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ORIGINAL ARTICLE

SWAT Model calibration and uncertainty analysis for streamflow prediction of the Tons River Basin, India, using Sequential Uncertainty Fitting (SUFI-2) algorithm

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Abstract Tons river basin has a great significance to states Madhya Pradesh and Uttar Pradesh in India, concerning water resources aspects and the ecological balances. A hydrological modeling approach was used to identify the sensitive hydrological parameters of the basin through Sequential Uncertainty Fitting (SUFI-2) technique. SUFI-2 was used for the calibration of SOIL WATER ASSESSMENT TOOL (SWAT) model. It was calibrated for period (1979–2000) including 3 years as warm up (1979–1982), subsequently model was validated on 11 years of datasets (2001–2011). The percentage of observation covered by the 95PPU (p-factor) and the average thickness of the 95PPU band divided by the standard deviation of the measured data (r-factor), were taken into an account for performance evaluation of model. In calibration and validation the p-factor and the r-factor was obtained as 0.54, 0.76 and 0.68, 0.56 respectively. The coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS) and RMSE-observations standard deviation ratio (RSR) have been used for goodness of fit between observation and final best simulation. The R^2, NSE, PBIAS and RSR are 0.74, 0.73, −3.55 and 0.54 respectively during the calibration whereas in validation period values are 0.75, 0.69, 18.55 and 0.56 respectively.

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Keywords Tons · SUFI-2 algorithm · Uncertainty analysis · Calibration · Validation

Introduction

Hydrologic cycle has a close relation with the earth surface and subsurface processes by its integration through its cycle, storage, and agricultural pattern. Hence to identify environmental problems in terms of land use/land cover changes, soil degradation, climate changes and its impacts on the ecosystem services, it needs the study of runoff above and below the earth surface using scientific methods and approaches. The Hydrologic and water quality models (H/WQ) are being used in the impact based analysis on water resources and its ecosystem services (Moriasi et al. 2012) and for assessing the influence of topography, land use and climate change on water resources using a distributed hydrological model is an effective tool (Patel and Srivastava 2013). The H/WQ models can simulate the hydrological component, sediment transport and chemical yield. SOIL WATER ASSESSMENT TOOL (SWAT) is a physical process based and distributed river basin model with spatial distributed parameters operating on a daily time step and it is widely accepted as robust interdisciplinary watershed-modeling tools (Gassman et al. 2007). Arnold and Fohrer (2005) have shown that SWAT can be used in assessment based analysis like predicting long term impacts of land management measure on water, sediment and agricultural yield (nutrient loss) in large complex watershed with varying soils, land and management conditions. Borah and Bera (2004) compared SWAT with Dynamic Watershed Simulation Model (DWSM), Hydrologic Simulation Program-Fortran (HSPF) model (Bicknell et al. 1997), and concluded that SWAT is useful in an agricultural watershed for monthly predictions except for extreme storm events and hydrologic conditions. A comparison was made between SWAT and HSPF for streamflow predictions and it was found that SWAT was more consistent in estimating streamflow for different climatic conditions and for investigating the long-term impacts of climate variability (Van Liew et al. 2003). Discharge prediction using SWAT model has been done in most of the country in world (Spruill et al. 2000; Zhang et al. 2010). Schuol et al. (2008a) used SWAT for modeling blue and green water availability in Africa and freshwater availability (Schuol et al. 2008b) in the West African sub-continent using the SWAT model. In recent years the uncertainty of model is now subjected to considerable area of research and reason behind it is that large uncertainties related to the distributed hydrological model (Abbaspour et al. 2007). Calibration is the process of adjusting input parameter values and their boundary conditions to match the simulated values with the observed values (Zeckoski et al. 2015).Various hydrological models predicts some degree of uncertainty in outputs so they require calibration of the output in order to reduce the uncertainty in the predictions (Engel et al. 2007). A hydrological model needs to be calibrated by observed hydrologic variables because of poor quality of input data and due to environmental processes held in conceptual simplification (Wagener et al. 2004; Gupta et al. 2008). Calibration requires the examination of the accuracy of output and process simulation (Sorooshian 1983) and through sensitivity (SA) and uncertainty analysis (UA) the model calibration can be evaluated (Zheng and Keller 2007). Uncertainty may be associated with input, model structure, parameter, and output, so the model predictions should be in a confidence range (Beven 2000; Van Griensven et al. 2008). Hence the SA and UA are used to reduce the uncertainties (Gupta et al. 2006; Wagener and Gupta 2005). Various types and sources of uncertainties coming in hydrologic outputs are well explained by Yang et al. (2008). For checking the applicability of SWAT model in hydrological investigation a careful calibration and validation is required using different algorithms (Duan et al. 1992; Vrugt et al. 2003). A calibrated model need performance measures (PMs) and its evaluation criteria (PEC). The PMs are the statistical and graphical methods which include the threshold value and PEC define the qualitative ratings of model performance (very good, good, satisfactory etc.) with corresponding quantitative threshold for the PMs (Moriasi et al. 2015). In the validation there is no need of further adjustment of calibrated parameters and it shows that model can run for the future condition (Zheng et al. 2012). Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley 1992), Sequential Uncertainty Fitting (SUFI-2) (Abbaspour et al. 2004, 2007), Parameter solutions (ParaSol) (Van Griensven and Meixner 2006) and Markov Chain Monte Carlo (MCMC) (Kuczera and Parent 1998) are four algorithms used for assessing the uncertainty in SWAT predictions and is compared by Yang et al. (2008). SWAT-CUP (Abbaspour et al. 2007) link all the algorithms (GLUE, Parasol, SUFI-2 and MCMC) to SWAT model and enable SA and UA of model parameters as well as structure (Rostamian et al. 2008). Setegn et al. (2009) used SUFI-2, GLUE and ParaSol to assess the performance and applicability of SWAT model for prediction of streamflow in the Lake Tana Basin. Zhang et al. (2009) used Genetic algorithms (GA) and Bayesian model averaging (BMA) for calibration and uncertainty analysis using SWAT for the southeastern USA and central China. Rostamian et al. (2008) performed model calibration and uncertainty analysis with SUFI-2 for estimating runoff and sediment in two mountainous basins in central Iran. SUFI-2 algorithm includes both graphical and statistical PMs for robust model performance. Yang et al. (2008) applied the SUFI-2 for evaluation of SWAT model and reported that SUFI-2 needs a minimum number of model simulations to attain a high-quality calibration and uncertainty analysis. The overall objective of the work was to calibrate and validate the SWAT model using SUFI-2 technique. The study area having undulating topography under the great influence of the land use/land cover and climate changes on the surface and sub surface hydrology.

Description of the study area

Tons River Basin (TRB) is flowing in Uttar Pradesh and Madhya Pradesh states of India. TRB is a subbasin of Ganga River Basin originated at Tamakund in the Kaimur Range at an elevation of 610 meters flowing Satna and Rewa and joins the Ganges at Sirsa, about 311 km downstream of the confluence of the Ganges and Yamuna. The geographical extent of the TRB lies between 80°18′–83°20′E longitudes and 23°58′–25°17′N latitudes (Fig. 1). It is an agricultural dominated watershed and total drainage area is approximately more than 17,000 km^2 out of which 11,974 km^2 lies in MP and the remaining area 5,643 km^2 lies in UP. Total land put to use for agriculture purpose in Tons basin is 8460 km^2 in the state for which 2244 hm of water is available for its use against total available water at 75% dependability is 2244 hm. The flowing direction of river is almost northerly in this area. Some tributaries of the Tons like Belan, Mahana, Beehar, Simrawal, Karihari and Nar are the perennial river and also principle sources of water in the river in which it meets the Belan River in Uttar Pradesh. There are some other intermittent streams which remains almost dry during most of the year but become an effective catchment in the rainy season. Since flow directions of the rivers are guided by joint of

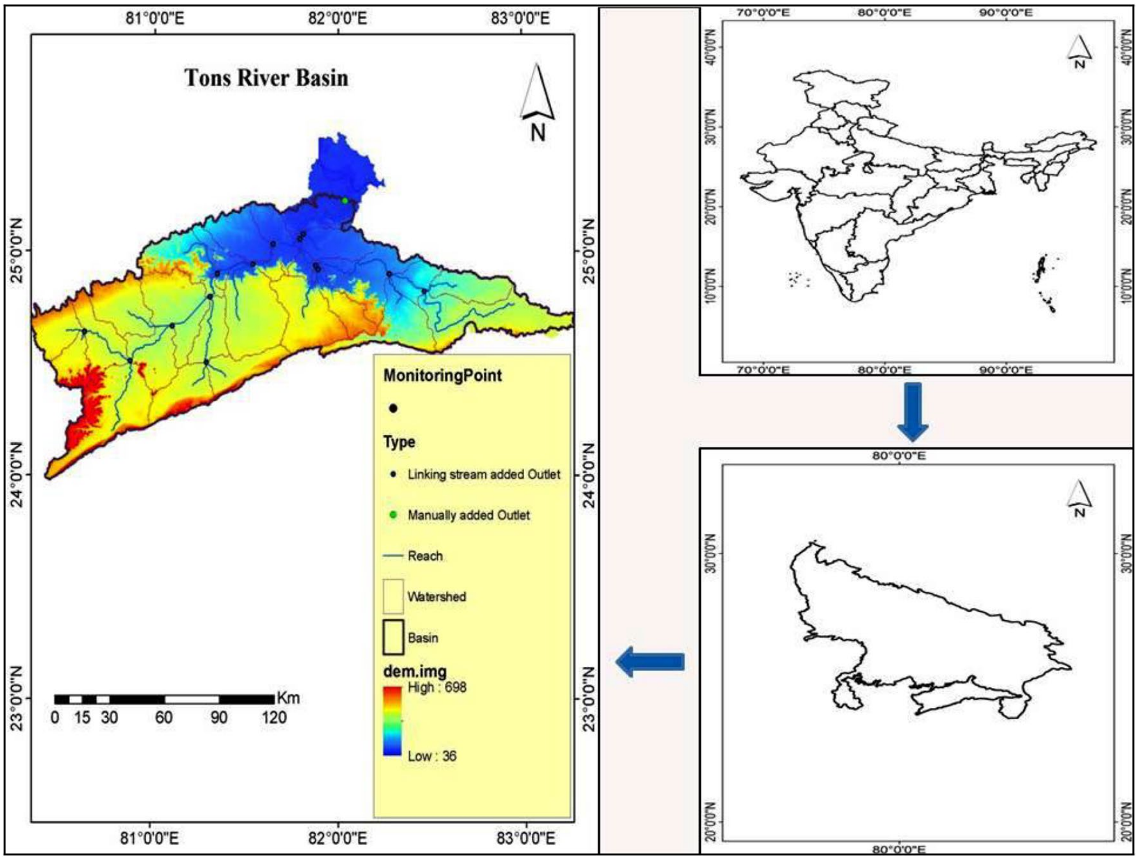

Fig. 1 Location map of Tons River Basin

the underlying rocks so most of the rivers are consequent type. The major soil groups are sandy_clay_loam, sandy_loam, and clay while major land use/land cover classes are water body, mixed crop, barren land, residential and forest. Major crops in this area are wheat, soya bean, gram, paddy, rice, jowar, cotton, and sunflower. Annual precipitation varies from 930 to 1116 mm/year in which June–September occupy 90% of the total rainfall while July and August are months of maximum rainy days. Maximum temperature in April and May ranges from 36 to 41 °C, whereas the minimum temperature occurs during the months of December and January ranging from 8 to 12 °C.

Materials and methods

Input datasets

Digital elevation model (DEM), land use/land cover (LULC), soil, weather and gauge (discharge) are the main datasets collected from different sources/agencies and prepared. The details of all the datasets used in this study are listed in Table 1.

Digital elevation model (DEM)

The SRTM digital elevation data has been processed to fill data voids. The SRTM 90 m DEM's has a resolution of 90 m at the equator. These are available in both ArcInfo ASCII and GeoTiff format to facilitate their ease of use in a variety of image processing and GIS applications. Here DEM has been used as an input in SWAT model for delineating watershed and for topographic parameterization of TRB watershed. The TRB has 29 sub-basins and 134 hydrological response units (HRU) with threshold of 1500 hectares. The HRUs of the catchment were categorized into different classes mainly on the basis of landuse, soil and slope.

Land use/land cover

LULC data set of the study area was prepared using Landsat satellite image (Landsat 8) by unsupervised

Table 1 Description of spatial datasets used for Tons River Basin

S. no	Spatial Data	Description	Source
1	Digital Elevation Model (DEM)	90 m×90 m grid DEM for delineation the watershed and analyze the drainage patterns of the terrain	Shuttle Radar Topography Mission (SRTM) of USGS (http://srtm.csi.cgiar.org/)
2	Land use and land cover (LULC)	The Landsat8 data containing 11 bands and so most suitable for use in Geographic Information System (GIS)	Landsat 8 & US Geological Survey (http://earth-explorer.usgs.gov/)
3	Soil data	The soil data has been obtained from FAO	Food And Organization (FAO) Digital Soil Map (http://gisserver.civil.iitd.ac.in/grbmp/)
4	Weather data	Weather data (Temperature, precipitation, relative humidity, solar radiation, wind speed)	Weather data (http://gisserver.civil.iitd.ac.in/grbmp/) and Indian Meteorological Department, India
5	Hydrological data	Hydrological data (Discharge)	Gauge data at Meja gauge Station from Central Water Commission (CWC) Ministry of Water Resources, Government of India, India

classification and ISODATA technique. A brief description of LULC types and descriptions of each class are given in Table 2. The mixed crop was most dominant class (58.46%) in the study area. Accuracy assessment has been performed to check the results which represent the each LULC category with their classification accuracy. The overall classification accuracy was 96.81% while overall kappa statistics was 0.9481. The LULC has forest mixed, barren land, forest deciduous, shrubland, mixed crop, residential, residential low density (LD) and water body (Fig. 2).

Soil data

Soil map has six major soil classes, presented in Table 3. The major SWAT soil classes are (Be80-2a-3681), (Lc5-1a-3772), (Lc75-1b-3780), (Lf10-1bc-3785), (Lo51-2a-3812), (Vc21-3a-3859). The most dominant soil class is (Lc75-1b-3780) (Fig. 3). Manually soil attributes were added into the SWAT user soil database.

SWAT model structure

SWAT delineate the watershed into number of sub basins which are joined by a stream network and further divides each sub basins into hydrologic response units (HRUs), with unique combinations of land cover, slope, and soil type (Patel and Srivastava 2013). The readers can found more details of SWAT model (http://swat.tamu.edu/documentation/). The model is based on principle of water balance Eq. (1):

$$Sw_t = Sw_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{qw}) \tag{1}$$

SW_t = Final soil water content (mm), SW_0 = Initial soil water content on day i (mm), R_{day} = Amount of precipitation on day i (mm), Q_{surf} = Amount of surface runoff on day i (mm), Ea = Amount of evapotranspiration on day i (mm), Q_{gw} = Amount of return flow on day i (mm). W_{seep} = Amount of water entering the vadose zone from the soil profile on day i (mm).

Table 2 Land use/land cover types and their descriptions

SWAT class	Description	Area (Km^2)	Area (%)	Producers Accuracy (%)	Users Accuracy (%)	KAPPA (K^)
WATR	Water body	445	2.429305	87.50	87.50	0.8736
RWSW	Mixed crop	10,709	58.46162	98.83	98.60	0.9655
BARN	Barren land	343	1.872475	86.67	92.86	0.9271
FRST	Shrub land	1511	8.248717	98.28	95.00	0.9456
URBN	Residential	564	3.078939	90.63	90.63	0.9019
URLD	Residential Low Density	1190	6.496342	86.67	88.64	0.8788
FRSD	Forest deciduous	1824	9.957419	98.51	100.00	1.0000
HAY	Forest mixed	1732	9.455181	94.03	94.03	0.9342
		Total area = 18,318	Total area = 100	Overall classification Accuracy = 96.81%		Overall K^= 0.9481

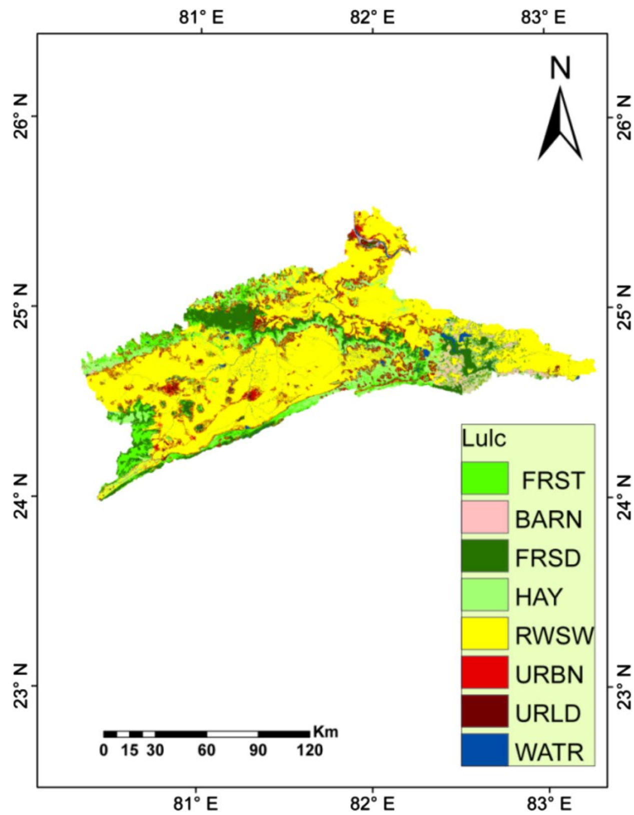

Fig. 2 Land use/land cover map of Tons River Basin

SUFI-2 algorithm

In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables, conceptual model, parameters, and measured data (Abbaspour 2015). The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling disallowing 5% of the very bad simulations (Abbaspour et al. 2007; McKay 1988). The strength of model calibration and uncertainty is determined by the r-factor and p-factor (Abbaspour et al. 2015; Arnold et al. 2012). Further, the degree to which all uncertainties are accounted is quantified by p-factor and its value varies from 0 to 1. The p-factor shows the percentage of measured data covered in 95% range of uncertainty (95PPU) and accounted all the uncertainties associated with the SWAT (Singh et al. 2013). The p-factor value 1 means the highest value, that is, 100% bracketing of the measured data and low value represents high uncertainties in the output (Setegn et al. 2009). The r-factor (Yang et al. 2008) (average thickness of the 95ppu band divided by the standard deviation of the measured data) describes the quality of the calibration and if its value be near zero then coincides with the measured data. The low value of r-factor is reported to be desirable for less uncertainty (Abbaspour et al. 2004, 2009) and approaching to 1 shows high uncertainty. It needs a balance between the two (p and r-factor) because larger p-factor can be achieved only at higher r-factor. When acceptable values of r and p-factors are reached, then the parameter uncertainties are in the calibrated parameter ranges. SUFI-2 allows usage of different objective functions such as Coefficient of Determination (R^2) (Krause et al. 2005), NSE (Nash–Sutcliff efficiency) (Nash and Sutcliffe 1970). Readers can found detailed information of SUFI-2 (in indicative literature: Abbaspour et al. 2004; Yang et al. 2008).

Performance indices

The p-factor, r-factor, R^2, NSE and PBIAS are five parameters that are used to evaluate the performance of model results. NSE is a normalized dimensionless statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Nash and Sutcliffe 1970) and its value varies from $-\infty$ to 1, with a high value indicating an accurate model.

NSE is calculated using the following define by equations no. 2:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_m - Q_s)_i^{2}}{\sum_{i=1}^{n} (Q_{m,i} - \overline{Q}_m)^{2}} \tag{2}$$

where, Q_m is mean of observed discharges, and Q_s is simulated discharge and n is the total number of observations.

The degree of collinearity between simulated and measured streamflow can be obtained using the coefficient of

Table 3 SWAT soil classes and soil texture

S. no	SWAT class	Texture	Area(Km^2)	Percentage (%)
1	3681 (Be80-2a-3681)	LOAM	35	0.189815
2	3772 (Lc5-1a-3772)	SANDY_CLAY_LOAM	155	0.84061
3	3780 (Lc75-1b-3780)	SANDY_CLAY_LOAM	11,120	60.30696
4	3785 (Lf10-1bc-3785)	SANDY_LOAM	428	2.321167
5	3812 (Lo51-2a-3812)	LOAM	5624	30.50057
6	3859 (Vc21-3a-3859)	CLAY	1077	5.840881

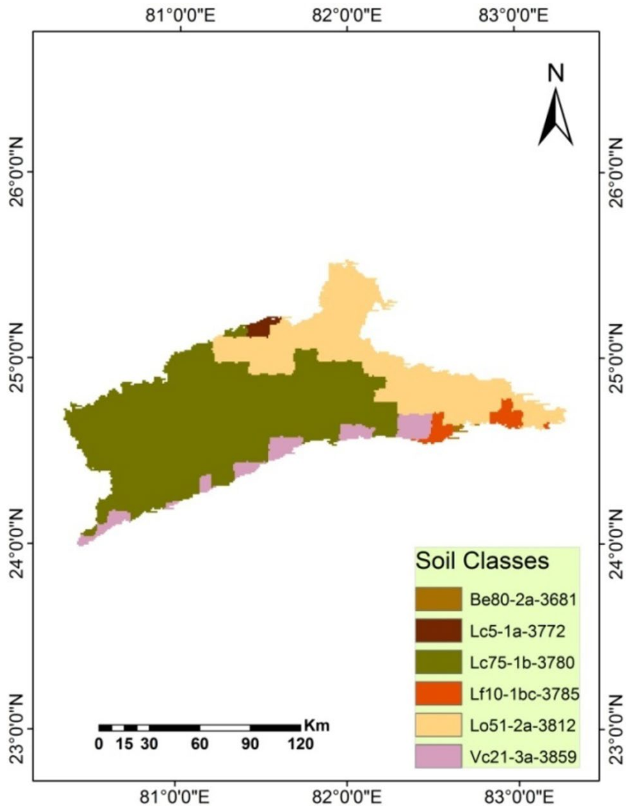

Fig. 3 Soil map of Tons River Basin

determination (R^2) and the range of R^2 is from 0 to 1, with a higher value meaning better performance. It can be calculated as following (Eq. 3):

$$R^2 = \frac{\left[\sum_i (Q_{m,i} - \overline{Q}_m)(Q_{s,i} - \overline{Q}_s)\right]^2}{\sum_i (Q_{m,i} - \overline{Q_m})^2 \sum_i (Q_{s,i} - \overline{Q_s})^2} \quad (3)$$

PBIAS (Percent bias) measures the average tendency of the simulated data to be larger or smaller than observed counterparts (Gupta et al. 1999). PBIAS values with small magnitude are preferred. It can be calculated as following (Eq. 4):

$$PBIAS = 100 * \frac{\sum_{i=1}^{n} (Q_m - Q_s)_i}{\sum_{i=1}^{n} Q_{m,i}} \quad (4)$$

where, Q is a variable (e.g. discharge), and m and s stand for measured and simulated, respectively. The optimum value of PBIAS is zero, where low magnitude values indicate better simulations. Positive values indicate model underestimation and negative values indicate model over estimation (Gupta et al. 1999).

RMSE-observations standard deviation ratio (RSR) is the ratio of the root mean square error (RMSE) and standard deviation of measured data. RSR varies from the optimal value of 0 to ∞ (Moriasi et al. 2015), where zero indicates zero RMSE or residual variation and therefore perfect model simulation, to a large positive value. The lower RSR shows the lower the RMSE and the better the model simulation performance (Moriasi et al. 2007). It can be calculated as following (Eq. 5):

$$RSR = \frac{\sqrt{\sum_{i=1}^{n} (Q_m - Q_s)_i^2}}{\sqrt{\sum_{i=1}^{n} (Q_{m,i} - \overline{Q_{m,i}})^2}} \quad (5)$$

Results

Sensitivity analysis (SA)

In the early stage of calibration global SA (Abbaspour et al. 2007) for 19 parameters (CN2, ALPHA_BF, GWQMN, ESCO, CH_K2, CH_N2, REVAPMN, SOL_AWC, HRU_SLP, SOL_K, SOL_BD, SLSUBBSN, GW_REVAP, EPCO, GW_DELAY, SFTMP, ALPHA_BNK, SURLAG and OV_N) was conducted at the monthly time-step using Latin hypercube sampling (McKay et al. 1979; Helton et al. 2003). The first step in calibration process is to adjust the input parameter values for closely matching the simulated results with the observed variables (Zeckoski et al. 2015) and to find out the most sensitive parameters affecting more a watershed or subwatershed than other parameter. So SA is to determine the change in model output with respect to changes in model inputs following the SWAT-CUP documentation (Neitsch et al. 2005; Arnold et al. 2012). SA was performed with 1000 times run and the results were examined. A t-stat and p-value (Abbaspour 2015) is used to measure the sensitivity and relative significance of each parameter. The parameters which have larger value of t-stat and smaller value of p are most sensitive parameters. The most sensitive parameter here is ALPHA_BF followed by SOL_K, SFTMP, and SLSUBBSN.hru. Ranges of parameter space were once again adjusted and ready for the next calibration and UA. The input parameters included along maximum and minimum value, fitted value, t-stat and p-values, rank of sensitivity and description are listed in Table 4.

Where the variation method used in Table 4 is as can be explained:

r = means the existing parameter value is multiplied by (1 + a given value).

Table 4 Sensitive SWAT parameters included in the calibration, t-Stat and p–value and new max, min value

Code	Description	Rank	Variation	t-Stat	p-value	Fitted value	New minimum	New maximum
V__CN2.mgt	Curve number II	13	v	−0.566	0.570	79.774506	79.422096	79.809998
V__ALPHA_BF.gw	Base flow alpha factor	1	v	−10.56	0.000	−0.593223	−0.929700	0.035800
V__GW_DELAY.gw	Groundwater delay	11	v	1.035	0.300	269.110992	81.550003	476.0000
V__GWQMN.gw	Threshold depth ….. occur	15	v	0.244	0.8068	1.319160	−0.007300	1.520000
V__ALPHA_BNK.rte	Baseflow …..storage (days)	12	v	0.639	0.522	0.953675	0.621000	0.971000
V__ESCO.hru	Soil evaporation compensation factor	16	v	−0.181	0.855	0.963592	0.934100	1.045600
V__CH_K2.rte	Effective … alluvium(mm/hr)	9	v	−1.476	0.140	18.297501	18.000000	103.0000
V__EPCO.hru	Plant uptake compensation factor	6	v	−1.565	0.117	−0.098896	−0.815000	0.137900
R__HRU_SLP.hru	Average slope steepness (m/m)	14	r	−0.446	0.655	0.186418	0.107900	0.212800
V__CH_N2.rte	Manning's n value for the main channel	18	v	−0.09	0.93	0.006952	−0.088000	0.088000
V__SFTMP.bsn	Snowfall temperature	3	v	2.192	0.028	0.362158	−2.680000	0.876000
V__OV_N.hru	Manning's n value for overland flow	10	v	−1.308	0.190	−0.053326	−0.053326	−0.038900
R__SLSUBBSN.hru	Average slope length (m)	4	r	2.174	0.029	0.192100	0.130000	0.250000
V__GW_REVAP.gw	Groundwater revap coefficient	7	v	−1.509	0.131	0.411217	0.156300	0.420600
R__SOL_K (...).sol	Saturated …of first (mm/hr)	2	r	2.241	0.025	0.284360	0.137700	0.987900
V__REVAPMN.gw	Threshold …. occur (mm H2O)	19	v	0.027	0.977	2.148250	1.524000	6.064000
R__SOL_BD (...).sol	Moist bulk ….. (Mg/m3)	8	r	−1.481	0.138	0.104658	0.054300	0.695800
R_SOL_AWC (...).sol	Available…. layer (mm/mm)	5	r	1.606	0.108	−0.028572	−0.145700	0.145300
V__SURLAG.bsn	Surface runoff lag coefficient (day)	17	v	0.182	0.855	0.198545	0.190000	0.200000

v = means the existing parameter value is to be replaced by the given value, and

a = means the given value is added to the existing parameter value.

Calibration and uncertainty analysis (UA)

Calibration and UA (Arnold 2001; Abbaspour et al. 2004, 2005) is an effort to better parameterize a model for a given set of local conditions, thereby minimize the prediction uncertainty. Model calibration is performed by carefully selecting values of model input parameters (within their respective uncertainty ranges). The simulated and observed discharge was compared at Meja gauge station (outlet) during calibration period 1982–2000. The performance indices (Moriasi et al. 2015) during the calibration period such as are listed in Table 5. Dotty plot (Fig. 4) is the plot of parameters versus objective function; indicating distribution of the sampling points which explain the parameter sensitivity (Abbaspour 2015). It has depicted the result of model run with NSE as an objective function during calibration. In this study the min value of objective function (threshold for the behavioral solutions) is 0.5.

The r-factor is 0.76 whereas p-factor (0.54) was obtained during calibration respectively. Figure 5 described the observed and simulated pattern with the high and low peak of precipitation during calibration period. The strength of calibration/UA as explained by r-factor (95ppu band) is shown in Fig. 6 by shaded region. Moriasi et al. (2007) recommended the general performance of objective functions on monthly time step calibration are satisfactory as if NSE > 0.50 and RSR ≤ 0.70, and if PBIAS ± 25% for streamflow, PBIAS ± 55% for sediment, and PBIAS ± 70% for N and P. Van Liew et al. (2003) shows the value of R^2 should be greater than 0.5. Nash and Sutcliffe (1970) described as NSE value greater than 0.75 (good simulation) and for satisfactory (greater than 0.36). The NSE and R^2 values were observed as 0.73 and 0.74, respectively. The PBIAS value is −3.55 while the RSR is 0.52 during calibration of model which indicate good model performance

Table 5 Summary statistics of calibration and uncertainty analysis

	Objective function values during calibration					
Method	p- factor	r- factor	R^2	NSE	RSR	PBIAS
Sufi-2	0.54	0.76	0.74	0.73	0.52	−3.55

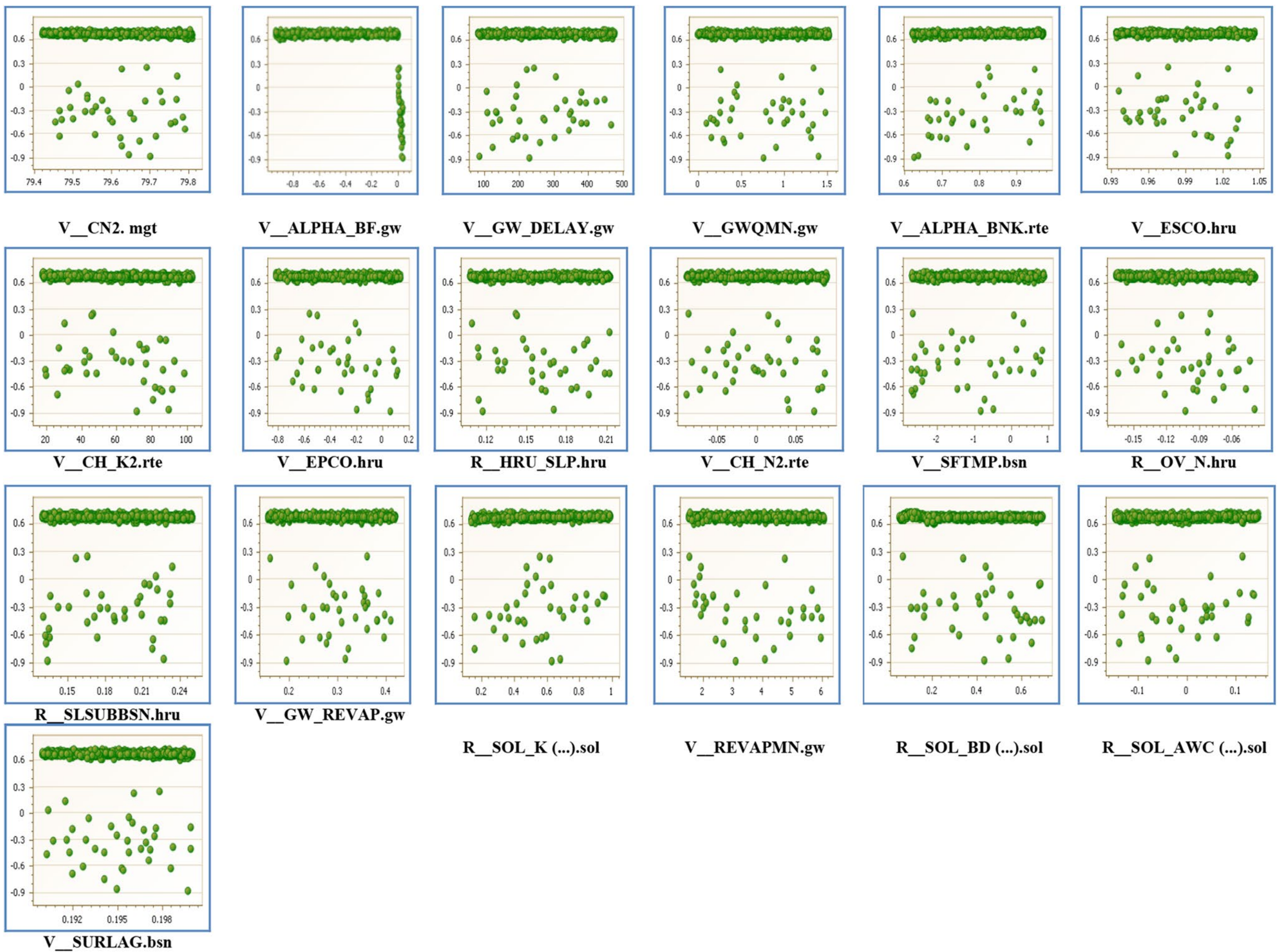

Fig. 4 Dotty plots with objective function of NS coefficient against each aggregate SWAT parameter

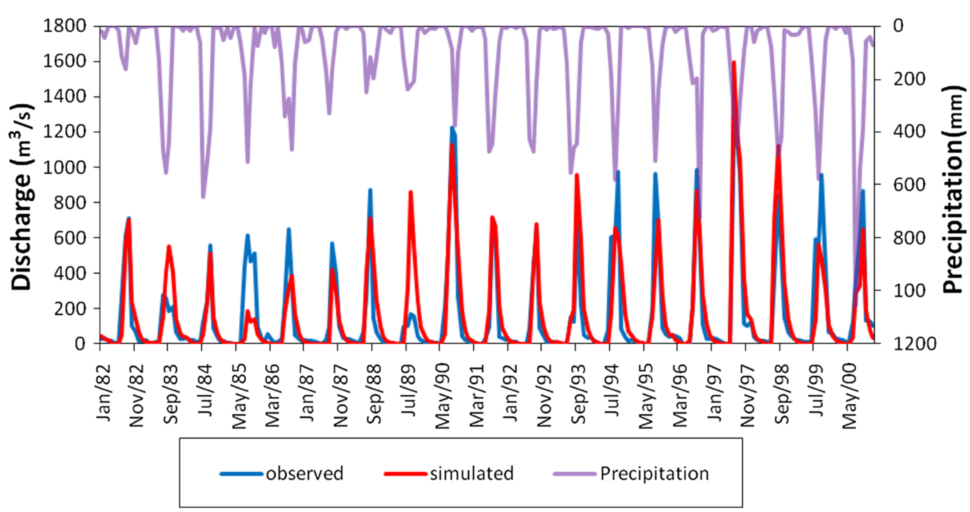

Fig. 5 Observed and simulated discharge and precipitation during calibration

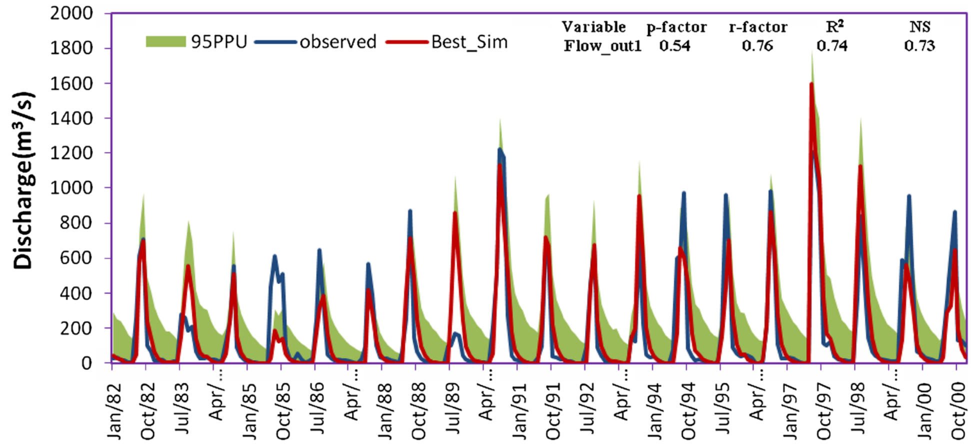

Fig. 6 95ppu plot and observed streamflow during calibration

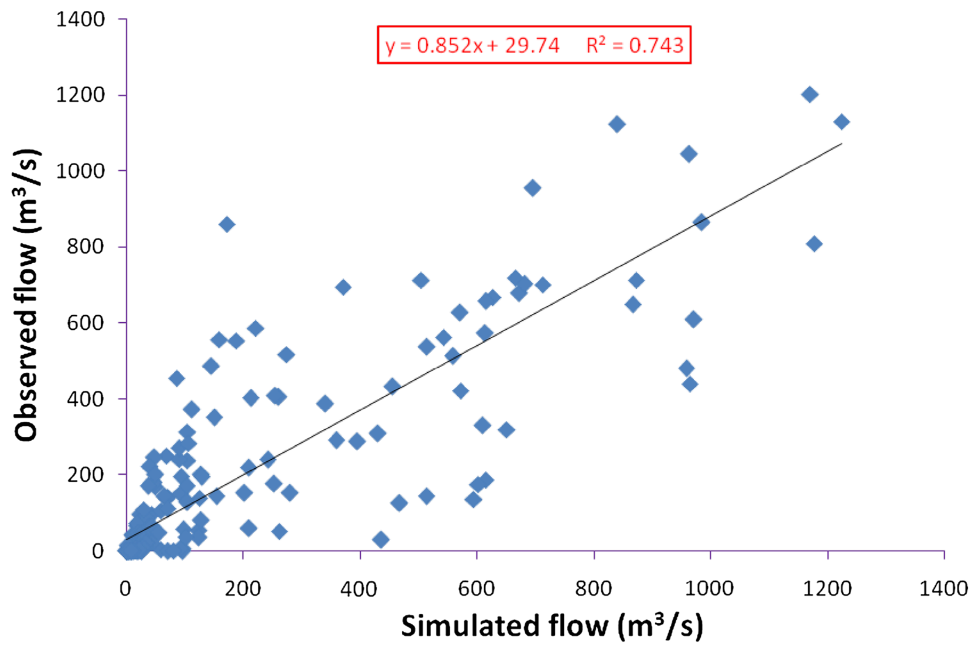

Fig. 7 Scatter plot of the observed vs. simulated flow (calibration)

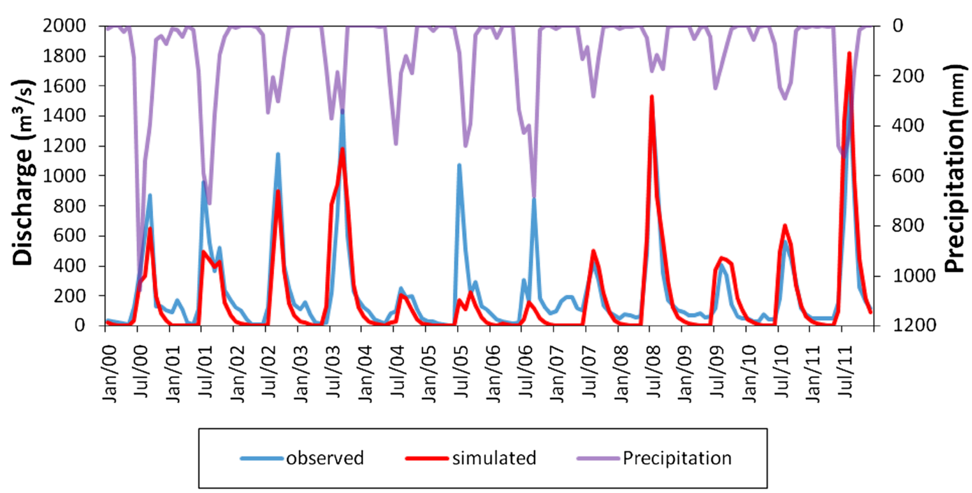

Fig. 8 Observed and simulated discharge, precipitation during validation

result (Moriasi et al. 2007). The scatter plot (Fig. 7) shows relationship between observed and simulated variables with good correlation (0.743).

Model validation

A calibrated model can be shown capable by its validation using same parameters used in calibration (Zheng et al. 2012). Model validation was performed using same algorithm as in calibration with 1000 times run for a period of 11 years (2001–2011). In validation year of 2000, 2001 and 2006 were a fairly wet year, with a total annual average rainfall greater than 600 mm. This also resulted in a high flow out at the basin outlet. Graphically, the model reproduces well the monthly flows (Figs. 8, 9). The model performance for the validation period is presented in Table 6. The value of r-factor (0.56) and p-factor (0.68) was obtained in validation process. The PBIAS value is 18.55 while the RSR is 0.56 during validation of model. The scatter plot (Fig. 10) of observed versus simulated showing R^2 (0.749) which is almost showing same R^2 as in 95PPU during validation.

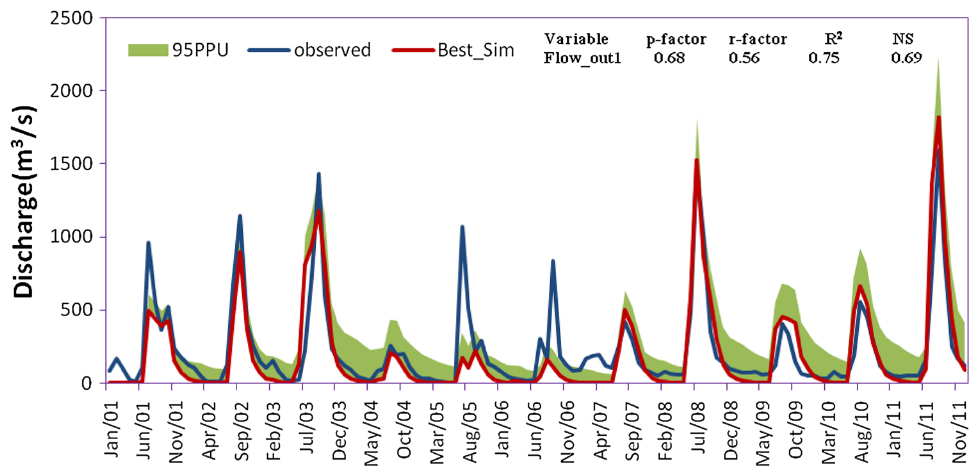

Fig. 9 95ppu plot and observed streamflow during validation

Table 6 Summary statistics of validation and uncertainty analysis

Objective function values during validation						
Method	p- factor	r- factor	R^2	NSE	RSR	PBIAS
Sufi-2	0.68	0.56	0.75	0.69	0.56	18.55

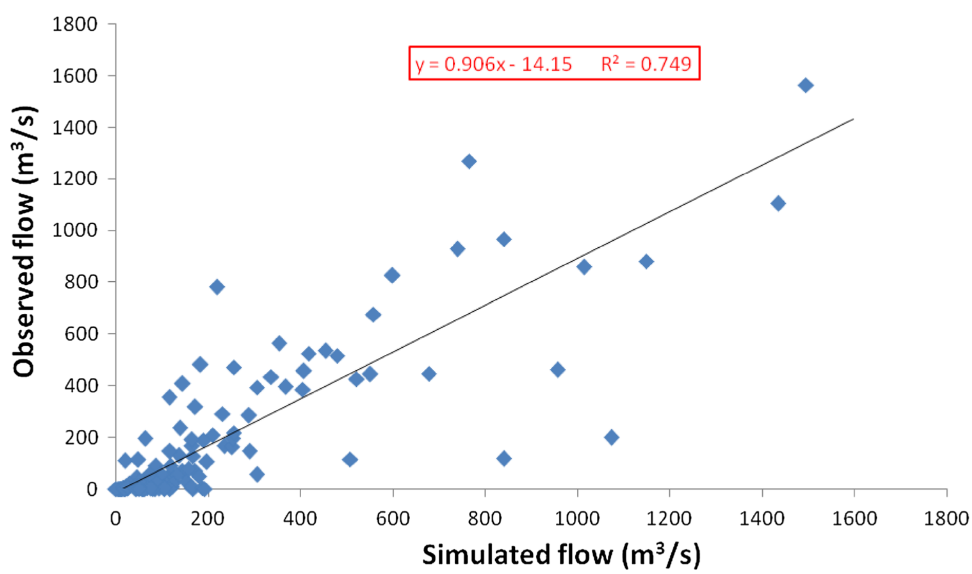

Fig. 10 Scatter plot of observed vs. simulated flow (validation)

Discussion

The main objective of the work was to calibrate and validate the SWAT model in an agricultural dominated watershed. The efficiency of model can be evaluated through SA, model calibration and validation. SA depends on the choice of parameters used which represents the details of the parameters being applied for SA in the early stage of calibration in SWAT-CUP using the default lower and upper limits. There are global sensitivity method (allowing all the parameters values to change) and one-at-a-time method (changing values one at a time). Since One-at-a-time method checks a single parameter so information about other constant parameters are unknown (Abbaspour et al. 2007). To avoid this global SA method was performed. Arnold et al. (2012) categorize the parameters by process as for surface runoff, baseflow, sediment and for nutrient and pesticide using the report of input parameters in SWAT model calibration for 64 selected watershed studies. CN2, AWC, ESCO, EPCO, SURLAG, OV_N are the parameters for the surface runoff while GW_ALPHA, GW_REVAP, GW_DELAP, GW_QWN, REVAPMN, RCHARG_DP are for the sediment calibration. Yusuf et al. (2016) calibrate the SWAT for the streamflow prediction in a tropical watershed and find the CN2 followed by AWC and ESCO are the most sensitive parameters among the sixteen parameters. Narsimlu et al. (2015) performed the global SA and found the ALPHA_BNK, ESCO followed by CH_K2 and CN2 as most sensitive parameters in a tropical agricultural watershed. Singh et al. (2013) calibrated SWAT for Tungabhadra River and found CH_K2, SOL_K, CN2, ALPHA_BF, ALPHA_BNK as most sensitive parameters. Mengistu et al. (2012) indicated the CN2 as a the most sensitivity parameter in addition Sol-AWC, ESCO, Sol-K in Eastern Nile River basin and concluded due to the fact that the curve number depends on several factors including soil types, soil textures, soil permeability and land use properties. In our study area among 19 sensitive parameters the SA shows that the parameters as ALPHA_BF, SOL_K, SFTMP, SLSUBBSN, and SOL_AWC are the most sensitive parameters and are in decreasing order of sensitivity rank. A limitation with SWAT is that it cannot rigorously simulate groundwater flow (Rostamian et al. 2008) and groundwater recharge is important in these regions and therefore the parameter ALPHA_BF (base flow factor) is the most sensitive parameters in this area. Since baseflow is not better simulated, the p and r-factor are not in desired limit (larger p and smaller r-factor) for a good calibration result. The parameters like baseflow and other related to groundwater-river interaction also influence the flow process. This can also be check by the calibration results showing a large number of un-bracketed data fall in the baseflow and hence the observation is not coming under 95 percent boundary in at the base flow. There are observed peak values in year 1985 (calibration) are not falling under 95ppu and same condition in 2001, 2005, and 2006 (validation), because of these extreme events cannot be simulated by SWAT and under-predicts the largest flow events in TRB (Tolson and Shoemaker 2007). To parameterize a model better and to minimize the uncertainty range a careful calibration and prediction UA are required in practical water resources (Duan et al. 1992; Van Griensven et al. 2008). The goodness of fit was assessed through the use of the R^2 and the NSE between the observed and the final simulated values (Narsimlu et al. 2015) and the closeness between these two during calibration indicates a good agreement which were verified by higher values of R^2 (0.74) and NSE (0.73) (Setegn et al. 2009). Since NSE are insensitive to systematic errors and yield good model performance even if low values are poorly fitted (Pfannerstill et al. 2014) and the major drawback with the R^2 is that model give good R^2 value when a model is systematically over or underestimate and even if all prediction is wrong (Krause et al. 2005). Moriasi et al. (2015) explained about the PMs and recommended not to use a single PMs to determine model performance but to use statistical PMs along with graphical PMs due to drawbacks associated with PMs. For the robust model performance statistical PMs such as PBIAS and RSR are also used with graphical analysis (Biondi et al. 2012). PBIAS has the ability to clearly indicate poor model performance (Gupta et al.1999) and RSR incorporates the benefits of error index statistics and in both cases when RSR is zero or has lower value, there are zero or lower the RMSE, and the better the model simulation performance (Moriasi et al. 2007). Graphical performance measures such as time series and scatter plots, cumulative charts and contour maps play a supplementary role where model in not performing well (Moriasi et al. 2015). Figure 7 shows the scatter plot (Palosuo et al. 2011) for the calibration period with a R^2 value (0.743) which is indicating good collinearity between observed and simulated flow and has almost same value as model predicted (Santhi et al. 2001; Van Liew et al. 2003).

Here the result of calibration shows that low value of p-factor (0.54) which indicates the low percentage (54%) of bracketing of measured data in 95ppu plot (Fig. 6) and range of uncertainty in the output. The thickness of uncertainty band can be seen in 95ppu by the r-factor (0.76). The low p and large r-factor indicate the uncertainty in simulation caused by error in the rainfall and temperature input (Setegn et al. 2009). Calibration result can also be justified by seeing the trend of simulated and observed flow rates in 95ppu plot (Fig. 6) which are usually following the same trend, with a slight underestimation of the simulated values compared to observed data. The r-factor during calibration is relatively large but it is less than one means good result.

Since most of part of TRB lies in mountainous regions and in such cases input uncertainty could be very large (Abbaspour et al. 2007). Yang et al. (2008) described the conceptual model uncertainty may be due to the processes that are actually occurring in the watershed but they have not included in the model such as the natural process (volcanoes, landslides, etc.) and landslides are common processes happening in TRB. Some other type conceptual uncertainty may be due to processes that are included in SWAT but are unaccountable to user as we have not accounted reservoirs due to non availability of reservoir data which may cause the uncertainty in output. The uncertainty in model may be due to the soil erosion which is not considered in model that affects the structure, infiltration capacity and other properties of the soil (Setegn et al. 2009). During validation there is an increment of 8% in p-factor from 0.54 to 0.68 and r-factor varies from 0.76 to 0.56 which shows good validation (high p and low r-factor value) result and lower uncertainty range. Figure 10 shows the best match ($R^2 = 0.749$) of observed and simulated value is supporting the validation.

Conclusion

The uncertainty, and its quantification overcomes as a challenging task in the SWAT model predictions that depends on the uncertainty technique that has been used and the way it is implemented. Therefore hydrologic model (SWAT) needs some efficient and effective algorithms. To check the uncertainty in the prediction of hydrological variables such as streamflow needs rigorous calibration. The results indicate a few parameters ALPHA_BF, followed by SOL_K, SFTMP, SLSUBBSN, and SOL_AWC are most sensitive and have a great impact on the stream flow. The evaluation of SWAT model for discharge is verified by PMs satisfies the PEC of model provided by Moriasi et al. (2015). The experimental watershed demonstrates that the SUFI-2 produces reasonable outcomes for calibration, UA, and validation of the SWAT model. The minimum differences between observed and SWAT simulated flow is shown by SUFI-2 algorithms which needs the adjustment of the parameter ranges for good results and more additional iterations. The monthly simulation for the Meja station may be satisfactory during the calibration period while during validation the SWAT model exhibit small uncertainties and good validation result.

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