Hydrological stream flow modelling on Tungabhadra catchment: parameterization and uncertainty analysis using SWAT CUP

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Adequate stream flow measurement is vital for agricultural watershed management and its effect on many aspects of water balance parameters. For this reason soil water assessment tool (SWAT) has been applied for the measurement of the stream flow to the Tungabhadra catchment in India. This article describes a methodology for calibration and parameter uncertainty analysis for distributed model based on generalized likelihood measures. The sequential uncertainty domain parameter fitting algorithm (SUFI-2) and generalized likelihood uncertainty equation (GLUE) of SWAT CUP (calibration and uncertainty program) work with multiple sets of parameter values and allow to user within the slight limitation of the model structure in boundary conditions and field observations. Performance of the SUFI-2 and GLUE techniques was evaluated using five objective functions, namely *P*-factor, *R*-factor, coefficient of determination R^2, Nash–Sutcliffe (NS) and coefficient of determination divided by coefficient of regression bR^2 calculated on daily and monthly time-steps. The obtained results showed that the observed and simulated discharge were not significantly different at the 95% level of confidence (95PPU). The results show excellent correlation during monthly calibration time-steps, whereas daily calibration exhibits relatively good agreement between the observed and simulated flows.

Keywords: Agricultural watershed, calibration, parameterization, stream flow.

A WATERSHED is a hydrologic unit which receives water as an end-product of the interaction of atmosphere, land surface and ocean systems. Stream flow is the main hydrological factor which influences the hydrological characteristics in many ways and shows their importance in balanced agricultural watersheds. Stream flow is the volume of water passing a fixed point over a unit of time and is usually expressed in cubic metres per second (cumecs). Stream flow reflects the amount of water moving off the watershed and into the channel and the amount being removed from the stream. Flow can be affected by a number of factors and can vary rapidly as those factors change. Stream flow is affected by both natural and human factors and can respond rapidly to changes in flow parameters. Evaporation and water use by plants significantly affect stream flow. Vegetation has the largest impact on flow during summer months when temperatures are high and streamside vegetation uses the most water. The flow is also being influenced by subsurface water flow which responds to the same factors, but at a delayed or slower rate. Seasonal variations in stream flow, coupled with increased and competing demands for water by a growing population, place considerable pressure upon efficient management of available water resources. This is especially true for the management of reservoir storage and water release during and at the end of the summer season when water demand is highest and stream flow supply is low. Adequate steam flow allows for erosion, transport and deposition of sediment or stream-bed load. Fast-moving streams will keep sediments suspended longer in the water column[1]. Therefore, the prediction and assessment of stream flow are essential for agricultural watershed management as well as sustainable development in the sector of water resources. The Tungabhadra river catchment as a whole receives good amount of rainfall throughout the year and has great significance in terms of ecological and economic diversity point of view in the western part of India, flowing through the Western Ghats, Karnataka. Apart from the hilly topography, faulty cultivation practices and deforestation within the basin result in huge loss of productive soil and water as run-off. There is an urgent need for developing an integrated watershed management plan based on hydrological simulation studies using suitable modelling approach. Use of mathematical models for hydrologic evaluation of watersheds is the current trend and extraction of the watershed using parameter-based hydrological models in high-speed computers are the aiding tools and techniques for it. Therefore, the current study was undertaken with the application of soil water assessment tool (SWAT) and SWAT CUP (calibration and uncertainty

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program) in integration with remote sensing and GIS environment to estimate the surface run-off trend over a long period of time. Calibration of watershed model is a challenging task because of input data uncertainties, model structure and algorithms, parameterization and output ambiguity. Sources of model structural uncertainty include processes not accounted for in the model such as unknown activities in the watershed and inaccuracy due to over-simplification of the processes considered in the model[2]. Input uncertainty might be related to inaccurate or spatially interpolated measurements of model input parameters such as elevation data, land-use data, rainfall data, temperature and other data.

Several methodologies and techniques have been developed to estimate the parameters and assess prediction errors in the hydrological modelling. An algorithm developed by Abbaspour *et al.*[3], the Bayesian uncertainty development algorithm (BUDA), can utilize all of the above techniques to achieve a higher reduction in uncertainty in environmental projects. A common problem with most of the inverse methods is stability and convergence[4]. The main objective of this study using SWAT CUP is to describe and demonstrate the use of different approaches, the sequential uncertainty domain parameter fitting (SUFI-2), generalized likelihood uncertainty equation (GLUE) for stream-flow measurement and best parameter estimation for stabilizing the correlation between the simulated parameters and observed parameters. The procedure is general, forward, sequential, iterative and Bayesian in nature. The method begins with prior uncertainty domains on the input parameters, usually invoking relatively large uncertainties and conditions in the model parameters on the measured data through an objective function. Finally, posterior uncertainty domains are obtained with much reduced uncertainty.

Previously, Tripathi *et al.*[5] had applied the SWAT model for the Nagwan watershed (92.46 km^2) with the objective of identifying and prioritizing critical sub-watersheds to develop an effective management plan. Daily rainfall, run-off and sediment yield data of 7 years (1992–1998) were used for the study. Singh and Imtiyaz[6] used SWAT, a river basin or watershed scale model, to predict the monthly stream flow of the Nagwa watershed in eastern India. The model was calibrated and validated based on measured stream flow and quantification of the uncertainty in SWAT model output was assessed using a sequential uncertainty fitting algorithm (SUFI-2). Setegn *et al.*[7] applied SWAT2005 to the Lake Tana basin for modelling of the hydrological water balance. The main objective of this study was to test the performance and feasibility of the SWAT model for prediction of stream flow in the Lake Tana basin. The model was calibrated and validated on four tributaries of Lake Tana; Gumera, GilgelAbay, Megech and Ribb rivers using SUFI-2, GLUE and ParaSol (Parameter Solution) algorithms. The sensitivity analysis of the model to sub-basin delineation and hydrologic response unit (HRU) definition thresholds showed that the flow is more sensitive to the HRU definition thresholds than sub-basin discretization effect. Yang *et al.*[2] determined the differences and similarities between uncertainty techniques and compared five uncertainty analysis procedures as GLUE, ParaSol, SUFI-2, a Bayesian framework implemented using Markov chain Monte Carlo (MCMC) and Importance Sampling (IS) techniques for a SWAT application to the Chaohe basin in China. The application of SWAT model and its parameterization using SWAT CUP (SUFI-2 and GLUE) under GIS platform provides advance option in hydrological modelling and create control environment between large amount of data sets during parameter sensitivity analysis. The long time-series real data of rainfall, minimum and maximum temperature and discharge were available at the Haralahalli gauging station and these were applied to simulate the model parameters and calibrate stream-flow correlation between simulated and observed data.

Study area and data sources

The study area is a part of the Tungabhadra sub-basin of the Krishna river basin in India. The current study area lies between long. 74°00′00″–76°30′00″E and lat. 13°00′00″–15°30′00″N, covering the catchment area around 14429.36 km^2 up to the Haralahalli gauge station, which is at the outlet of the catchment (Figure 1). The Tungabhadra derives its name from two tributaries, viz. Tunga and Bhadra, which rise in the Varaha Parvata hill in the Western Ghats, Chickmagalur district, Karnataka. After running widely different courses, they unite at the sacred village Kudali, 13 km northeast of Shimoga to form the River Tungabhadra which is 640 km (400 mile) in length and joins River Krishna at Sangameshwaram near Kurnool, Andhra Pradesh. It is a perennial river influenced by the SW monsoon and however, it decreases volume (few cumecs) in the summer month. Most parts of the Tungabhadra valley receive on an average 560 mm rainfall in a year. The monsoon used to be rarely average, exposing the valley in the Peninsula to looming famine and drought. The elevation area of the catchment varies from 500 to 1900 m, which represent enormous topographical variations over the study area.

Methodology

SWAT modelset-up

The SWAT is one of the most recent models developed jointly by the United States Department of Agriculture–Agricultural Research Services (USDA–ARS) and Agricultural Experiment Station in Temple, Texas[8–10]. It is a physically based, continuous-time, long-term simulation,

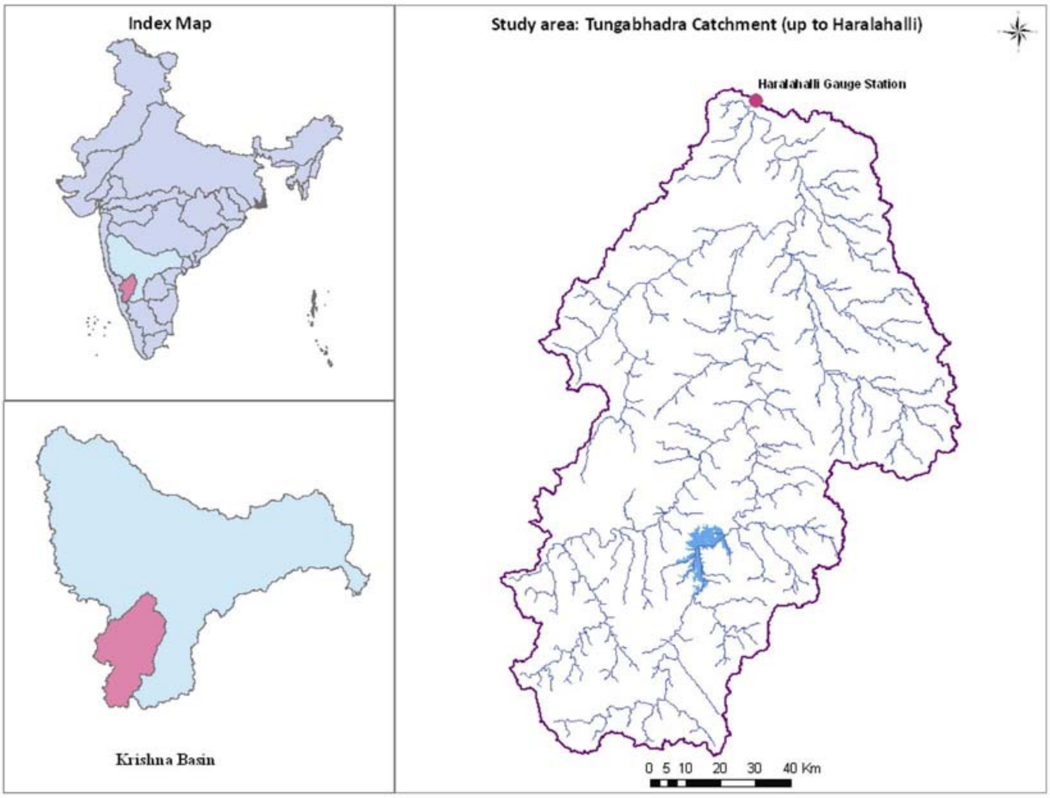

Figure 1. Index map of the study area.

lumped parameter, deterministic and originated from agricultural models. The computational components of SWAT can be placed into eight major divisions: hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides and agricultural management. The SWAT model uses physically based inputs such as weather variables, soil properties, topography, vegetation and land-management practices occurring in the catchment. The physical processes associated with water flow, sediment transport, crop growth, nutrient cycling, etc. are directly modelled by SWAT[11–16]. The hydrologic cycle as simulated by SWAT is based on the water balance equation[8].

$$SW_t = SW_o + \sum_{i=1}^{n}(R_{day} + Q_{sur} + E_a + W_{seep} + Q_{gw}), \tag{1}$$

where SW_t is the final soil water content (mm H_2O), SW_o the initial soil water content (mm H_2O), t time in days, R_{day} amount of precipitation on day i (mm H_2O), Q_{surf} the amount of surface run-off on day i (mm H_2O), E_a the amount of evapotranspiration on day i (mm H_2O), W_{seep} the amount of percolation and bypass exiting the soil profile bottom on day i (mm H_2O) and Q_{gw} is the amount of return flow on day i (mm H_2O).

Surface run-off is computed using a modification of the SCS curve number (USDA Soil Conservation Service 1972) or the Green and Ampt infiltration method[11]. Surface run-off volume predicted in SWAT using SCS curve number method is given below

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)}, \qquad R > 0.2S, \tag{2}$$

where Q_{surf} is the accumulated run-off or rainfall excess (mm), R_{day} the rainfall depth for the day (mm) and S is retention parameter (mm).

Run-off will occur when $R_{day} > 0.2S$. The retention parameter varies spatially due to changes in soil, land use, management and slope and temporally due to changes in soil water content. The retention parameter is defined as

$$S = 25.4\left(\frac{1000}{\text{CN}} - 10\right), \tag{3}$$

where CN is the curve number for the day.

In SWAT, a basin is delineated into sub-basins, which are then further subdivided into HRUs. The HRUs consist of homogeneous land use and soil type (also, management characteristics) and based on two options in SWAT, they may either represent different parts of the sub-basin or sub-basin area with a dominant land use or soil type (also management characteristics). The major inputs, viz. digital elevation model (DEM), land-use/land-cover, soil

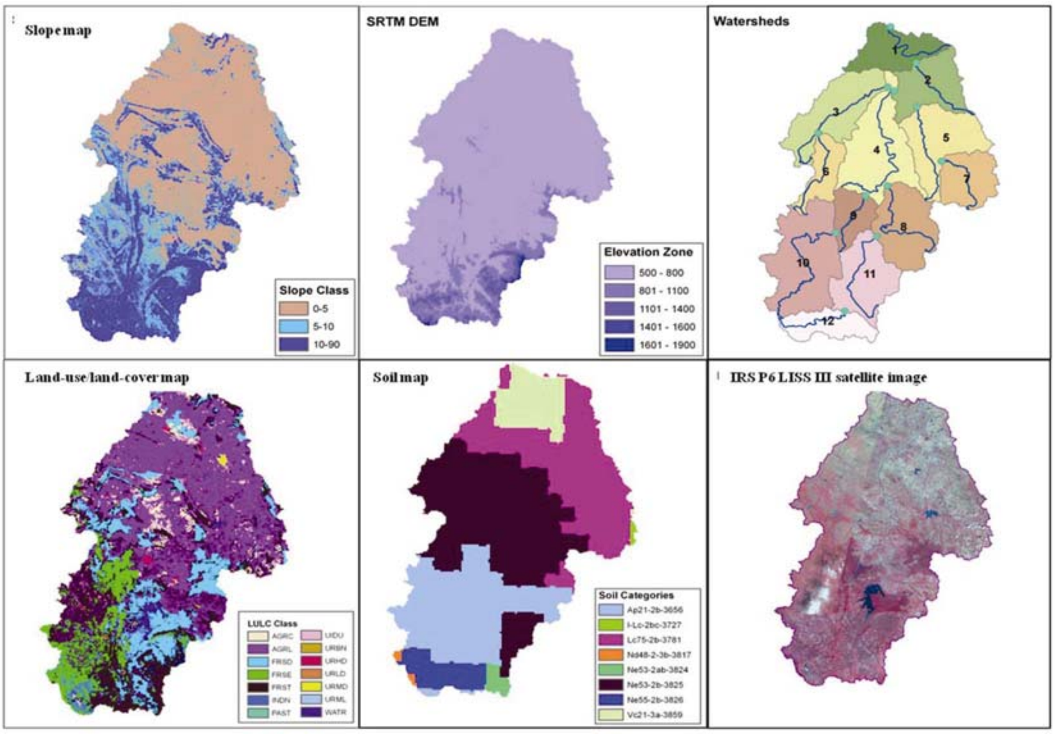

Figure 2. SWAT model inputs and delineated outputs.

Table 1. Characteristics of land-use, soil and slope in the Tungabhadra catchment

Land-use category	Class	Area (km^2)	Watershed area (%)
Agricultural land – close grown	AGRC	482.623	3.340
Agricultural land – generic	AGRL	6768.856	46.910
Forest – deciduous	FRSD	1944.461	13.180
Residential – high density	URHD	55.292	0.380
Water	WATR	453.548	3.140
Forest – mixed	FRST	3498.193	24.240
Forest – evergreen	FRSE	1114.983	7.330
Indian grass	INDN	111.406	0.770
Soil category	Class	Area (km^2)	Watershed area (%)
Chromic Luvisols	Lc75-2b-3781	3911.349	27.110
Chromic Vertisols	Vc21-3a-3859	1074.460	7.450
Eutric Nitosols	Ne53-2b-3825	4980.532	34.520
Plinthic Acrisols	Ap21-2b-3656	3647.771	25.280
Eutric Nitosols	Ne55-2b-3826	656.373	4.550
Eutric Nitosols	Ne53-2ab-3824	142.809	0.990
Dystric Nitosols	Lc75-2b-3781	16.067	0.110
Slope	Slope class (degree)	Area (km^2)	Watershed area (%)
1	0–5	9111.606	63.150
2	5–10	2125.837	14.730
3	10–90	3191.919	22.120

data and hydro-meteorological data like daily rainfall (mm), minimum and maximum daily temperature (°C) have been used for the initial SWAT model set-up (Figure 2). SRTM elevation data were obtained from the global land cover facility (GLCF) of the University of Maryland, USA[12]. The GLCF provides SRTM data in GRID format after a short processing at 3 arc sec/90 m can be downloaded for the whole world (srtm.csi.cgiar.org). The SRTM data were provided into a WGS84 datum and Lambert conformal conic projection system.

The DEM was used as an initial parameter for generating slope and drainage based on the pour point (generally known as outlet points). The other sub-basin parameters such as slope gradient, slope length of the terrain and stream network characteristics such as channel slope, channel length and channel width were derived from DEM processing in the SWAT model. Finally the Tungabhadra basin has been divided into 12 watersheds. The SWAT model requires different soil textural and physico-chemical properties such as soil texture, available water content, hydraulic conductivity, bulk density and organic carbon content for different layers of each soil type. The FAO–UNESCO global available soil data (1 : 500,000 scale) in vector format had been downloaded from the FAO GeoNetworkportal. Next we converted it into a grid format for SWAT model input parameters[13]. The soil parameters have been categorized according to SWAT model geodatabase. The main soil categories which fall in the Tungabhadra catchment, namely Chromic Luvisols, Chromic Vertisols, Eutric Nitosols, Plinthic Acrisols and Dystric Nitosols are shown in Table 1 (ref. 14). Land-use/land-cover is one of the most important factors that controls the main hydrological behaviour of the catchment and protects it from events such as soil erosion, run-off, evapotranspiration and sediment deposition. The land-use map of the Tungabhadra catchment area was generated using IRS P6 LISS III satellite imageries having 23 m spatial resolution. The LISS III images were obtained from the BHUWAN portal of Indian Space Research Organisation (ISRO). We have categorized the land-use map into 14 major classes using ERDAS Imagine image processing software and these classes have been reclassified according to SWAT model. The Tungabhadra catchment is mostly an agriculture-dominated area which covers about 50.25% of agricultural land of the total catchment area (Table 1). The SWAT model requires daily hydrometeorological data for simulation of the model. The weather-generator variables used in this study for driving the hydrological balance are daily rainfall, minimum and maximum air temperature for the period 1990–2002. These data were obtained from India Meteorological Department (IMD) published in 0.5° grid format and processed into SWAT model. The 13 years daily river discharge data have been used for calibration and parameterization into the model. The daily discharge data for 1990–2002 were obtained from the Haralahalli gauge site under the India-WRIS project, Regional Remote Sensing Centre West Jodhpur. The starting three years' data during 1990–1992 have been used as warming periods for initial model set-up and data during the years 1993–2002 have been analysed for stream-flow calibration.

We have used the ArcSWAT 9.0 version of SWAT model interface with ArcGIS 9.3.1 of ESRI product for processing the analysis. The main steps in the model set-up involved data preparation, sub-basin discretization, HRU definition and overlay, parameterization, sensitivity analysis and calibration. After importing the weather data, the next step was to set up a small number of additional input parameters for simulating the SWAT model. These inputs were management data, soil hydrochemical data, manning roughness coefficient for overland flow and stream water-quality parameters[15]. These input files were set up and edited according to the condition and purpose of the study. In the management data file, run-off curve numbers for Indian conditions as well as those prescribed in the SWAT user manual were adopted for different land-use classes based on the land-use type and hydrologic soil group (HSG). Finally, we have set-up the SWAT model to simulate the various hydrological components. The simulation part of the Tungabhadra catchment was completed using the ArcSWAT interface of SWAT model, whereas model calibration and sensitivity analysis have been done using SWAT CUP tool. Thirteen parameters were considered and tested for the model parameterization and sensitivity analysis. The model uncertainties have been tested and analysed using SUFI-2 and GLUE uncertainty analysis procedures.

SUFI-2 and GLUE procedure

In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables (e.g. rainfall), conceptual model, parameters and measured data. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the *P*-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). The goodness of calibration and prediction uncertainty is judged on the basis of closeness of the *P*-factor to 100% (i.e. all observations bracketed by the prediction uncertainty) and the *R*-factor to 1 (i.e. achievement of rather small uncertainty band). The goodness-of-fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. GLUE is an uncertainty analysis technique inspired by importance sampling and regional sensitivity analysis[16]. The procedure is simple and requires few assumptions when used in practical applications. GLUE assumes that, in the case of large over-parameterized models, there is no unique set of parameters, which optimizes goodness-of-fit criteria[17,18]. The number of iterations required to get the best parameter ranges in the simulation result.

In SWAT, the HRU is the smallest unit of spatial disaggregation. As a watershed is divided into HRUs based on elevation, soil, land use and distributed parameters such as hydraulic conductivity can potentially be defined for each HRU. An analyst is, hence, confronted with the difficult task of collecting or estimating a large number of input parameters, which are usually not available. An alternative approach for the estimation of distributed parameters is by calibrating a single global modification term that can scale the initial estimates by a multiplier, or an additive term. This leads to the proposed parameter identifiers. An important consideration for applying parameter identifiers is that the changes made to the parameters should have physical meaning and should reflect physical factors such as soil, land use, elevation, etc.

The parameters responsible for stream-flow assessment for the Tungabhadra catchment, viz. r_CN2.mgt (curve number), v__ALPHA_BF.gw (base flow alfa factor), v__GW_DELAY.gw (groundwater delay time), v__GWQMN.gw (threshold depth of water in shallow aquifer required for return flow), v__GW_REVAP.gw (groundwater 'revap' coefficient), v__ESCO.hru (soil evaporation compensation factor), v__CH_N2.rte (manning roughness for main channel), v__CH_K2.rte (effective hydraulic conductivity in main conductivity), v__ALPHA_BNK.rte (base flow alpha factor for bank storage), r__SOL_AWC.sol (soil available water capacity), r__SOL_K.sol (soil hydraulic conductivity) have been considered for model parameterization and calibration process. Five objective functions, viz. *P*-factor (ranges between 0% and 100%), *R*-factor (ranges between 0 and infinity), coefficient of determination R^2, Nash–Sutcliffe coefficient NS and bR^2, i.e. coefficient of determination multiplied by the coefficient of regression line have been selected to analyse model efficiency of stream-flow calibration for the Tungabhadra catchment. The goodness-of-fit of the model that can be quantified by the coefficient of determination (R^2) and Nash–Sutcliffe efficiency (NSE) between the observations and the final best simulations[16,19,20].

Results and discussion

Hydrological response units and their characteristics

The identification of critical source areas provides the most advantageous placement of best management and conservation practices. The Tungabhadra catchment has been divided into 12 sub-basins and 179 HRUs (Table 2). The HRUs of this catchment have been categorized into different classes mainly on the basis of landuse, soil and slope. These have been further divided into different classes based on the topography and elevation of the Tungabhadra catchment. Table 1 and Figure 2 clearly show that this is an agriculture-dominated area and it has mixed forest-type classes which contribute to the significant economic importance of the area. The slope of this catchment has been divided into three classes, viz. 0–5°, 5–10° and 10–90°. It is found that most of the catchment area has general smooth slope and it covers about 60–70% of the total catchment area but the rest of region especially near the river origin falls under steep slope category. This high-altitude area contributes to a significant amount of soil erosion as well as high run-off, especially during monsoon periods due to faulty management practices. Chromic luvisols and Eustric nitosols are the most dominating soil categories found in this catchment.

Parameters and sensitivity analysis using SUFI-2 and GLUE

The water balance components of the catchment have been calculated using water balance equation (eq. 1) of SWAT model and the computed results were analysed in the SWAT Check tool. The SWAT model initials parameters and water balance ratio results are shown in Table 2, which demonstrate the general hydrological properties of the catchment area. For the Tungabhadra catchment, we have analysed the relative sensitivity of the parameters during model calibration and ten parameters were found to be more sensitive according to the relative sensitivity values (Table 3). Table 4 shows the minimum and maximum ranges of the parameters fitted for the daily and monthly calibration in the SUFI-2 and GLUE uncertainty techniques. The global sensitivity of stream-flow parameters has been calculated using Latin hypercube regression systems. The parameters have given ranks for their sensitivity to the model calibration for both procedures (Table 5). The most sensitive parameters recorded after sensitivity analysis for monthly calibration in SUFI-2 and GLUE procedures are shown in Table 5. It has been

Table 2. Simulation details of SWAT model set-up

General details	
Simulation length (years)	10
Warm up (years)	3
Hydrological response units	179
Sub-basins	12
Precipitation method	Measured
Watershed area (km^2)	14,429
Hydrology (water balance ratio)	
Stream flow/precipitation	0.65
Base flow/total flow	0.44
Surface run-off/total flow	0.56
Percolation/precipitation	0.29
Deep recharge/precipitation	0.01
ET/precipitation	0.34
Hydrological parameters (all units in mm)	
Average curve number	81.7
ET and transpiration	487.8
Precipitation	1438.5
Surface run-off	527.09
Lateral flow	23.59
Return flow	384.38
Percolation to shallow aquifer	415.26
Recharge to deep aquifer	20.76
Revaporation from shallow aquifer	12.93

Table 3. Description of stream flow calibration parameters

Stream flow parameters selected for calibration	Description of parameters
r__CN2.mgt	Curve number
v__ALPHA_BF.gw	Base flow alfa factor
v__GW_DELAY.gw	Groundwater delay time
v__GWQMN.gw	Threshold depth of water in shallow aquifer required for return flow
v__GW_REVAP.gw	Groundwater 'revaporation' coefficient
v__ESCO.hru	Soil evaporation compensation factor
v__CH_N2.rte	Manning roughness for main channel
v__CH_K2.rte	Effective hydraulic conductivity
v__ALPHA_BNK.rte	Base flow alpha factor for bank storage
r__SOL_K.sol	Soil hydraulic conductivity

Table 4. Stream flow calibration parameter uncertainties

	On daily basis			
	SUFI-2		GLUE	
Parameter	Minimum value	Maximum value	Minimum value	Maximum value
r__CN2.mgt	–0.384	0.008	–0.2	0.2
v__ALPHA_BF.gw	0	0.658	–0.01	2
v__GW_DELAY.gw	200.287	450.313	200	450
v__GWQMN.gw	0.804	2.436	0	2
v__GW_REVAP.gw	0.09	0.274	0	0.2
v__ESCO.hru	0.878	1.038	0.8	1
v__CH_N2.rte	0.114	0.348	0	0.3
v__CH_K2.rte	–22.278	79.778	5	130
v__ALPHA_BNK.rte	–0.249	0.589	0	1
r_SOL_K.sol	–0.8	0.8	–0.6	0.8
	On monthly basis			
	SUFI-2		GLUE	
r__CN2.mgt	–0.2	0.2	–0.2	0.2
v__ALPHA_BF.gw	0	1	0	1
v__GW_DELAY.gw	30	450	30	450
v__GWQMN.gw	0	2	0	2
v__GW_REVAP.gw	0	0.2	0	0.2
v__ESCO.hru	0.8	1	0.8	1
v__CH_N2.rte	0	0.3	0	0.3
v__CH_K2.rte	5	130	5	130
v__ALPHA_BNK.rte	0	1	0	1
r_SOL_K.sol	–0.8	0.5	–0.6	0.8

observed that these sensitive parameters were mostly responsible for the model calibration and parameter changes during model iteration processes. The remaining parameters had no significant effect on stream-flow simulations. Changes in their values do not cause significant changes in the model output. The dotty plots show the distribution of the number of simulations in parameter sensitivity analysis after comparing the parameter values with the objective functions for the daily and monthly calibrations respectively, for SUFI-2 and GLUE. In SUFI-2, during daily calibration CN2 (curve number), groundwater revaporation coefficient and effective hydraulic conductivity have shown large distribution in their values (Figure 3), whereas on monthly basis prediction, soil effective hydarualic conductivity and main hydraulic conductivity with curve number have shown significant variation in their values (Figure 4). Similarly, while assessing GLUE procedure, during daily calibration, roughness for main channel, base flow alpha factor for bank storage and CN2 have shown significant variations (Figure 5), while during monthly prediction groundwater delay has contributed some variation among those parameters (Figure 6). The Tungabhadra catchment has a curve number around 81.7, which shows enormous

Table 5. Parameter sensitivities for SUFI-2 and GLUE

	On daily basis					
	SUFI-2			GLUE		
Parameter	Ranking	*t*-stat	*P*-value	Ranking	*t*-stat	*P*-value
v__GW_DELAY.gw	10	0.19	0.85	8	0.35	0.73
v__ESCO.hru	9	0.26	0.79	9	–0.07	0.94
v__ALPHA_BF.gw	8	–0.3	0.78	10	0	1
v__ALPHA_BNK.rte	7	0.91	0.37	3	–3.84	0
v__GWQMN.gw	6	1	0.32	6	0.76	0.45
v__CH_N2.rte	5	1.11	0.27	2	4.59	0
r_SOL_K.sol	4	1.39	0.17	5	–1.12	0.27
v__GW_REVAP.gw	3	3.36	0	8	0.35	0.73
r__CN2.mgt	2	–3.7	0	1	–8.41	0
v__CH_K2.rte	1	4.24	0	4	2.54	0.02
	On monthly basis					
	SUFI-2			GLUE		
v__ALPHA_BNK.rte	10	–0.6	0.56	2	–2.84	0.01
v__CH_N2.rte	9	–0.6	0.54	8	0.36	0.72
v__ALPHA_BF.gw	8	0.73	0.47	9	0.3	0.77
v__GW_REVAP.gw	7	0.89	0.38	4	1.41	0.17
v__GWQMN.gw	6	1.3	0.2	6	1.21	0.23
v__GW_DELAY.gw	5	1.4	0.17	3	2.57	0.01
v__ESCO.hru	4	1.43	0.16	10	0.14	0.89
v__CH_K2.rte	3	–1.6	0.11	7	0.65	0.52
r_SOL_K.sol	2	1.75	0.09	5	–1.34	0.19
r__CN2.mgt	1	–11	0	1	–13	0

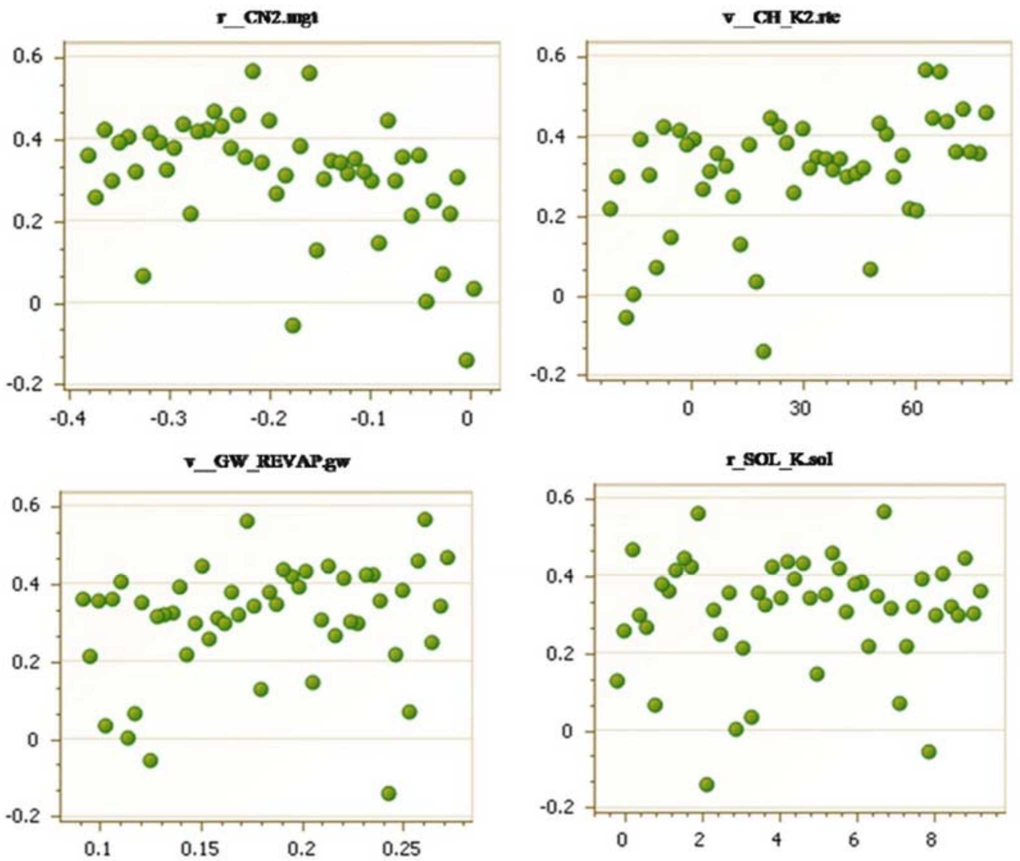

Figure 3. Plots showing most identified sensitive parameters during daily calibration in SUFI-2.

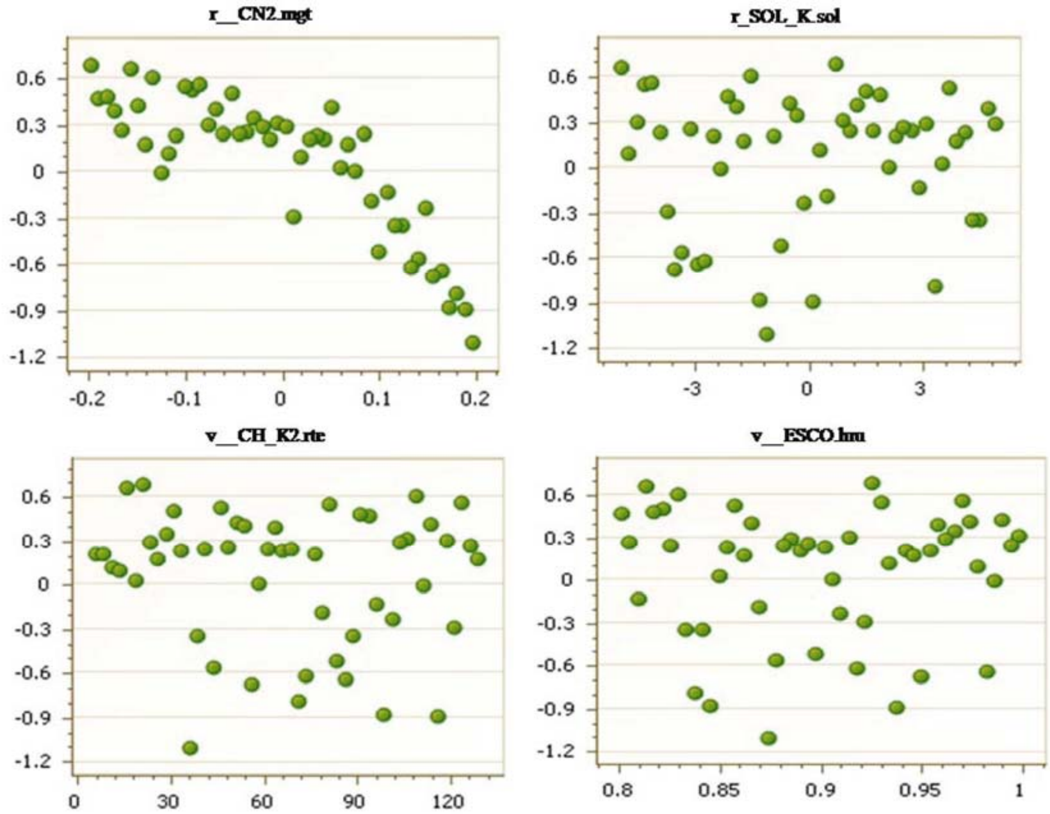

Figure 4. Plots showing most identified sensitive parameters during monthly calibration in SUFI-2.

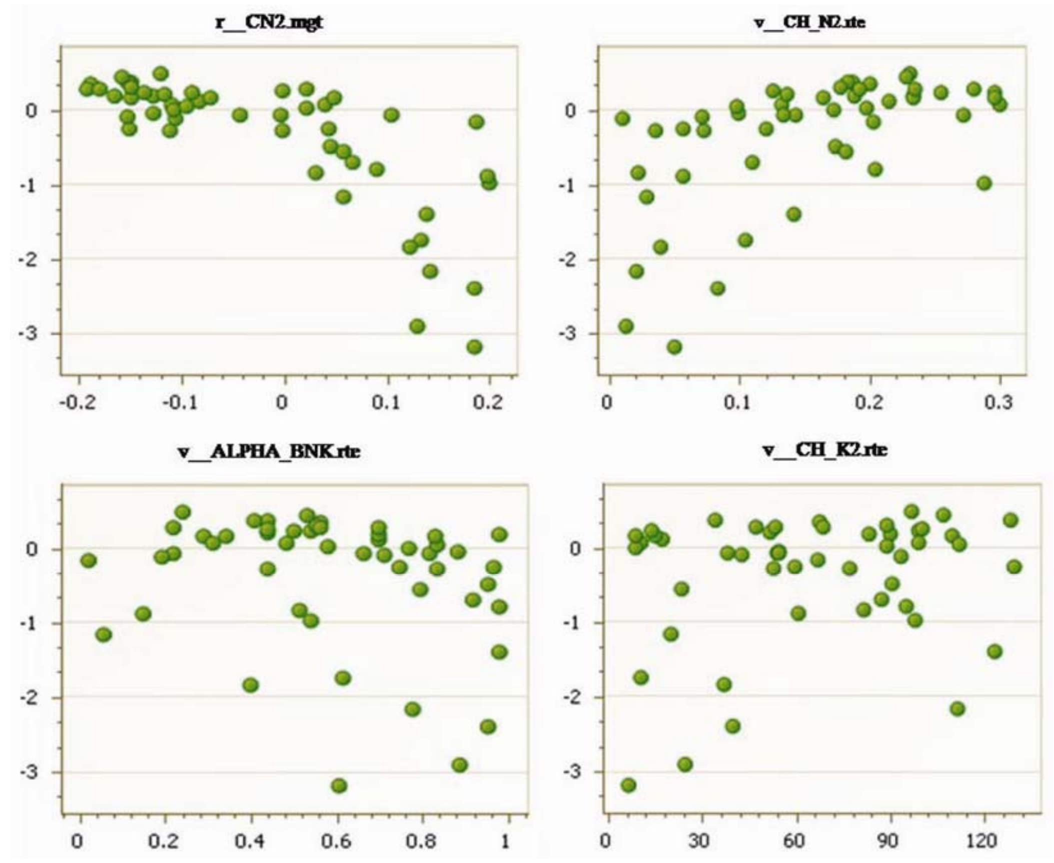

Figure 5. Plots showing most identified sensitive parameters during daily calibration in GLUE.

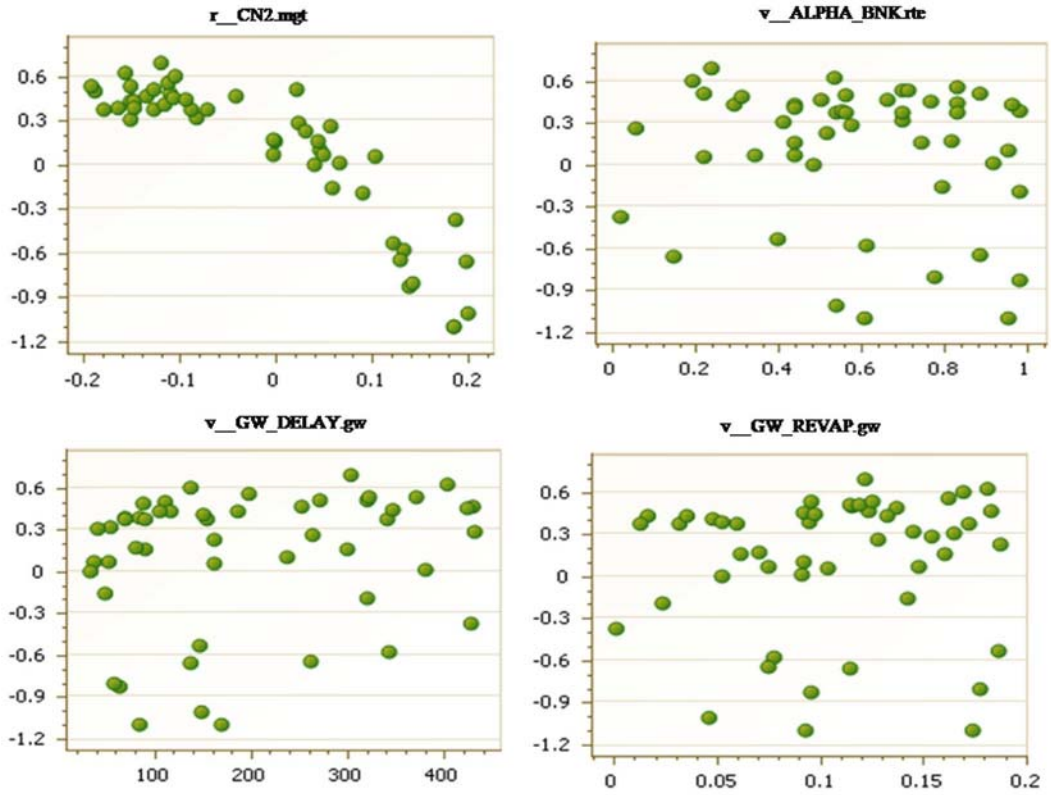

Figure 6. Plots showing most identified sensitive parameters during monthly calibration in GLUE.

amount of run-off (Table 2). The higher run-off potential will be followed by higher curve number. Curve depends on the majority of the soil and moisture conditions (anticident moisture conditions) based on the average fraction of the basin slope. SWAT does not adjust curve number for the slope. However, we can adjust the curve number for slope effects prior to entering the curve numbers in the data-management input files. In SWAT model, alpha factor for groundwater is defined as the groundwater recession or the rate at which groundwater is returned to the stream[11,15]. The water balance ratio of the base flow and total flow is recorded as 0.44 (Table 2). Base flow recession is a function of the overall topography, drainage pattern, soil and geology of the watershed. The run-off during non-monsoon seasons, especially during long periods without rainfall can be considered base flow and this is not constant as it will vary or increase after the monsoon periods, when precipitation dominates. The alpha factor is a direct index of the intensity with which the groundwater outflow responds to changes in recharge. SWAT CUP is highly parameterized and typically can achieve a decent calibration statistics by keeping some parameters at default and adjusting with others according to observed and predicted values. As the alpha level was increased, the deviation between observed and simulated discharge increased. Among all the sensitive parameters, curve number has been recorded as the key parameter in the Tungabhadra catchment.

Model calibration on daily and monthly basis using SUFI-2 and GLUE

The stream-flow comparison has been done between the observed and simulated discharge values for 13 years time-steps during 1990–2002 on daily and monthly basis. Initially, three years of flow data during 1990–1992 were taken as the warming period and rest of the period was used for model calibration, i.e. 1993–2002. To quantify the correlation between rainfall (mm) and discharge data, average monthly correlation has been examined in the Haralahalli gauge station at the outlet of Tungabhadra catchment (Figures 7 and 8). The model was calibrated using ten parameters which were recorded as the most sensitive parameters for the stream-flow measurement. Several simulations have been run and applied to achieve the best model efficiency between the observed and simulated flows. The goodness-of-fit and efficiency of the model have been tested using the five main objective functions mentioned earlier. These five objective functions have been analysed on a daily and monthly basis correspondingly for both SUFI-2 and GLUE uncertainty techniques (Table 6).

The time-series data of the observed and simulated flows on daily and monthly basis for the period 1993–2002 were plotted for visual comparison to explore the similarity within the peak values resulting from both procedures, i.e. SUFI-2 and GLUE (Figure 9 *a*–*d*). The

Table 6. Stream flow calibration results on daily and monthly basis during 1993–2002

	SUFI – 2		GLUE	
Variables	Daily	Monthly	Daily	Monthly
P-factor	42%	92%	23%	59%
R-factor	0.87	1.54	0.56	0.77
R^2	0.60	0.78	0.58	0.82
NS	0.57	0.68	0.48	0.69
bR^2	0.38	0.74	0.42	0.80

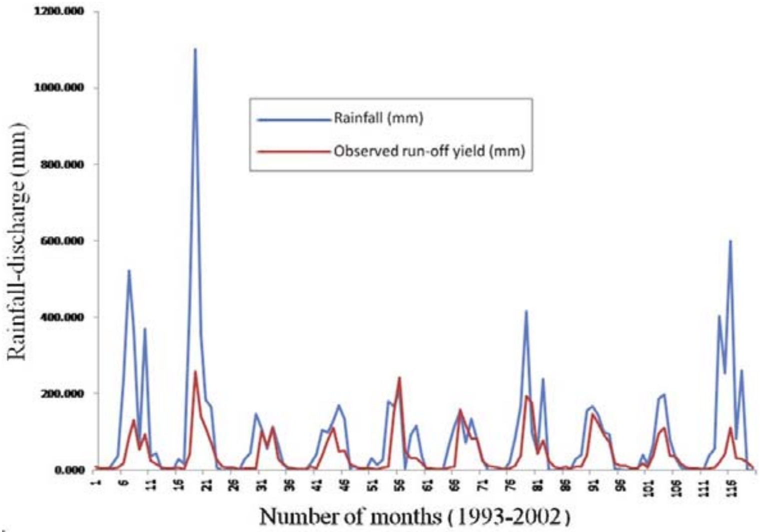

Figure 7. Monthly average comparison of rainfall and run-off at the outlet of the catchment during 1993–2002.

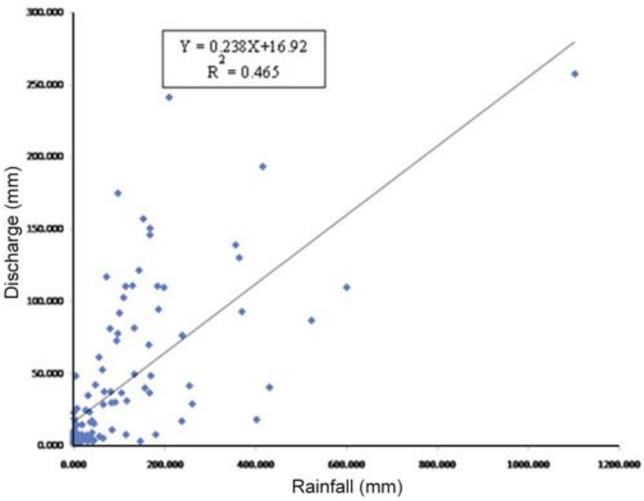

Figure 8. Monthly average correlation of rainfall and run-off at the outlet of the catchment during 1993–2002.

shaded region in the plots shows uncertainty in the model because it brackets a large amount of the measured data which contains all uncertainties in the model (95PPU band). Table 4 shows daily and monthly basis prediction parameters analysed in SUFI-2 and GLUE procedures corresponding to 95PPU. In SUFI-2, parameter uncertainty accounts for various sources like input data uncertainty, conceptual model uncertainty and parameter uncertainty because desegregation of the error into its source components is difficult, particularly in cases common to hydrology where the model is nonlinear and different sources of error may interact to produce the measured deviation[21]. In daily stream flow calibration about 42% and 23% data were bracketed by 95PPU, whereas in monthly stream flow calibration about 92% and 59% data were bracketed by 95PPU for SUFI-2 and GLUE procedures respectively. The daily data show slightly large prediction uncertainties against monthly prediction. These model uncertainties can be accounted for due to some errors in data input sources, data preparation and parameterization[22]. However, the uncertainties may also result due to human and instrumental errors during processing the data. The Tungabhadra catchment has large variations in topography and rainfall in the form of land-use and soil. It sometime receives good rainfall during the monsoon period and but in the non-monsoon periods sometimes it receives below average rainfall. This can contribute some uncertainties in the model because of insufficient data availability, especially at micro level.

The average annual flow of the total time-series computed from the model is 552.23 (cumec) against the

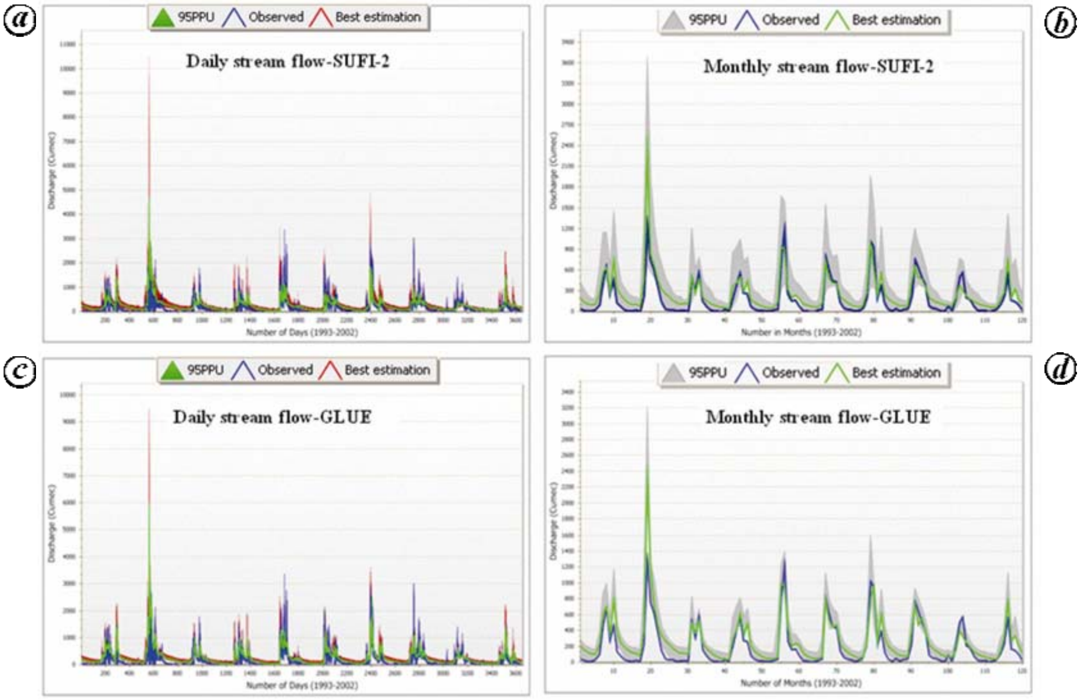

Figure 9. Daily (***a***, ***c***) and monthly (***b***, ***d***) stream flow calibration during 1993–2002.

observed annual flow is 424.39. The daily and monthly coefficient of determination $R^2 = 0.60$ and 0.78 has been recorded for SUFI-2 procedure, and 0.58 and 0.82 for GLUE procedures. The calculated R^2 between the simulated and observed flows on both daily time-periods shows effective similarity and correlation between them. On the other hand, monthly calibration results show significance in terms of model efficiency. The Nash–Sutcliffe equation has been applied for model testing between simulated and observed flows on daily and monthly basis for both procedures (Table 6). The NS values calculated on monthly basis, i.e. 0.68 and 0.69 respectively, for SUFI-2 and GLUE show better efficiency than daily basis prediction, i.e. 0.57 and 0.48 similarly (Table 6). The strength of the model calibration and uncertainty procedure has been analysed using the *R*-factor. The *R*-factor functions have been calculated as 0.87 and 1.54 on daily and monthly basis for SUFI-2, whereas 0.56 and 0.77 have been recorded for GLUE procedure in the same way. The *R*-factor shows the average thickness of 95PPU band divided by the standard deviation of the observed data.

The model shows a few prediction uncertainties, especially in the daily flow data in both uncertainty techniques. The main inputs used for weather data in the model are gridded rainfall and temperature. The limitations of meteorological data in terms of less availability of data did not permit considering additional factors. We have used the global available FAO soil data with coarser resolution and properties (1 : 500,000 scale) for SWAT model input set-up. We have assumed that the model deficiency in the Tungabhadra catchment has been examined mainly due to the input data uncertainty. However, the efficiency of the model and prediction uncertainty capability can be improved with enhancement of the data inputs. For this reason our results agree reasonably well with the observed and simulated values.

Conclusions

The Arc SWAT interface of SWAT model has been used successfully for exploring hydrological characteristics of the Tungabhadra catchment using HRU based approach. The automatic watershed delineation at HRU level clearly shows how the basic features like land use, soil and slope have an effect on the hydrology of the catchment. SWAT CUP advance calibration and uncertainty analysis tool has been used for automatic calibration of stream-flow measurements on daily and monthly basis for the period 1993–2002 using SUFI-2 and GLUE procedures. It provides an effective graphical interface for visualization of outputs, including simulated data, observed data, best-fit model results and 95PPU for all variables used in model calibration. The sensitivity analysis adopted for the stream-flow calibration shows variations between the parameter ranges which had been initialized for the model calibration on daily and monthly basis. The global sensitivity of the parameters for stream-flow calibration shows variations mainly in the efficacy of the parameters which were analysed according to Latin hypercube regression systems. SUFI-2 and GLUE procedures gave good results in minimizing the differences between observed and simulated flows at the outlet of the Tungabhadra catchment. The *P*-factor and *R*-factor calculated using SUFI-2 and GLUE procedures have given good agreement by bracketing around 23–42% observed data on a daily basis, though on a monthly basis factors have given better results by bracketing around 60–90% observed data for both procedures. SUFI-2 and GLUE algorithms are effective methods but require additional iterations as well as adjustment of the parameter ranges for enhancement of the results. However, a difficulty of the GLUE method is its excessive computational burden due to its random sampling strategy, especially for long time-series data.

The hydrological water balance analysis using the ArcSWAT model shows excessive run-off due to high curve number value. The base flow and percolation are notified as important components and responsible for total discharge at the given outlet in the study area that contributes slightly lower than the surface run-off. More than 33% of losses in the watershed are found through evapotranspiration. After considering all the uncertainties during model inputs and parameterization, the SWAT model gave good simulation results for daily and monthly time series for the Tungabhadra catchment. The other objective functions, viz. R^2, NS and bR^2 have been tested and show better correlation and agreement between the simulated and observed stream flows on daily and monthly basis for both techniques. Finally, it has been noticed that the GLUE and SUFI-2 procedures are flexible by allowing for uninformed likelihood measures and objective functions. However, the results of this analysis could be improved by adding some ground-based measurements and analysis. This whole model uncertainty and calibration analysis can be used for futuristic prediction and assessment of water balance and climate change studies as well as other management scenarios for streamflow measurements especially for the Tungabhadra catchment.

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ACKNOWLEDGEMENTS. We thank the India-WRIS project, Regional Remote Sensing Centre-West (RRSC-W), National Remote Sensing Centre, Jodhpur for providing the opportunity to carry out this work. We also thank the staff of RRSC-West for their support.

Received 2 December 2012; revised accepted 28 January 2013