techniques [9–13].

Due to its unique geographical setting, the Tapi river basin (TRB) is climatically heterogeneous in Peninsular India. The TRB is subdivided into Upper (UTB), Middle (MTB) and Lower (LTB) Tapi basins based on the geographic location of major hydraulic structures/dams. The MTB, an agriculture-dominated landmass, gets frequently affected due to scarce rainfall, and prolonged dry spell durations over the year [14] may lead to over-dependency on groundwater resources. The anthropogenic changes, hydro-climatic variability and streamflow regulation from major hydraulic structures (Hatnur and Girna dams) have severely impacted aquatic life and water demand for socio-economic growth in the region [15–17]. Thus, understanding the hydro-climatic variability and hydrological modeling can help derive better regional water management practices. The key objective is to develop a SWAT hydrologic model for MTB, calibrate and validate using streamflow data and ascertain the reliability of the developed model by comparing the simulated PET from hydrologic model with PET data of Climate Research Unit; [https://crudata.uea.ac.uk/cru/data/hrg\(CRU\)](https://crudata.uea.ac.uk/cru/data/hrg(CRU))).

2 Study Area and Data Sources

2.1 Middle Tapi Basin

The TRB is India's sixth largest river basin with total flow length of 724 km and drainage area of 65,145 km². At an elevation of 752 m, the Tapi River rises from Multai in the Betul Plateau and flows into the Arabian Sea, where it joins the Gulf of Khambhat. The MTB lies between Hatnur and Ukai dam/reservoir, having total watershed area of 32,925 km² (see Fig. 1). The study region has basaltic hills in peripheral part and alluvial plains in central region. The Middle Tapi River has five major tributaries on its left side, i.e., Girna, Waghur, Bori, Panjhra and Buray, while three are on its right side, i.e., Aner, Arunavati and Gomai. The Hatnur dam, an earthen dam in Maharashtra with gross (live) storage capacity of 388.0 (255.0) MCM (10⁶ m³), forms the upstream boundary for MTB, while Ukai dam, Gujarat's second largest earth-cum masonry dam with gross (live) storage capacity of 7414.29 (6730.00) MCM and located 300 km downstream of the Hatnur dam, serves the downstream boundary for MTB. The watershed elevation varies from 63 to 1563 m above mean sea level as shown in Fig. 1.

The climatology of MTB can be characterized by a hot summer and persistent dryness throughout the year with low monsoon rainfall. The daily minimum (maximum) temperature ranges from 8 °C (34 °C) in January month to 22 °C (44 °C) in May month. The average annual rainfall and PET (period 1990–2013) in the basin

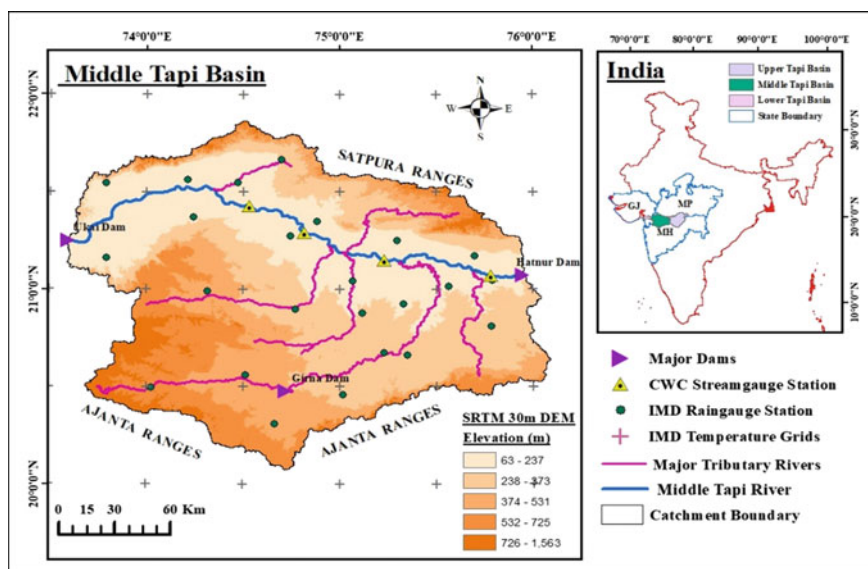


Fig. 1 Index map of study area

are 791 mm and 2248 mm, respectively. The aridity index (ratio of rainfall to PET) in the research area is 0.35, indicating that the climate is semi-arid. Agricultural land is the most frequent land use in the region, followed by deciduous forest and fallow land. The dominant soil classes in the region vary from very gentle sloping to moderate and level surface. The soil texture ranges from loamy to clayey and deep black soil. The major historical floods were observed in the years 1998 and 2006 in the MTB, after the construction of Hatnur dam [15].

2.2 Data Sources

The SWAT model requires topography, land use and land cover, soil, slope and weather data. For delineation of watershed features, the open-source Shuttle Radar Topographic Mission (SRTM, <https://earthexplorer.usgs.gov>) Digital Elevation Model (DEM) of 30 m grid size was used. The LULC data from NRSC, Hyderabad, with a spatial resolution of 56 m and soil map of NBSS&LUP, Nagpur (at a scale of 1:2,50,000) have been used for the development of the model. The daily rainfall data of 24 stations and daily maximum and minimum temperature data, interpolated to $0.5^\circ \times 0.5^\circ$ from $1.0^\circ \times 1.0^\circ$ using bilinear interpolation, have been obtained from India Meteorological Department (IMD), Pune. The daily streamflow data and releases from the Hatnur dam were obtained from Central Water Commission, Surat Division, and Tapi Irrigation Development Corporation, Jalgaon. The monthly PET data of CRU, at $0.5^\circ \times 0.5^\circ$, is used as a reference dataset for assessing simulated PET from the model.

3 SWAT Model

The SWAT model demarcates the watershed and sub-watersheds depending upon user-specified outlet points and the drainage area threshold. Each sub-watershed/subbasin is further subdivided into multiple hydrological response units (HRUs), representing a unique combination of land use, soil and slope class in the watershed. The SWAT uses land phase hydrology to control the amount of water, sediments and nutrients entering the main channel while the routing phase controls the flow of water, sediments and nutrients from the watershed drainage network to the outlet. The mathematical representation of the hydrologic cycle adopted by the SWAT model is based on the water balance equation (see Eq. (1), all having unit as mm H₂O).

$$S_{\text{final}} = S_{\text{initial}} + \sum_{i=1}^t (P_{\text{day}} - Q_{\text{overflow}} - E_{\text{actual}} - W_{\text{seepage}} - Q_{\text{ground}}) \quad (1)$$

where S_{initial} , S_{final} , P_{day} , Q_{overflow} , E_{actual} , W_{seepage} , Q_{ground} represents the initial soil moisture content, final soil moisture content, precipitation, surface runoff, evapotranspiration, percolation and return flow, respectively, on day i ; and t is time in days. The hydrological response is anticipated separately for each HRU and subsequently routed through each subbasin in the watershed [2, 3]. In this study, the SCS-CN method with slope adjustment in CN2, plant ET method and Hargreaves method are employed to estimate land phase water balance parameters in the catchment, whereas the variable storage method is used to develop a hydrograph at the outlet of each basin in the main channel.

In the watershed delineation process, 48 subbasins were delineated in the MTB between the Hatnur dam, at the upstream boundary and Ukai dam, at the downstream boundary, wherein releases from the Hatnur dam act as inlet points to the MTB. The SWAT model resamples the spatial inputs, i.e., soil and land use, to match the input DEM grid size. The LULC map (see Fig. 2) obtained from NRSC is reclassified into six major classes, namely agriculture (AGRC- 49.88%), wasteland (BARR-10.58%), built-up (URML -1.79%), current fallow land (AGRR-16.26%), deciduous forest (FRSD-17.80%) and water body (WATR-3.70%). The primary soil texture, particularly hydrologic soil groups C and D, ranges from silty clay to clays and clay loam. The soil database comprising soil properties including hydrological soil group, texture, soil water content, soil depth, saturated hydraulic conductivity, bulk density, organic carbon content and percentage of soil texture was given as an input database to the SWAT model. In addition, the basin is divided into three major slope classes, 0–2%, 2–5% and more than 5%, fairly representing flat, moderately sloping and steep sloping land features, respectively. The area under smaller HRUs was restructured/redefined using HRU thresholds of 2, 5 and 10% for land use, soil and slope, thereby reducing total HRUs from 5186 to 2144. The CN values for each HRU are corrected for the slope class greater than 5% in the subbasin. The current study used a freely available weather generator database derived from IMD daily gridded data of 85 years with a spatial resolution of $1^\circ \times 1^\circ$. The station-based (24 nos.) rainfall data and grid-based minimum and maximum temperature data are used, remaining weather parameters, i.e., solar radiation, wind velocity, and relative humidity, are simulated by a weather generator. The Hatnur dam outflow from the spillway crest was given as inlet discharge into the MTB hydrological model.

The SWAT model's parameters are process-based and should be adjusted within an acceptable uncertainty range. The most frequent causes of model uncertainty are anomalies in the spatial inputs, meteorological data, calibration variables and model assumptions. The calibration process involves the identification and regionalization, if permissible, of sensitive parameters and minimizing the uncertainty for a particular set of local conditions in the watershed or sub-watershed. The approach of calculating the average rate of change of the output variable/objective function of the model in relation to changes in model parameters is known as sensitivity analysis. The key parameters with specific range must be identified in the calibration process, followed by independent validation to determine whether the model will precisely replicate the watershed process-based on objectives [6]. The model is calibrated and validated for observed streamflow data for the period of 1998–2007 and 2008–2013, respectively.

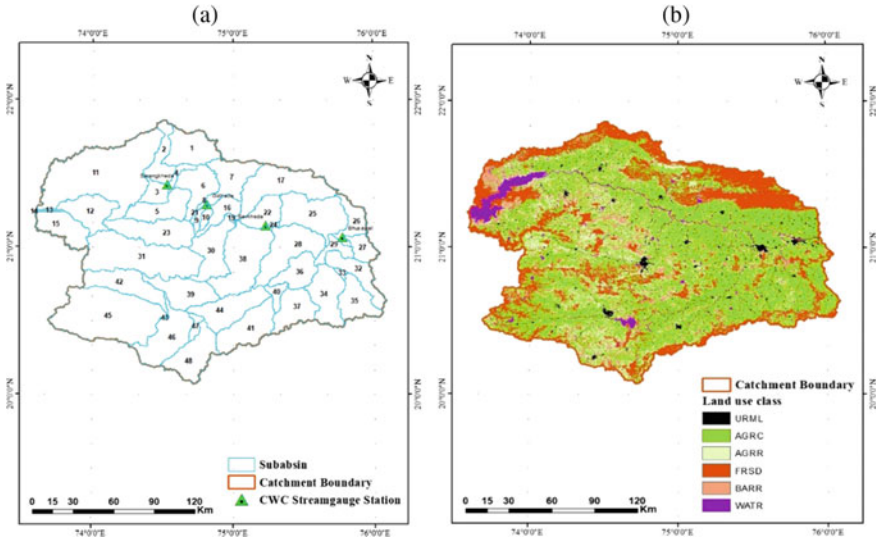


Fig. 2 **a** Sub-watersheds during watershed delineation, **b** LULC map of MTB

The four-year warm-up period (1994–1997) has been used for the stabilization of the initial model parameters. The model performance is regarded as acceptable if $NSE \geq 0.5$, $R^2 \geq 0.5$, and $PBIAS < \pm 25\%$ [18]. Furthermore, the reliability of the simulation of the watershed process was ascertained by independent validation of the simulated PET with the PET data obtained from CRU due to the non-availability of the measured meteorological variables in the study region.

4 Results and Discussion

The calibration being an inverse modeling process invites parametric uncertainties; thus, parameter selection plays a crucial role for a model to represent the watershed hydrology. The parameters selected for calibration of the model comprise parameters related to water in various phases of hydrological processes, i.e., groundwater (.*gw*), land management (.*mgt*), soil (.*sol*), main channel (.*rte*), hydrological response units (.*hru*) and basin parameters (.*bsn*) (see Table 1). The uncertainty in simulated streamflow is determined statistically based on the *p*-factor, the percentage of observations encapsulated by the 95PPU (percentage prediction uncertainty) band, and *r*-factor, relative thickness of the 95PPU band with respect to the standard deviation of observed flow [5]. The objective function adopted for selecting the best parameters is *Kling–Gupta Efficiency (KGE)*. The model calibration, validation, sensitivity ranks of the parameter during the final calibration range and uncertainty in the model simulation are assessed by SUFI-2 in SWAT-CUP. Table 1 lists the model

calibration parameters and their original and calibrated ranges, fitted values and sensitivity ranks. At a 5% level of significance, the global sensitivity analysis ranks demonstrate that groundwater ($GW_REVAP.gw$, $GWQMN.gw$, $REVAPMN.gw$), soil moisture ($SOL_AWC.sol$), and plant ET CN coefficient ($CNCOEF.bsn$) are the most dominating water balancing components affecting the streamflow, corresponding to KGE objective function.

The internal consistency of fit for observed and simulated inflows in the Ukai reservoir is assessed using the model performance indicators, i.e., KGE , $Nash-Sutcliffe$ (NSE), *coefficient of determination* (R^2) and *percentage bias* ($PBAIS$). The respective values of model performance statistics through calibration (validation) period are 0.99 (0.97), 0.98 (0.97), 0.98 (0.97) and 0.0 (−1.7), respectively (see Table 2). The uncertainty estimators, i.e., *p-factor* (*r-factor*), through the calibration and validation are 0.48 (0.65) and 0.52 (0.59), respectively. The model performance statistics and the flow hydrograph (see Fig. 3) infer that the developed SWAT model is capable of simulating monthly inflow into the Ukai reservoir with fair confidence and accuracy. The annual water balance during calibration and validation is obtained from the *output.std* file. The average evapotranspiration and water yield from the MTB are 55% and 19%, respectively. Out of the 19% of the water yield, on average, the contributions from overland flow and groundwater flow/baseflow are 80% and 20%, respectively. The average curve number (CN) of the MTB during the simulation period was found to be 79.

The reliability of the simulated hydrological variables has been ascertained by using a variable that is not used as calibrating variable. Due to the lack of field observations, readily available PET data from CRU was used as a reference dataset in this work, and the assessment was done at the basin level, i.e., MTB. The simulated PET for MTB has been extracted from the *output.std* file of SWAT, and the average basin PET from CRU gridded dataset has been derived using Thiessen weights. The performance evaluation indicators, namely KGE , NSE , R^2 , and $PBIAS$ through the simulation period (1998–2013), are found to be 0.73, 0.84, 0.94 and −4.36%, respectively (see Table 2). The average monthly estimates of PET during the same period are shown in Fig. 4. The model performance indicator demonstrates high agreement between CRU-PET and simulated PET values on a monthly scale. The average monthly PET values have shown deviations ranging from −12.6% (in May) to 21.5% (in December), while the average annual estimates have shown a variation of 7%. Considering the various statistical indicators for calibrating variable (streamflow) and independent variable (PET), the SWAT model developed in the present study has shown reliable estimates for the watershed hydrological process from the period 1998- to 2013. Thus, a developed model can be utilized to accurately simulate the hydrologic alteration to the climate instability in the research area, and better water management practices can be employed. The model can also be used to assess the impact of LULC change, climate change, land management practices, etc., in individuals and in combination.

Table 1 Model calibration parameters, initial and calibrated range, fitted value and their sensitivity ranks

Parameter name	Initial range	Calibrated range	Fitted value	Sensitivity rank
V__ALPHA_BF.gw	0.1–0.7	0.228–0.738	0.592	24
V__GW_DELAY.gw	7–90	7.579–83.812	55.256	7
V__GWQMN.gw	110–2838	112.303–3238.197	2728.937	2
V__GW_REVAP.gw	0.1–0.2	0.02–0.2	0.169	1
V__REVAPMN.gw	85–410	132.651–430.016	317.389	3
V__RCHRG_DP.gw	0.01–0.17	0.001–0.017	0.013	28
R__CN2.mgt	–0.18 to –0.05	–0.18 to –0.012	–0.028	8
R__SOL_AWC().sol	0.14–0.48	–0.014 to 0.478	0.33	4
R__SOL_K().sol	–0.75 to –0.12	–0.357 to –0.048	–0.198	29
R__SOL_BD().sol	–0.46 to –0.1	–0.464 to –0.114	–0.213	26
V__SOL_ZMX.sol	320–2800	344.092–2781.408	2571.19	22
R__SOL_ALB().sol	0.08–0.24	0.073–0.24	0.142	18
V__CH_N2.rte	0.03–0.09	0.02–0.069	0.026	13
V__CH_K2.rte	5–85	3.601–87.135	51.111	11
R__CH_S2.rte	–0.07 to 0.01	–0.074 to 0.005	–0.021	10
V__ALPHA_BNK.rte	0.4–0.93	0.281–0.843	0.758	25
V__ESCO.hru	0.15–0.6	0.228–0.46	0.265	27
V__EPCO.hru	0.7–0.96	0.44–0.99	0.465	19
V__CANMX.hru	12–45	12.089–42.248	21.074	6
V__OV_N.hru (URML)	0.02–0.05	0.012–0.046	0.029	16
V__OV_N.hru (FRSD)	0.26–0.58	0.261–0.684	0.327	15
V__OV_N.hru (WATR)	0.01–0.04	0.017–0.036	0.031	9
V__OV_N.hru(AGRR, BARR)	0.02–0.05	0.018–0.042	0.032	30
V__OV_N.hru (AGRC)	0.02–0.05	0.023–0.046	0.034	20
R__HRU_SLP.hru	0.01–0.23	0.011–0.187	0.067	12
V__CH_N1.sub	0.02–0.06	0.019–0.047	0.024	31
V__CH_K1.sub	4–85	4.111–78.298	41.05	23
R__CH_S1.sub	0.03–0.2	0.035–0.184	0.163	14
V__SURLAG.bsn	2.5–17	2.358–16.274	4.938	17
V__EVRCH.bsn	0.6–0.98	0.646–0.985	0.832	21
V__CNCOEF.bsn	1.14–2.0	1.142–2.0	1.991	5

Table 2 Summary of model performance statistics

Performance indices	Observed streamflow		Potential evapotranspiration
	Calibration (1998–2007)	Validation (2008–13)	Simulation period (1998–2013)
KGE	0.99	0.97	0.73
NSE	0.98	0.97	0.84
R^2	0.98	0.97	0.94
PBIAS	0.00	-1.70	-4.36
p -factor	0.48	0.65	-
r -factor	0.52	0.59	-

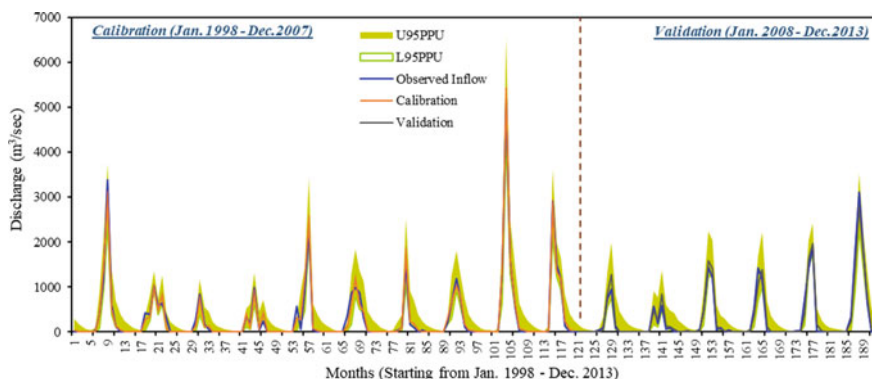


Fig. 3 Observed and simulated inflow in Ukai reservoir

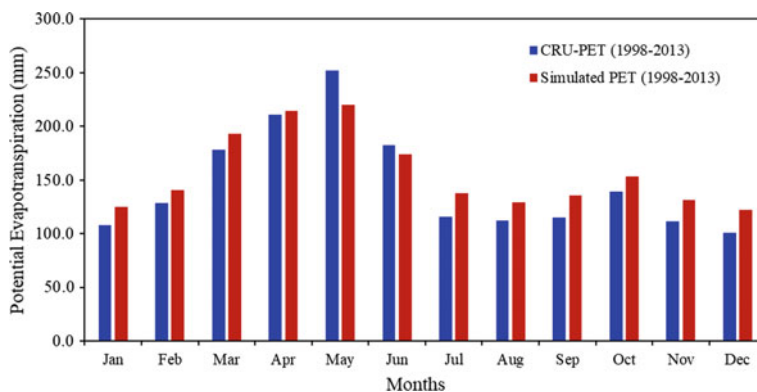


Fig. 4 Average monthly PET values

5 Conclusions

The present study has developed a SWAT hydrologic model for a semi-arid Middle Tapi basin (MTB) with releases from the Hatnur dam as an upstream boundary. The model has been successfully calibrated and validated on a monthly time scale to estimate inflows into the Ukai reservoir, which serves as the downstream boundary. The model reliability is also ascertained using PET as an independent variable, and the simulated PET has been compared with CRU-PET data at the basin scale. Since ET holds a significant portion of total water available in the global/regional hydrological cycle, the present study emphasizes reliable simulation of non-calibrating variables, i.e., PET. The main findings of the current investigation are as follows:

- The model performance metrics, namely KGE , NSE , R^2 , and $PBIAS$ concerning observed monthly streamflow through the calibration (validation) period, are 0.99 (0.97), 0.98 (0.97), 0.98 (0.97) and 0.0 (−1.7), respectively, signifying good competence of the hydrologic model to simulate monthly inflows through extensive drainage network of MTB into the Ukai reservoir.
- The respective values of the performance statistics for PET are 0.73, 0.84, 0.94 and −4.36%, respectively, indicating model capability to simulate the other hydrologic variables with fair accuracy and a high degree of confidence. Thus, the present model can give a reliable forecast of monthly inflows in the Ukai reservoir for future climate data.
- The present study used a single-site single variable approach, i.e., inflows into the Ukai reservoir, which may be considered a limitation. Based on the data's availability, the model's functioning can be further improved by incorporating a multi-metric calibration approach, i.e., multiple variables under calibration at multiple gauging sites.

Acknowledgements The authors would like to acknowledge the Indian National Committee on Climate Change, Ministry of Jal Shakti, Department of Water Resources, River Development & Ganga Rejuvenation, Government of India (GoI), and Centre of Excellence on 'Water Resources and Flood Management,' TEQIP-II, Ministry of Education, GoI, respectively, for providing funding and infrastructure facilities for this research. All data disseminating agencies, i.e., IMD Pune, TIDC Jalgaon, Ukai Civil Circle, NBSS&LUP Nagpur, and NRSC, Hyderabad, are duly acknowledged for providing necessary data to conduct the present study.

References

1. Ghoraba SM (2015) Hydrological modeling of the Simly Dam watershed (Pakistan) using GIS and SWAT model. *Alex Eng J* 54(3):583–594
2. Arnold JG, Srinivasan R, Muttiyah RS, Williams JR (1998) Large area hydro-logic modeling and assessment part I: model development 1. *JAWRA J Am Water Resour Assoc* 34(1):73–89
3. Arnold JG, Allen PM, Volk M, Williams JR, Bosch DD (2010) Assessment of different representations of spatial variability on SWAT model performance. *Trans ASABE* 53(5):1433–1443

4. Abbaspour KC (2015) SWAT Calibration and uncertainty programs—A user manual. Swiss Federal Institute of Aquatic Science and Technology, Eawag, Switzerland
5. Abbaspour KC, Vaghefi SA, Srinivasan R (2018) A guideline for successful calibration and uncertainty analysis for soil and water assessment: a review of papers from the 2016 international SWAT conference.
6. Kouchi DH, Esmaili K, Faridhosseini A, Sanaeinejad SH, Khalili D, Abbaspour KC (2017) Sensitivity of calibrated parameters and water resource estimates on different objective functions and optimization algorithms. *Water* 9(6):384
7. Leta OT, Van Griensven A, Bauwens W (2017) Effect of single and multisite calibration techniques on the parameter estimation, performance, and output of a SWAT model of a spatially heterogeneous catchment. *J Hydrol Eng* 22(3):05016036
8. Nkiaka E, Nawaz NR, Lovett JC (2018) Effect of single and multisite calibration techniques on hydrological model performance, parameter estimation and predictive uncertainty: a case study in the Logone catchment, Lake Chad basin. *Stoch Environ Res Risk Assess* 32(6):1665–1682
9. White KL, Chaubey I (2005) Sensitivity analysis, calibration, and validations for a multisite and multivariable SWAT model 1. *JAWRA J Am Water Resour Assoc* 41(5):1077–1089
10. Cao W, Bowden WB, Davie T, Fenemor A (2006) Multivariable and multisite calibration and validation of SWAT in a large mountainous catchment with high spatial variability. *Hydrol Process: Int J* 20(5):1057–1073
11. Chiang LC, Yuan Y, Mehaffey M, Jackson M, Chaubey I (2014) Assessing SWAT's performance in the Kaskaskia River watershed as influenced by the number of calibration stations used. *Hydrol Process* 28(3):676–687
12. Franco ACL, Bonumá NB (2017) Multivariable SWAT model calibration with remotely sensed evapotranspiration and observed flow. *RBRH* 22
13. Zhang J, Li Q, Guo B, Gong H (2015) The comparative study of multisite uncertainty evaluation method based on SWAT model. *Hydrol Process* 29(13):2994–3009
14. Gehlot LK, Jibhakate SM, Sharma PJ, Patel PL, Timbadiya PV (2021) Spatio-temporal variability of rainfall indices and their teleconnections with El Niño-Southern Oscillation for Tapi Basin, India. *Asia-Pacific J Atmos Sci* 57:99–118
15. Sharma PJ, Patel PL, Jothiprakash V (2019) Impact assessment of Hathnur reservoir on hydrological regimes of Tapi River, India. *ISH J Hydraulic Engin* 1–13
16. Ramkar P, Yadav SM (2019) Identification of critical watershed using hydrological model and drought indices: a case study of upper Girna, Maharashtra, India. *ISH J Hydraul Eng* 1–12
17. Sahana V, Timbadiya PV (2020) Spatiotemporal variation of water availability under changing climate: case study of the Upper Girna Basin, India. *J Hydro-I Eng* 25(5):05020004
18. Moriasi DN, Gitau MW, Pai N, Daggupati P (2015) Hydrologic and water quality models: performance measures and evaluation criteria. *Trans ASA-BE* 58(6):1763–1785