

# Calibration and validation of SWAT model using stream flow and sediment load for Mojo watershed, Ethiopia

Zelalem Biru<sup>1</sup> · Devendra Kumar<sup>2</sup>

Received: 1 December 2015 / Accepted: 7 September 2017 / Published online: 6 October 2017  
© Springer International Publishing AG 2017

**Abstract** The main aim of this study was to setup and evaluate the applicability of physically based soil and water assessment tool (SWAT) model with ArcGIS version 9.3 in assessing the runoff and sediment load from Mojo watershed having a total area of 2017.21 km<sup>2</sup> situated in central Oromia Regional state, Ethiopia. In this study for stream flow simulation parameters involving surface runoff (CN<sub>2</sub>.mgt) and ground water (ALPHA\_BNK.rte) are found the most sensitive parameter and the parameters representing channel process (SPCON.bsn, SPEXP.bsn & ADJ\_PKP.bsn), geomorphology (SLSUBBSN.hru) and surface runoff (CN<sub>2</sub>.mgt, & HRU\_SLP.hru), were found more sensitive for sediment load simulation. There are a good agreement between the observed and simulated discharge, which was verified using both graphical technique and quantitative statistics. The value of  $R^2 = 0.75$ , NSE = 0.76, RSR = 0.49 and PBIAS = 10.9 obtained during calibration and  $R^2$  value 0.71, NSE value 0.70, RSR value 0.59 and PBIAS 9.5 obtained during validation as well as the uniformly scatter points along the 1:1 line during calibration and validation justify that the model is good in simulating runoff from Mojo watershed. For sediment load the computed statistical indicators  $R^2 = 0.77$ , NSE = 0.76, RSR = 0.49 and PBIAS = 48.70 were obtained during calibration and during validation the

computed statistical indicators were found 0.67 for  $R^2$ , 0.65 for NSE, 0.59 for RSR and 50.5 for PBIAS. From the calibration and validation result, it can be concluded that the calibrated parameter values of SWAT model can be used for hydrologic simulation of the un-gauged watershed that is having the similar agro-climatic condition.

**Keywords** Mojo watershed · Sensitivity analysis · Calibration · Validation · Distributed watershed model · Efficiency measure

## Introduction

To prevent and minimize soil erosion, sound understanding of the process is very essential. To compare the magnitude and determine factors, causes and effects that help extension workers for better design and monitoring of SWC techniques, and to ensure sustainable land management there is a need to understand the mechanics and mechanism of soil erosion (Wischmeier and Smith 1978). For this, soil erosion models and experimental setup, installing test plot and measuring sediment loss at the outlet of the catchments, can be employed. Monitoring of soil erosion with the installation of various gauging stations is rather expensive and often unaffordable. Also, it is unusual to extrapolate values from gauged catchments to un-gauged catchments, unless required for general overview of the problems and policy issues. Under such circumstances, soil erosion models have great importance, as primary tools for making soil erosion assessments.

Fortunately, many hydrologic models have been developed over time to allow for better understanding of the hydrologic and erosion processes which occur on agricultural watersheds. These models are basically categorized

✉ Zelalem Biru  
zgonfa@yahoo.com  
Devendra Kumar  
kumar\_drdevendra@rediffmail.com

<sup>1</sup> Adama Science and Technology University, Oromia Regional State, P.O.Box-1888, Adama, Ethiopia

<sup>2</sup> G.B. Pant, University of Agriculture and Technology, U.S. Nagar, Pantnagar 263145, Uttarakhand, India

into three types namely empirical, conceptual and physically based (Morgan 1995; Merritt et al. 2003). But, in humid tropics area where heterogeneous physical environments and seasonality of meteorological and hydrologic events exists the use of physically-based, distributed and continuous hydrologic models is imperative to better understand the environment.

The applicability of some of the models had been evaluated under different condition by different researcher in different parts of the world. Matamoros et al. (2005) tested SWAT and AGNPS model to evaluate their potential applicability under data scarcity. The result of their study reveal that the SWAT model with less basin subdivision showed to be more accurate than AGNPS model. Mishra et al. (2008) made a comparison of SWAT with HSPF model in predicting hydrologic processes of a small multi-vegetated watershed. Although both SWAT and HSPF models showed high capability of simulating runoff and sediment load within the acceptable level of accuracy, the SWAT model being more responsive to the seasonal variations of precipitation, predicted monthly runoff and sediment load more accurately than HSPF model. Ogwo et al. (2012) compared the performances of AGNPS, WEPP and SWAT model for application in the Humid Tropics. WEPP applications were found to provide good capability to simulate sediment load followed by SWAT while AGNPS applications were found satisfactory. Parajuli and Ouyang (2013) compared SWAT and HSPF models in assessing long term hydrological impacts due to future climate change scenarios in which the performance of SWAT model found to be better in simulating mean monthly stream flow.

Among all hydrological models SWAT is selected for this study as it has been used in many countries all over the world intensively for the estimation of sediment, nutrient and pesticides, runoff, and conservation measure impact assessments in the watershed (Arnold and Fohrer 2005). SWAT is one of the process-based and distributed models that replaced traditional lumped and empirical models. Empirical models are still used because of their simple structure and ease of application. Since they are based on coefficients computed or calibrated from measurements, they cannot describe or simulate the erosion process as a set of physical phenomena. On the other hand SWAT, physically based, can describe with detail the physical mechanism of sediment load and can simulate the individual components of the entire erosion process by solving the corresponding equations; and so it is argued that it has a wider range of application. Therefore, the main aim of this study is to examine the applicability of SWAT model in estimating the soil erosion and runoff in the central agricultural watershed, Ethiopia, with the view to simplify the subsequent watershed management planning process.

## Materials and methods

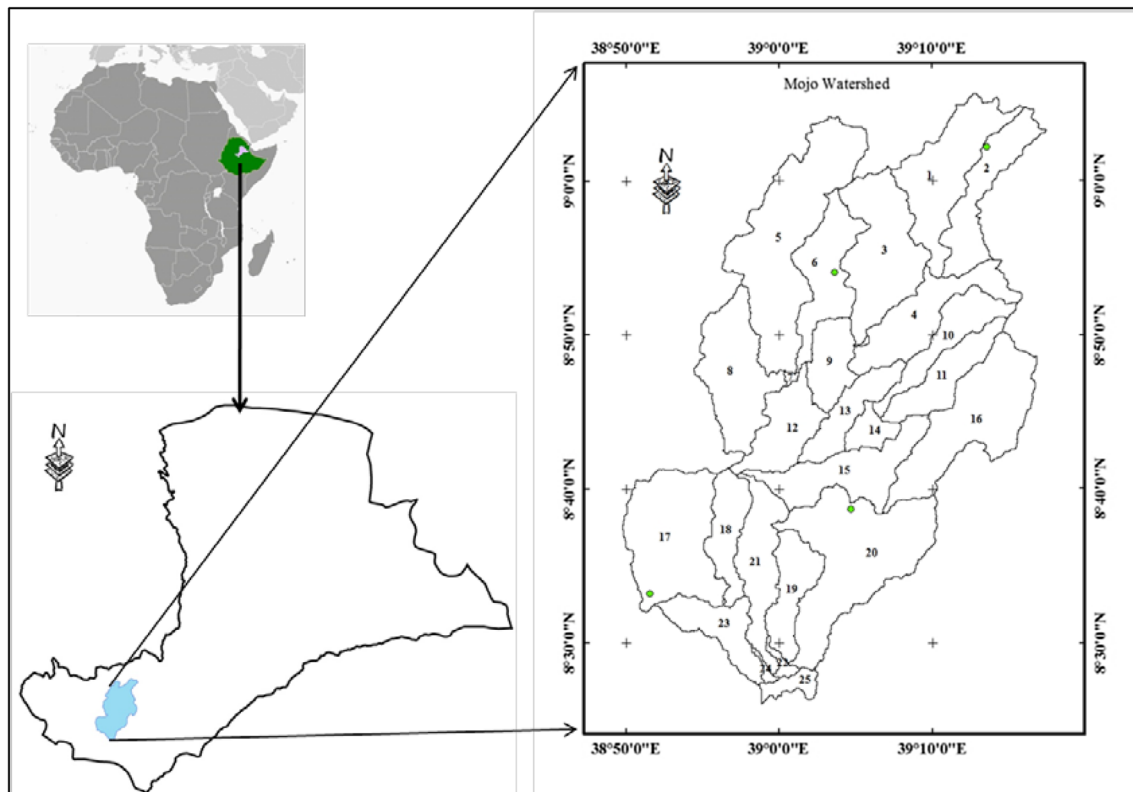
### Study area description

Mojo watershed having a total area of 2017.21 km<sup>2</sup> is situated in Central Oromia Regional State, Ethiopia, (Fig. 1). Geographically it is located between latitudes of 8°16' and 9°18' and longitude of 37°57' and 39°17'. The watershed drains to Mojo river and finally into Awash River. The majority of the watershed particularly the central and lower part of the watershed has monomodal rainfall pattern whereas the upper part of the watershed characterized as bimodal. The mean annual rainfall of the watershed is 930.33 mm. More than 85% of the annual rainfall occurs during June–September with peak in July–August. The mean maximum temperature of the watershed is ranging from 21 to 27 °C the highest being recorded in the month of May and the lowest in July. The altitude of the watershed ranges from 1592 masl at the river bed to 3065 masl at the upper part the watershed. The major dominant soil types of the watershed are Vitric Andosols (60.11%) followed by Chromic Luvisols (29.73%), Chromic Cambisols (7.59%), and Umbric Leptosols (1.3%). The major farming system of the watershed is mixed farming mode of production. Agriculture is the dominant land use, about 97% of the total land used for agricultural activities; mostly for the production of cereals crop like Teff, Wheat, Lentils, Haricot beans and Chickpea. Close to 1.16% of the total land area is considered as degraded land and about 0.68% of the land area is covered by shrubs and forest. The rest of the area is occupied by settlement, flower farm and water body.

### Description of SWAT model

SWAT model is a physically based watershed-scale continuous time-scale model, which operates on a daily time step developed and supported by the United State Department of Agriculture-Agricultural Research Service (USDA-ARS). The SWAT model is an advancement of the Simulator for Water Current Perspectives in Contaminant Hydrology and Water Resources Sustainability Resources in Rural Basins (SWRRB) and Routing Outputs to Outlet (ROTO) models. The SWAT model development was influenced by other models like chemical, Runoff and Erosion from Agricultural Management (CREAMS) (Knisel 1980), Groundwater Loading Effects on Agricultural Management Systems (GLEAMS) (Leonard et al. 1987), and Erosion Productivity Impact Calculator (EPIC) (Williams et al. 1984; Neitsch et al. 2002).

The SWAT model can simulate runoff, sediment, nutrients, pesticide, and bacteria transport from agricultural



**Fig. 1** Mojo watershed location map

watersheds (Arnold et al. 1998). The SWAT model delineates a watershed, and sub-divides that watershed into sub-basins. In each sub-basin, the model creates several hydrologic response units (HRUs) based on specific land cover, soil, and topographic conditions. Model simulations that are performed at the HRU levels are summarized for the sub-basins. Water is routed from HRUs to associated reaches in the SWAT model. SWAT first deposits estimated pollutants within the stream channel system then transport them to the outlet of the watershed. Major model components include weather, hydrology, soil temperature, plant growth, nutrients, pesticides, and land management.

To accurately predict the movement of runoff, sediment or nutrient, and pesticide simulation of the watershed separated into two major divisions as land phase and routing phase of hydrologic cycle. The land phase controls amount of water, sediment, nutrient, and pesticide loading to the main channel in each sub-watershed. Where as, the routing phase defined as the movement of water, sediments, etc., through the channel network of the watershed to the outlet. The simulation of the hydrologic cycle by SWAT is based on the water balance equation, which is written as:

$$SW_t = SW + \sum_{t=1}^t (R_t - Q_t - ET_t - P_t - QR_t), \quad (1)$$

where,  $SW_t$  is the final soil water content (mm),  $SW$  is the initial soil water content on day  $i$  (mm),  $t$  is time (days),  $R_t$  is the amount of precipitation on day  $i$  (mm),  $Q_t$  is the amount of surface runoff on day  $i$  (mm),  $ET_t$  is the amount of Evapo-transpiration on day  $i$  (mm),  $P_t$  is amount of percolation on day  $i$  (mm), and  $QR_t$  is the amount of return flow on day  $i$  (mm).

#### Surface runoff

In the hydrologic module of the model, the surface runoff is estimated separately for each sub-basin and routed to quantify the total surface runoff for the watershed. The most commonly used method for estimating surface runoff in SWAT models is the modified SCS-CN<sub>2</sub> with daily time step or Green-Ampt Mein–Larson infiltration equation with hourly or sub-daily time step (Migliaccio and Srivastava 2007). SWAT simulates surface runoff volumes and peak runoff rates for each Hydrologic Response Unit (HRU). SCS curve number method is less data intensive over the Green-Ampt method (Fontaine et al. 2002). Therefore, the SCS curve number method was used to estimate surface runoff volumes in this study because of the unavailability of sub daily data for Green-Ampt method. One distinct feature in the SCS curve number method with respect to the Green-Ampt method is that it lumps canopy interception in

the term initial abstraction. Then SWAT estimates the peak runoff rate, time of concentration for overland and channel flow and surface runoff lag separately for each sub basin (Neitsch et al. 2002). The SCS curve number (SCS 1972) equation is:

$$Q_{\text{surf}} = \frac{(R_{\text{day}} - I_a)^2}{(R_{\text{day}} - I_a + S)}, \quad (2)$$

where  $Q_{\text{surf}}$  is the accumulated runoff or rainfall excess (mm),  $R_{\text{day}}$  is the rainfall depth for the day (mm),  $I_a$  is the initial abstractions which includes surface storage, interception and infiltration prior to runoff (mm), and  $S$  is the retention parameter (mm). The retention parameter varies spatially due to changes in soils, Land use, management and slope and temporally due to changes in soil water content. The retention parameter is defined as:

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

where, CN is the curve number for the day. The initial abstraction,  $I_a$  is commonly approximated as  $0.2S$  and the above equation becomes

$$Q_{\text{surf}} = \frac{(R_{\text{day}} - 0.2S)^2}{(R_{\text{day}} + 0.8S)} \quad \text{for } R_{\text{day}} > I_a (= 0.2S). \quad (4)$$

#### Sediment component

Erosion and sediment yield for each sub-basin, in the SWAT model, is computed using Modified Universal Soil Loss Equation (MUSLE), Williams (1975), given as below,

$$\text{sed} = 11.8 \times (Q_{\text{surf}} \times q_{\text{peak}} \times \text{area}_{\text{hru}})^{0.56} \times K \times C \times P \times \text{LS} \times \text{CFRG}, \quad (5)$$

where, sed is the sediment yield on a given day (metric tonnes),  $Q_{\text{surf}}$  is the surface runoff volume (mm/ha),  $q_{\text{peak}}$  is the peak runoff rate ( $\text{m}^3/\text{s}$ ),  $\text{area}_{\text{hru}}$  is the area of the HRU (ha),  $K$  is the soil erodibility factor [ $0.013 \text{ metric } t \text{ m}^3 \text{ h} / (\text{m}^3\text{-metric } t \text{ cm})$ ],  $C$  is the cover and management factor,  $P$  is support practice factor, LS is the topographic factor and CFRG is the course fragment factor.

#### Data collection

The climatic variables of the watershed required by the model were obtained from the National Metrology Service Agency (NMSA), Ethiopia. Whereas daily average stream flow and sediment load data at Mojo stream gauging station were obtained from the Federal Ministry of Water Resources of Ethiopia (FMWRE). Oromia Water Works

Design and Supervision Enterprise (OWWDSE) and FAO-UNESCO Soil map of the world is another major source of data utilized for the definition and characterization of the different soil properties of the watershed. A digital soil and land use/cover maps (1:50,000 scale) of Awash basins, from which soil and land use map of the Mojo watershed extracted, were obtained from OWWDSE. Soil and land use map of the watershed was clipped and converted to raster datasets from the obtained soil and land use map to obtain the physical description and characteristics of the major soil types and present land use of the watershed. Whereas, the digital elevation model (DEM) of  $90 \times 90 \text{ m}$  resolution was downloaded from website [www.srtm.csi.org](http://www.srtm.csi.org).

#### Input data preparation for SWAT model

##### Weather parameter

Daily precipitation data used by the weather generator of the SWAT model are calculated using computer program of Stefan (2003) for each station using daily precipitation data of the 30 years (1980–2009). The other weather parameter, average daily dew-point temperature per month of each station was calculated using another computer program, dew02.exe from daily temperature and humidity of each station. Sunshine hours of each station obtained from NMSA were converted to solar radiation as required by the SWAT using Angstrom formula (Adopted from FAO 1998) which relates solar radiation to extraterrestrial radiation and relative sunshine duration.

##### Soil parameter

Apart from the physical properties of the soils obtained from FAO (1998) soil map, additional soil characteristics such as soil saturated hydraulic conductivity, bulk density, soil available water and texture class at different soil depths were computed using the Soil Plant Air Water (SPAW) model. Further, the soil erodibility K factor has been calculated using erodibility equation of Williams et al. (1984) considering soil texture and organic carbon content as an input variable.

#### SWAT model set up

After all weather and soil parameters prepared in tabular form and transferred to SWAT weather generator data base and user's soil data base, delineation of the watershed into sub-watershed and stream net work generation from DEM  $90 \text{ m} \times 90 \text{ m}$  resolution at a scale of 1:50,000 were processed using Arc SWAT2009 with ArcGIS version 9.3. In this process, prior to the application of the maps in the

model, preprocessing work was carried out to make the unit of the map the same to facilitate overlaying of DEM, land use, soil and slope map. Further, land use and soil map along with their respective look up tables prepared were uploaded to the model for reclassification according to SWAT coding convention. Moreover, the whole watershed slopes were categorized into five slope classes using the existing model interface. Then, Land use, soil and slope maps were overlaid to create HRU's that is having similar hydrologic condition. Finally, location table of weather data file were loaded to link them up with the corresponding files already created for the purpose. After loading all the necessary input data and generating all the required database files, then, SWAT model was set to run on monthly bases considering the first 3 years (1980–1982) data for warm-up of the model. The SWAT model setup flow diagram is shown in Fig. 2.

### Sensitivity analysis

Prior to model calibration parameter sensitivity analysis was done using the SWAT-CUP (SWAT Calibration and Uncertainty Procedures) Sequential Uncertainty Fitting ver. 2 (SUFI-2) global sensitivity methods, for the whole catchment area. Generally, twenty-three hydrological parameters related to stream flow and sixteen hydrological parameters related to sediment load simulation were considered for sensitivity analysis in the study area. The parameters selected for sensitivity analysis were based on a review of calibration parameters used in past studies (Reungsang et al. 2005; Griensven et al. 2006; Zhang et al. 2008, 2009, Margaret and Chaubey 2010; Jajarmizadeh et al. 2012; Mengistu and Sorteberg 2012; Xie et al. 2012).

### Model calibration and validation

A general calibration process flowchart for flow and sediment load is shown in Fig. 3. Automatic calibration and uncertainty analysis incorporated in SWAT2009 via the SWAT-CUP software developed and tested by Abbaspour (2012) with the semi-automated program SUFI2 was used for this study. The relevant model parameter based on their sensitivity analysis the top thirteen ranking parameters were selected as starting points for model calibration on monthly bases first for stream flow and followed by sediment load, as suggested by Neitsch et al. (2011), being sediment outflow from each HRU and sub-basin is primarily governed by soil physical properties, surface runoff, stream discharge and stream flow velocity. Calibration of the model were done by changing the parameter value within the range until the predicted value was reasonably in line with that of observed value and its accuracy was evaluated with Nash–Sutcliffe coefficient (NSE) and

coefficient of determination ( $R^2$ ). After the model was calibrated using stream flow and sediment load data of 1983–1995, the accuracy of the model was evaluated during the validation process with the help of the data, which were not used during the calibration of the model. Thus, for this purpose monthly simulated stream flow and sediment load for 1996–2009 were compared with observed monthly stream flow and sediment load data of the same period. All the model evaluation parameters used for calibration were also used in the validation process.

### Model performance evaluation

Coffey et al. (2004) as cited by Arnold et al. (2012) describe nearly twenty potential statistical tests that can be used to judge SWAT predictions, including  $R^2$ , NSE, root mean square error (RMSE), nonparametric tests,  $t$  test, objective functions, autocorrelation, and cross-correlation. For the present model performance evaluation techniques the recommendation given by Moriasi et al. (2007), Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS), root mean square error observation standard deviation ratio (RSR) and coefficient of determination ( $R^2$ ), were considered.

#### Nash–Sutcliffe efficiency (NSE)

The Nash–Sutcliffe efficiency (NSE) indicates how well the plot of observed versus simulated data fits the 1:1 line. It generally ranges from  $-\infty$  to 1. Higher value of NSE indicates better accuracy of model prediction whereas lower NSE indicates poor model prediction. In general, model simulation can be judged as satisfactory if  $NSE > 0.50$ , Moriasi et al. (2007). NSE is computed as shown below:

$$NSE = 1 - \frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2}, \quad (6)$$

where, NSE = Nash–Sutcliffe efficiency,  $P_i$  = simulated flow,  $O_i$  = observed flow,  $\bar{O}$  = the mean of observed data, and  $N$  is the total number of observation.

#### Percent bias (PBIAS)

Percent bias measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias (Gupta et al. 1999) as cited in Moriasi et al. (2007). PBIAS is computed as shown below:

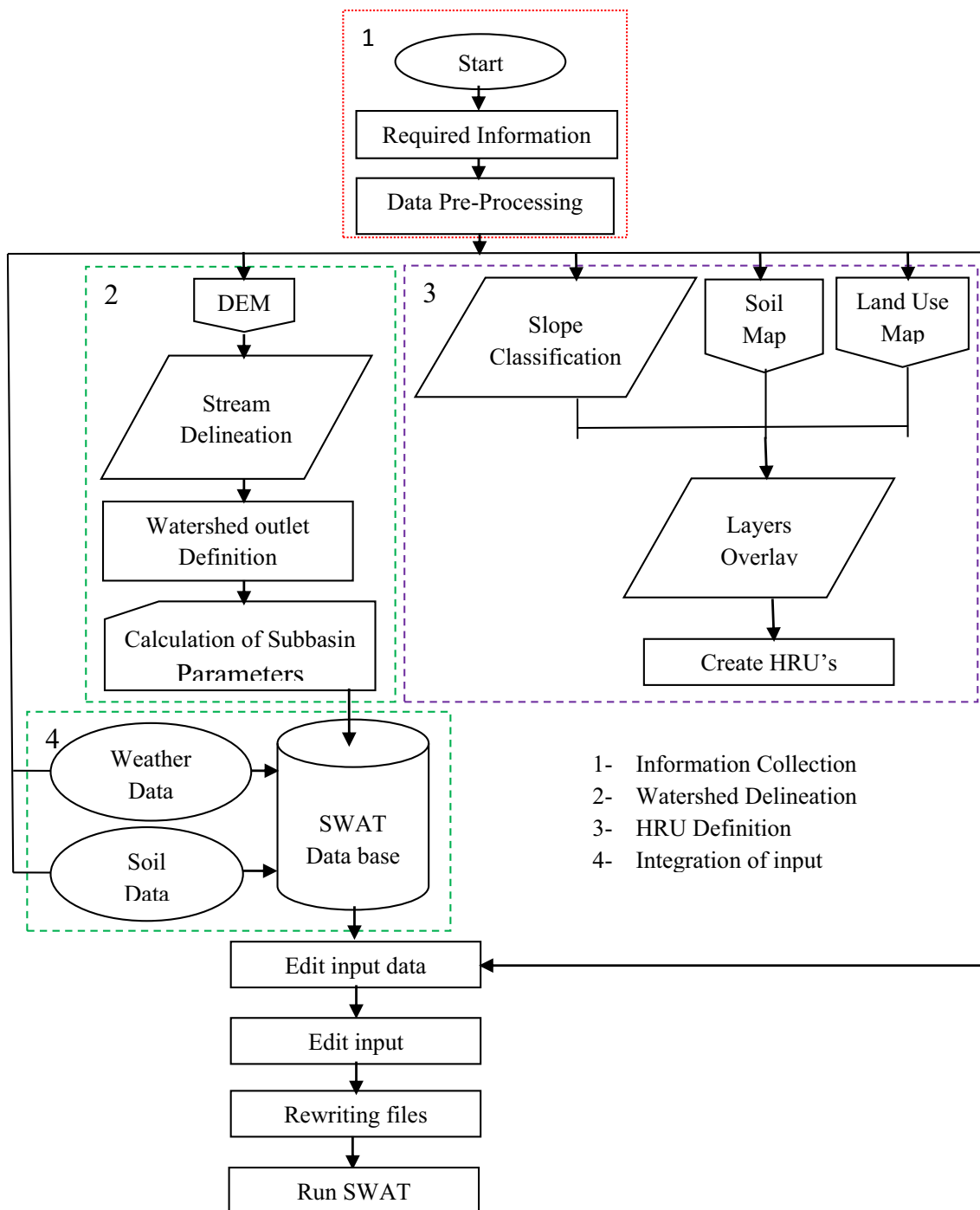


Fig. 2 SWAT model setup flow diagram

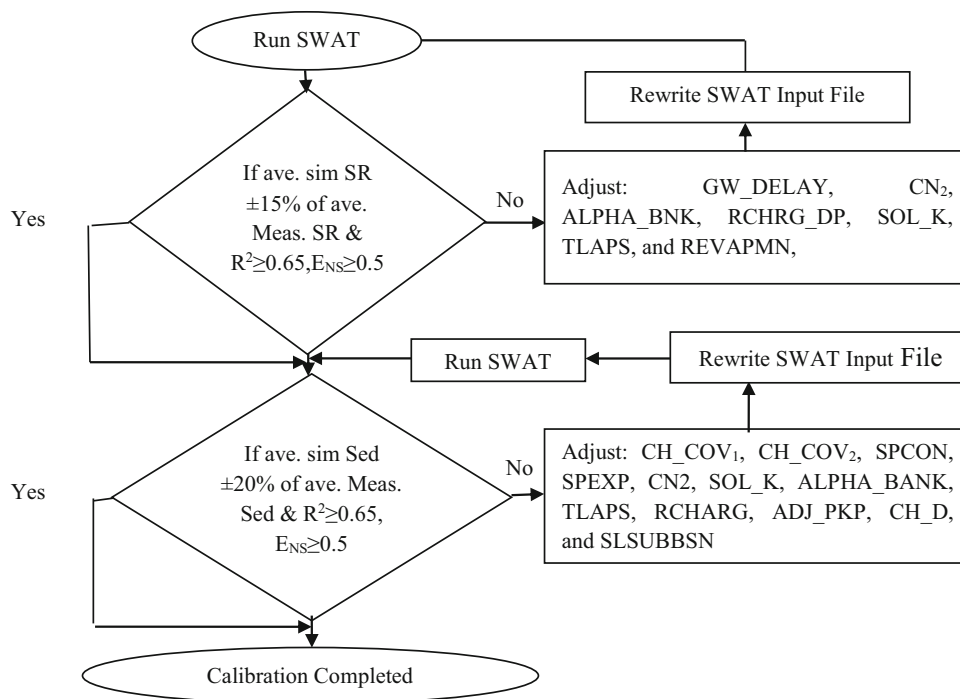
$$PBIAS = \frac{\sum_{i=1}^n (O_i - S_i) \times 100}{\sum_{i=1}^n (O_i)} \tag{7}$$

where, PBIAS is the deviation of data being evaluated, expressed as a percentage. If PBIAS ±25% for stream flow and PBIAS ±55% for sediment, the model simulation can be judged as satisfactory.

Root mean square error observation standard deviation ratio (RSR)

RSR incorporates the benefits of error index statistics and includes a scaling/normalization factor, so that the resulting statistic and reported values can apply to various constituents. RSR varies from the optimal value of “0”, which indicate zero root mean square error (RMSE) or residual

**Fig. 3** Semi automated calibration flow procedure used in this study



variation and therefore perfect model simulation, to a large positive value. Generally, if the value of  $RSR \leq 0.70$  the model simulation can be considered as satisfactory (Moriassi et al. 2007).

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^n (O_i - S_i)^2}}{\sqrt{\sum_{i=1}^n (O_i - \bar{S})^2}} \quad (8)$$

*Coefficient of determination ( $R^2$ )*

The coefficient of determination ( $R^2$ ) described the proportion of the variance in the measured data explained by the model.  $R^2$  ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Santhi et al. 2001) as cited in Moriassi et al. (2007).

$$R^2 = \left( \frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \right)^2 \quad (9)$$

where  $P_i$  = simulated flow,  $O_i$  = observed flow, and  $\bar{O}$  and  $\bar{P}$ ; average of observed and predicted flow respectively.

One of the major drawbacks of  $R^2$  is that only dispersion is quantified if it is considered alone. Therefore, a model which over or under predicts all the time will still result in good  $R^2$  value close to 1 even if all prediction were wrong

(Krause et al. 2005). In order to overcome the major drawback of  $R^2$  additional information had been taken into consideration. For a proper model assessment using  $R^2$  the gradient “ $b$ ” should be combined to provide a weight version ( $wR^2$ ) of  $R^2$ . Such a weight is performed as follows:

$$wR^2 = \begin{cases} |b| \times R^2 & \text{for } b \leq 1 \\ |b|^{-1} \times R^2 & \text{for } b > 1 \end{cases} \quad (10)$$

Generally, to decide the accuracy of the model the value of each index obtained by the model were compared with the value of hydrologic model performance ratings given by Moriassi et al. (2007) in Table 1.

**Results and discussion**

**SWAT model setup**

Basic parameters required to set up SWAT2009 model, soil physical property and climatic elements, have been analyzed and transferred to the model weather generator database. Then, Mojo watershed was delineated from Awash basin DEM and subdivided into 25 sub-watershed based on the minimum threshold area of 5000 ha (Yongwei et al. 2010). Moreover, multiple Hydrological Response Units (HRUs) were defined based on ten percent threshold combination for land use, soil and slop to have better estimation of stream flow and sediment load. Finally, HRU

**Table 1** Performance ratings of hydrologic models

Performance rating	RSR	NSE	PBIAS %	
			Stream flow	Sediment
V.Good	$0.00 \leq RSR \leq 0.50$	$0.75 < NSE \leq 1.00$	$PBIAS \leq \pm 10$	$PBIAS \leq \pm 15$
Good	$0.50 \leq RSR \leq 0.60$	$0.65 < NSE \leq 0.75$	$\pm 10 \leq PBIAS \leq \pm 15$	$\pm 15 \leq PBIAS \leq \pm 30$
Satisfactory	$0.60 \leq RSR \leq 0.70$	$0.50 < NSE \leq 0.65$	$\pm 15 \leq PBIAS \leq \pm 25$	$\pm 30 \leq PBIAS \leq \pm 55$
Unsatisfactory	$RSR > 0.70$	$NSE \leq 0.50$	$PBIAS \geq \pm 25$	$PBIAS \geq \pm 55$

is obtained by overlaying land use, soil type and slope class map that have been developed independently as shown in Fig. 4. As the result the watershed is further sub-divided into 123 HRUs that consist of homogeneous land use, management, topography and soil characteristic.

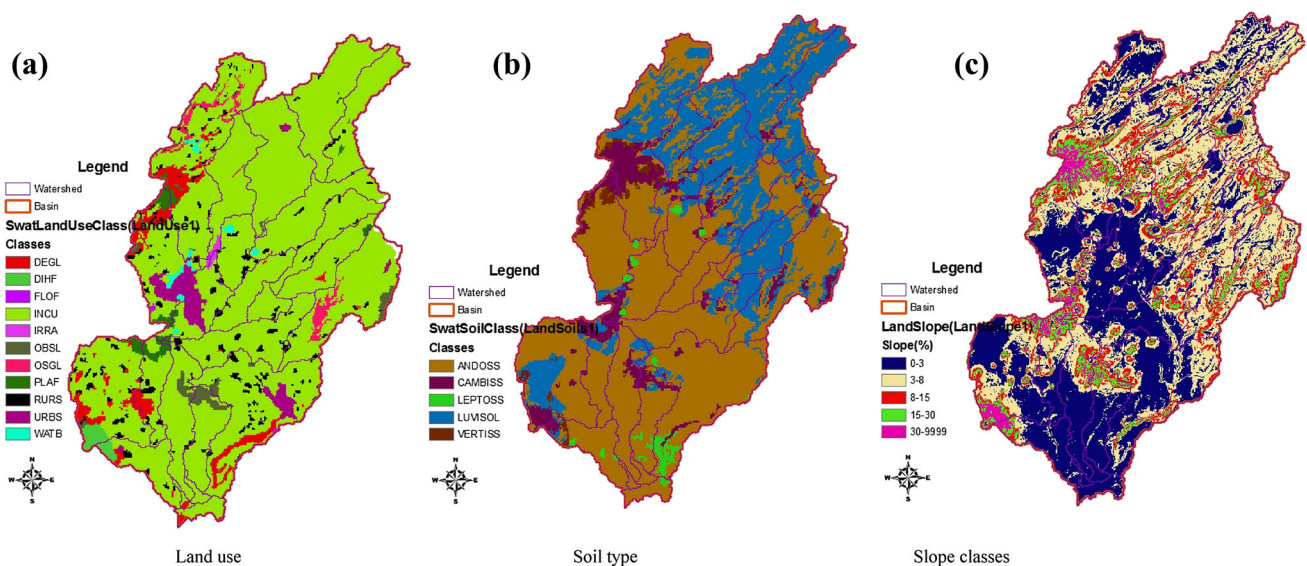
**Sensitivity analysis**

In this study for stream flow simulation, the response of the model towards parameter involving evaporation (EPCO and ESCO), surface runoff (CANMX), and groundwater (ALPHA\_BF, and GWQMN) are very low. On the other hand parameters involving surface runoff (CN<sub>2</sub>) and ground water (ALPHA\_BNK) are found the most sensitive parameter in flow simulation. In addition, parameters involve groundwater (RCHARG\_DP, and REVAPMN), and soil water (SOL\_K) are also showed considerable sensitivity in water yield simulation. SWAT-CUP,SUFI-2 95ppu plot show that under all case observed flow peaks coincide with simulated flow peaks, though in some years’ over-prediction and under-predication by the model were observed.

As in the case of stream flow simulation the model exhibits over predication and under prediction for sediment load. Generally, out of the total considered parameters for sediment load sensitivity analysis the model did not show any response towards parameters related to channel processes (CH\_S2, CH\_WDR and PRF). On the other hand the following parameters were found to be more sensitive through sensitivity analysis mainly those representing channel process (SPCON, SPEXP and ADJ\_PKP), surface runoff (CN<sub>2</sub> and HRU\_SLP), and geomorphology (SLSUBBSN).

**Model calibration and validation**

To improve the efficiency of the model during calibration the top twelve ranking parameters were considered to account for the over and under prediction responses of the model as suggested by Neitsch et al. (2011). The final fitted value of the most sensitive parameters for steam flow and sediment load for the watershed is given in Tables 2, 3, respectively according to its rank. The over prediction nature of the model is controlled by decreasing CN<sub>2</sub> from



**Fig. 4** Land use, soil type and slope classification distribution of Mojo watershed



the initial value 73–65.46. On the other hand under prediction of the model were adjusted by increasing REVAPMN from 1.12 to 278.75. Moreover, the simulated flow patterns with observed flow pattern were adjusted with ALPHA\_BNK, RCHRG\_DP and TLAPS value. For sediment load performance efficiency of the model were improved by adjusting the parameters related to channel process, sediment, surface run-off, soil water and geomorphology. Accordingly, increasing the values related to channel process (SPCON, CH\_D, and ADJ\_PKP), sediment (CH\_COV1, and CH\_COV2), soil water (SOL\_K), geomorphology (TLAPS) and decreasing parameter related to surface runoff (CN2), groundwater (ALPHA\_BNK) and geomorphology (SLSUBBSN) gives a better result of the model.

X\_Code indicate the type of change to be applied to the parameter, V\_ means the existing parameter value is to be replaced by the given value, a\_ means the given value is added to the existing parameter value, and r\_ means the existing parameter value is multiplied by  $(1 + a \text{ given value})$ .

The comparison made between the observed and simulated stream flow indicated that a good agreement were obtained between the observed and simulated discharge, which was verified using both graphical technique and quantitative statistics. The value of coefficient of determination ( $R^2 = 0.75$ ), Nash–Sutcliffe efficiency (NSE = 0.76), error index (RSR = 0.49) and percent bias (PBIAS = 10.9) obtained during calibration and  $R^2$  value 0.71, NSE value 0.70, RSR value 0.59 and percent bias 9.5 obtained during validation justify that the model is very good in simulating runoff from Mojo watershed. Calibrated and validated model predictive performances values for Mojo River on monthly flows base are summarized in Table 4 and the time series plot of measured and simulated monthly flow for calibration and validation are shown in Fig. 5.

Further, as it can be seen from Fig. 6 most of the scatter points are uniformly clustered along the 1:1 line during

calibration and validation of the model. The SUFI-2 results indicated that the  $p$ -factor for the calibration period was 0.73, while it was 0.70 for the validation period. This implies that 73 and 70% of the measured data during calibration and validation respectively captured or accounting for the correct simulated flow by the model while the remaining occur due to an errors in an input data such as rainfall, temperature, etc. The  $r$ -factor that measures the quality of the calibration and the thickness of the 95 ppu is 0.67 for calibration and 0.49 for validation indicating the performance of the model as average.

The performance of the model for sediment load was evaluated in the same way as for the stream flow. The computed statistical indicators  $R^2 = 0.74$ , NSE = 0.76, RSR = 0.49 and PBIAS = 48.7 were estimated during the calibration periods. Similarly, for the validation period, the computed statistical indicators have been computed as 0.71 for  $R^2$ , 0.65 for NSE, 0.59 for RSR and 50.5 for PBIAS. The indicators have been found to be within the range of good performance level except for the validation PBIAS value which is in the range of satisfactory criteria.

The value of  $p$ -factor indicated that 64% of the measured date during calibration and 50% during validation captured or accounting for the correct simulation of sediment load by the model while the remaining occur due to an errors in an input data such as soil physical properties and climatic data. The  $r$ -factor is 0.59 for calibration and 0.49 for validation indicating the performance of the model as an average. Calibrated and validated model predictive performances values for Mojo River on the bases of monthly sediment load are summarized in Table 5 and the time series plot of measured and simulated monthly sediment load for calibration and validation are shown in Fig. 7. Figure 8 shows the scatter plot of simulated and observed data during calibration and validation of the model. From the graph it can be seen that all data point are uniformly clustered along the 1:1 line except three to four data in the case of calibration.

**Table 2** Hydrological parameter selected only for stream flow calibration

Name	Definition	Threshold value	Initial value	P value	Fitted value
r_CN <sub>2</sub> .mgt	SCS runoff curve number for moisture condition II	−0.20–0.20	73.0	0.0	65.46
v_ALPHA_BNK.ret	Base flow alpha factor for bank storage	0.00–1.00	0.0	0.0	0.113
a_RCHARG_DP.gw	Deep aquifer percolation fraction	0.00–0.20	0.05	0.1	0.987
v_TLAPS.sub	Temperature laps rate (°C/km)	−10–10	0.0	0.15	−6.65
v_REVAPMN.gw	Threshold depth of water in the shallow aquifer for revap to occur (mm)	0.0–500.0	1.12	0.06	278.75
r_SOL_K.sol	Soil conductivity (mm/h)	−0.50–0.50	250.0	0.6	1378.53
a_GW_DELAY.gw	Groundwater delay (days)	0–50	31.0	0.05	350.25

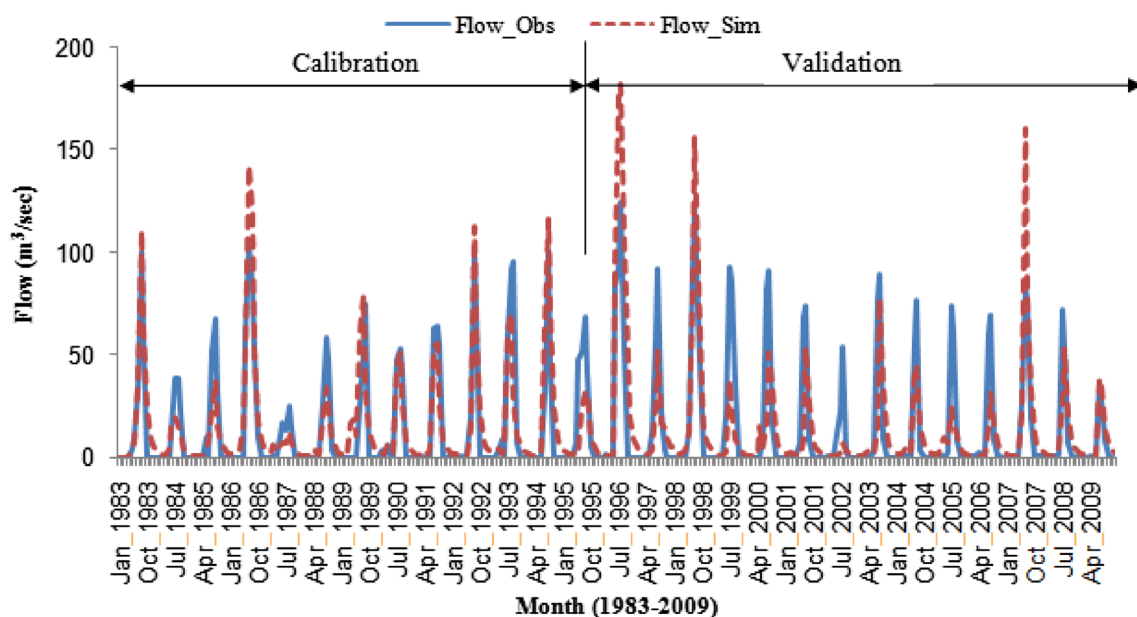
X\_Code indicate the type of change to be applied to the parameter, V\_ means the existing parameter value is to be replaced by the given value, a\_ means the given value is added to the existing parameter value, and r\_ means the existing parameter value is multiplied by  $(1 + a \text{ given value})$

**Table 3** Hydrological parameter selected after stream flow calibration for sediment load calibration

Name	Definition	Threshold value	Initial value	P value	Fitted value
r_CN2.mgt	SCS runoff curve number for moisture condition II	−0.20–0.20	65.46	0.0	68.57
v_SPCON.bsn	A linear parameter used in channel sediment routing	0–0.01	0.0001	0.05	0.0012
r_SOL_K.sol	Soil conductivity (mm/h)	−0.50–0.50	1378.53	0.70	1621.70
a_CH_COV <sub>2</sub> .rte	Channel erodibility factor	0–0.20	0.00	0.45	0.799
a_CH_COV <sub>1</sub> .rte	Channel cover factor	0–0.20	0.00	0.40	0.60
a_ADJ_PKP.bsn	Peak rate adjustment factor for sediment routing in the subbasin	0–0.20	0.00	0.65	0.903
v_CH_D.rte	Average depth of main channel	0–30	2.73	0.30	2.91
v_ALPHA_BNK.ret	Base flow alpha factor for bank storage	0.00–1.00	0.113	0.80	0.057
v_TLAPS.sub	Temperature laps rate (°C/km)	−10–10	−6.65	0.65	−4.26
r_SLSUBBSN.hru	Average slope length	−0.5–0.50	150.0	0.0	55.13
a_RCHARG_DP.gw	Deep aquifer percolation fraction	0.00–0.20	0.987	0.75	1.0
v_SPEXP.bsn	An exponent parameter used in channel sediment routing	1.0–1.50	1.00	0.45	1.31

**Table 4** Model performance indicator for monthly stream flow simulation

Statistical test	Monthly model efficiency measure						
	NSE	R <sup>2</sup>	wR <sup>2</sup>	PBIAS	RSR	P-factor	r-factor
Calibration	0.76	0.75	0.60	10.90	0.49	0.73	0.67
Validation	0.70	0.71	0.50	9.5	0.59	0.70	0.49

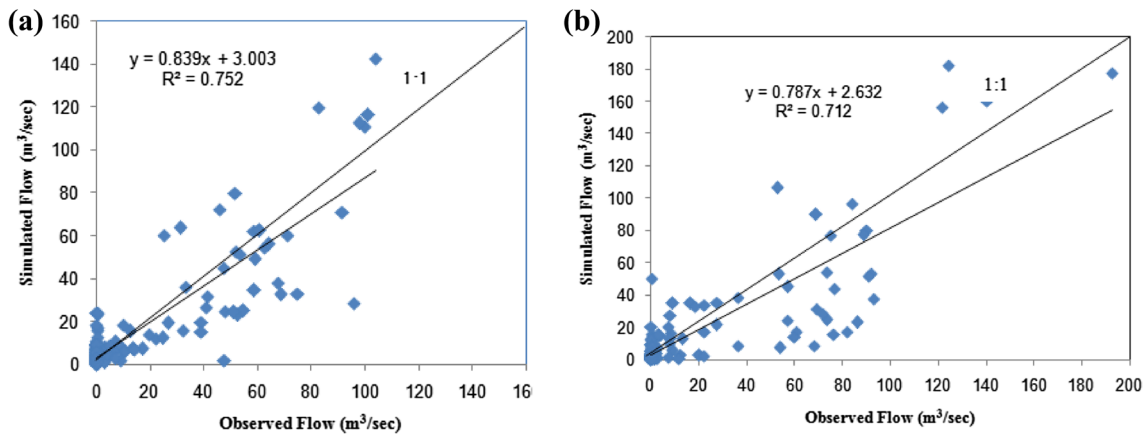


**Fig. 5** Simulated vs observed monthly flow at the watershed outlet for model calibration and validation

**Conclusions**

To analyze runoff and sediment load from Mojo watershed SWAT model was developed successfully. The parameter identification for model calibration of the

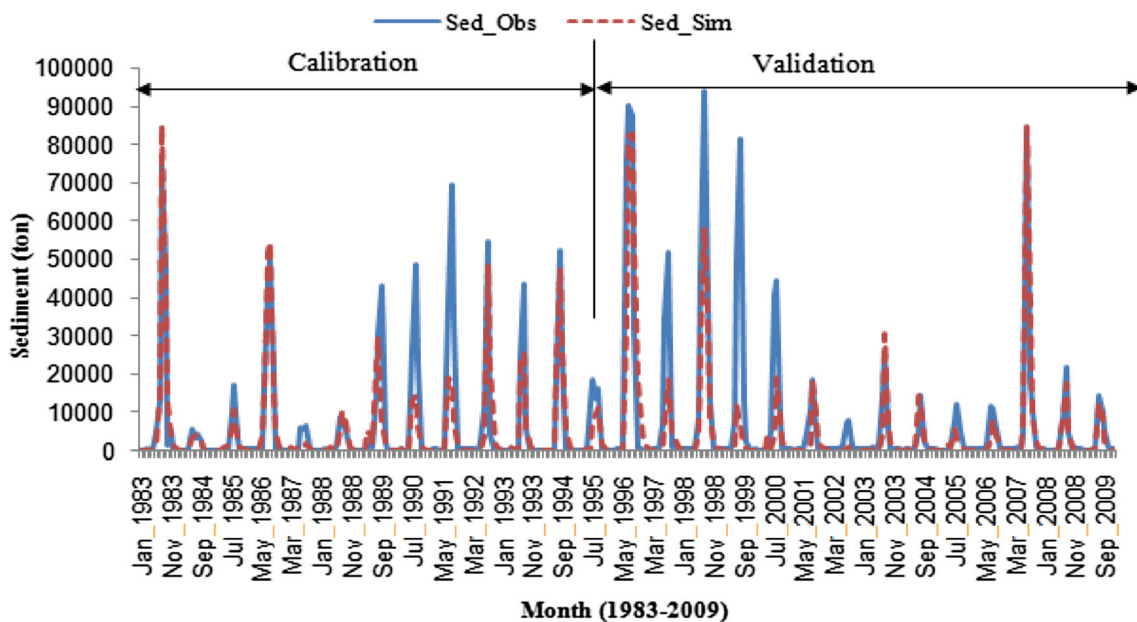
model is accomplished using SWAT\_CUP global sensitivity analysis method of SUFI2 that has become popular in recent years. The parameter identification process effectively reduced the number of parameters to be calibrated in SWAT model for stream flow and sediment



**Fig. 6** Comparison between simulated flow and observed flow for calibration (a) and validation (b)

**Table 5** Model performance indicator for monthly sediment load simulation

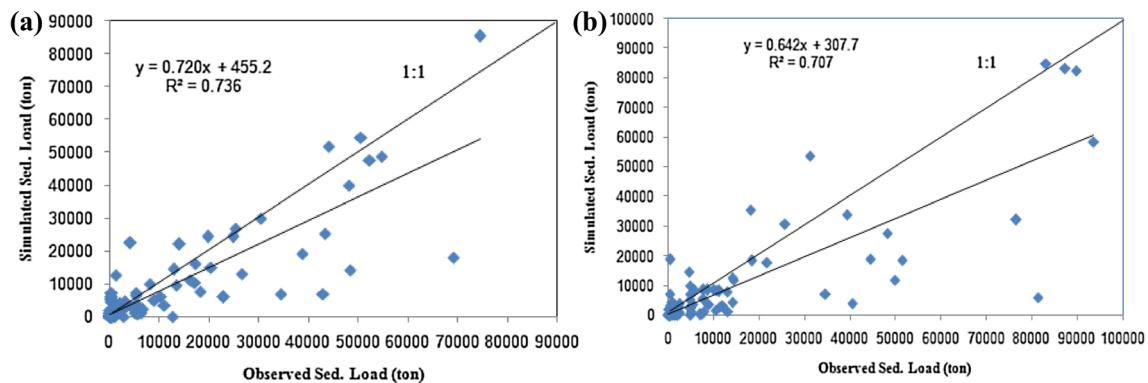
Statistical test	Monthly model efficiency measure						
	NSE	$R^2$	w $R^2$	PBIAS	RSR	$P$ -factor	$r$ -factor
Calibration	0.76	0.74	0.66	48.70	0.49	0.64	0.59
Validation	0.65	0.71	0.51	50.5	0.59	0.50	0.49



**Fig. 7** Simulated vs observed sediment at the watershed outlet for calibration and validation

load simulation. The parameters related to surface and subsurface flow was found to be more sensitive to the stream flow of the watershed, signifying the watershed is rich in ground water as a result of good recharge capacity. On the other hand parameter involves soil and surface runoff was found more sensitive for sediment load from the watershed. Clearly, the choice of values of these inputs can greatly affect the predicted stream flow

and sediment load results, underscoring that care must be taken in selecting the most accurate input values possible. Generally, by changing the value of thirteen hydrological parameters, selected through sensitivity analysis, the wide uncertainty band arising from input data, model algorithms and assumptions, parameters estimates reduced to narrow this uncertainty in steps until a satisfactory 95PPU is reached.



**Fig. 8** Comparison between simulated and observed sediment load for calibration (a) and validation (b)

The results of uncertainty estimation, narrow band uncertainty, calibration and validation result of this studies showed that SWAT model was able to accurately track monthly measured stream flows and sediment load at Mojo watershed outlet. Therefore, it can be concluded that the calibrated parameter values can be considered for hydrologic simulation of the un-gauged watershed in Ethiopia having the same agro-climatic condition. Furthermore, the model can be used for future studies on Mojo watershed to address different watershed management issues related to plant nutrient loss, water quality and best management practices evaluation.

**Acknowledgements** The authors wish to thank the staff member of Ethiopian National Metrology Service Agency and Ethiopian Federal Ministry of Water Resources for their kind cooperation and support in providing the necessary data for this study. The authors also would like to acknowledge the cooperation of Mr. Dawit Endale in providing soil and land use data.

## References

- Abbaspour KC (2012) SWAT-calibration and uncertainty programs. <http://swat.tamu.edu/software/swat-cup/>. Accessed 18 June 2015
- Arnold JG, Fohrer N (2005) SWAT2000 current capabilities and research opportunities in applied watershed modeling. *Hydrol Process* 19:563–572
- Arnold JG, Srinivasan R, Muttiah RS, Williams JR (1998) Large area hydrologic modeling and assessment. *J Am Water Resour Assoc* 34(1):73–89
- Arnold JG, Moriasi DN, Gassman PW, Abbaspour KC, White MJ, Srinivasan R, Santhi C, Harmel RD, van Griensven A, Van Liew MW, Kannan N, Jha MK (2012) SWAT model use, calibration, and validation. *Trans ASABE* 55(4):1491–1508
- Coffey AE, Workman SR, Taraba JL, Fogle AW (2004) Statistical procedures for evaluating daily and monthly hydrologic model predictions. *Trans ASAE* 47(1):59–68
- FAO (1998) World reference base for soil resources, world soils report no. 84, Rome
- Fontaine TA, Cruickshank TS, Arnold JG, Hotchkiss RH (2002) Development of a snowfall–snowmelt routine for mountainous terrain for the soil and water assessment tool. *J Hydrol* 262(1–4):209–223
- Griensven A, Meixner T, Grunwald S, Bishop T, Diluzio M, Srinivasan R (2006) A global sensitivity analysis tool for the parameters of multi-variable catchment models. *J Hydrol* 324:10–23
- Gupta HV, Sorooshian S, Yapo PO (1999) Status of automatic calibration for hydrologic models: comparison with multilevel expert calibration. *J Hydrol Eng* 4(2):135–143
- Jajarmizadeh M, Harun S, Abdullah R, Salarpour M (2012) Using soil and water assessment tool for flow simulation and assessment of sensitive parameters applying SUFI-2 algorithm. *Casp J Appl Sci Res* 2(1):37–44. <http://www.cjasr.com>. Accessed 20 June 2015 (ISSN: 2251-9114)
- Knisel WG (1980) CREAMS, a field scale model for chemicals, runoff and erosion from agricultural management systems. USDA Conservation Research Rept. No. 26, Washington DC
- Krause P, Boyle DP, Base F (2005) Comparison of different efficiency criteria for hydrological model assessment. *Adv Geosci* 5:89–97
- Leonard RA, Knisel WG, Still DA (1987) GLEAMS: groundwater loading effects of agricultural management systems. *Trans ASAE* 30:1403–1418
- Margaret WG, Chaubey I (2010) Regionalization of SWAT model parameters for use in ungauged watersheds. [www.mdpi.com/journal/water](http://www.mdpi.com/journal/water). Accessed 15 June 2015
- Matamoros D, Guzman E, Bonini J, Vanrolleghem PA (2005) AGNPS and SWAT model calibration for hydrologic modeling of an Ecuadorian river basin under data scarcity. IWA Publishing, London
- Mengistu D, Sorteberg A (2012) Sensitivity of SWAT simulated stream flow to climatic changes within the Eastern Nile River basin. *Hydrol Earth Syst Sci* 16:391–407
- Merritt WS, Letcher RA, Jakeman AJ (2003) A review of erosion and sediment transport models. *Environ Model Softw* 18:761–799
- Migliaccio KW, Srivastava P (2007) Hydrologic components of watershed-scale models. *Trans ASABE* 50(5):1695–1703
- Mishra A, Kar S, Pandey AC (2008) Comparison of SWAT with HSPF model in predicting hydrologic processes of a small multi-vegetated watershed. *J Agric Eng* 45(4):29–35
- Morgan RPC (1995) Soil erosion and conservation, 2nd edn. Longman Group Unlimited, London, p 198
- Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans ASABE* 50(3):885–900
- Neitsch SL, Arnold JG, Kiniry JR, Williams JR, King KW (2002) Soil and water assessment tool, theoretical documentation, Black land research center, grassland, soil and water research laboratory, agricultural research service, Temple, TX

- Neitsch SL, Arnold JG, Kiniry JR, Williams JR, King KW (2011) Soil and water assessment tool. Theoretical documentation: version 2009. TWRI TR-406. Texas Water Resources Institute, College Station, TX, pp 647
- Ogwo V, Ogbu KN, Okoye CJ, Okechukwu ME, Mbajioru CC (2012) Comparison of soil erosion models for application in the humid tropics. *Spec Publ Niger Assoc Hydrol Sci* 266–278
- Parajuli PB, Ouyang Y (2013) Watershed-scale hydrological modeling methods and applications. <http://creativecommons.org/licenses/by/3.0>. Accessed 21 May 2015
- Reungsang P, Kanwar RS, Jha M, Gassman PW, Ahmad K, Saleh A (2005) Calibration and validation of SWAT for the Upper Maquoketa River watershed. Center for Agricultural and Rural Development, Iowa State University. [www.card.iastate.edu](http://www.card.iastate.edu). Accessed 5 July 2015
- Santhi C, Arnold JG, Williams JR, Dugas WA, Srinivasan R, Hauck LM (2001) Validation of the SWAT model on a large river basin with point and nonpoint sources. *J Am Water Resour Assoc* 37(5):1169–1188
- Stefan L (2003) The PCPSTAT program user's manual. <http://swat.tamu.edu/media/83150/manual-PCPSTAT>. Accessed 5 Apr 2015
- Williams JR (1975) Sediment routing for agricultural watersheds. *Water Resour Bull* 11(5):965–974
- Williams JR, Jones CA, Dyke PT (1984) A modeling approach to determining the relationship between erosion and productivity. *Trans Am Soc Agric Eng* 27(1):129–144
- Wischmeier WH, Smith DD (1978) Predicting rainfall erosion losses: a guide to conservation planning. Agricultural Handbook No. 537 (USDA), Washington, DC
- Xie H, Longuevergne L, Ringler C, Scanlon BR (2012) Calibration and evaluation of a semi-distributed watershed model of Sub-Saharan Africa using GRACE data. *Hydrol Earth Syst Sci* 16:3083–3099
- Yongwei G, Zhenyao S, Ruimin L, Xiujuan W, Chen T (2010) Effect of watershed subdivision on SWAT modeling with consideration of parameter uncertainty. *J Hydrol Eng* 2010(15):1070–1074
- Zhang X, Srinivasan R, Zhao K, Van Liew M (2008) Evaluation of global optimization algorithms for parameter calibration of a computationally intensive hydrologic model. Wiley Inter Science. <http://www.interscience.wiley.com>. doi:10.1002/hyp.7152
- Zhang X, Srinivasan R, Bosch D (2009) Calibration and uncertainty analysis of the SWAT model using genetic algorithms and Bayesian model averaging. *J Hydrol* 374:307–317