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Hydrological Modelling in the Lake Tana Basin, Ethiopia Using SWAT Model

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Abstract: The SWAT2005 model was applied to the Lake Tana Basin for modeling 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 streamflow 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 algorithms. The sensitivity analysis of the model to subbasin delineation and HRU definition thresholds showed that the flow is more sensitive to the HRU definition thresholds than subbasin discretization effect. SUFI-2 and GLUE gave good result. All sources of uncertainties were captured by bracketing more than 60% of the observed river discharge. Baseflow (40% - 60%) is an important component of the total discharge within the study area that contributes more than the surface runoff. The calibrated model can be used for further analysis of the effect of climate and land use change as well as other different management scenarios on streamflow and soil erosion.

Key Words: SWAT, Lake Tana, hydrological modeling, watershed modeling, streamflow, SUFI-2, GLUE, ParaSol, water balance.

1. INTRODUCTION

In the Lake Tana Basin the available land and water resources are not utilized effectively to improve the livelihood and socioeconomic conditions of the inhabitants. The existing land and water resources system of the area is adversely affected by the rapid growth of population, deforestation, surface erosion and sediment transport. There is a need for hydrological research of the Lake Tana Basin that can support improved catchment management programs that can better safeguard the alarmingly degradation of soil and water resources in Ethiopian highlands. The lack of decision support tools and limitation of data concerning weather, hydrological, topographic, soil and land use are factors that significantly hinder research and development in the area. The tools concern various hydrological and soil erosion models. In recent years, distributed watershed models are increasingly used to implement alternative management strategies in the areas of water resources allocation, flood control, impact of land use change and climate change, and finally environmental pollution control. Many of these models share a common base in their attempt to incorporate the heterogeneity of the watershed and spatial distribution of topography, vegetation, land use, soil characteristics, rainfall and evaporation. Some of the watershed models developed in the last two decades are CREAMS (Chemicals, Runoff, and Erosion from Agricultural Management Systems) [1], EPIC - Erosion Productivity Impact Calculator [2], AGNPS (Agricultural None Point Source model) [3], SWAT (Soil and Water Assessment Tool) [4] and HSPF (Hydrologic Simulation Program – Fortran) [5]. Many of these watershed models are applied for runoff and soil loss prediction [e.g. 6-8], water quality modelling [e.g. 9-11], land use change effect assessment [e.g. 12-14] and climate change impact assessment [e.g. 15-17]. Among the foregoing models, physically based distributed models such as SWAT are well established models for analyzing the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds. A comprehensive review of SWAT model applications is given by [18]. In this study we focus on calibration, evaluation and application of SWAT2005 model for simulation of the hydrology of Lake Tana Basin. The main objective of this study was to test the performance and feasibility of the SWAT2005 model for prediction of streamflow in the Lake Tana Basin. There are few applications of SWAT model to Ethiopian conditions in relatively small watershed areas [e.g. 19-21]. The present study considers large scale application of the model on a catchment area where most of the topographic features have slopes greater than 5%. For estimation of curve number to slopes above 5% an equation developed by reference [2] was used. Many distributed watershed models use different factors and parameters for the simulation of the hydrological processes. Hence it is important for these models to pass careful calibration tests and uncertainty analysis. Different researchers used several calibration and uncertainty analysis techniques [e.g. 22-25]. In this paper application of SUFI-2, ParaSol and GLUE calibrations and uncertainty algorithms are discussed.

2. STUDY AREA

The Lake Tana basin comprises an area of 15,096 km^2 including the lake area (Fig. **1**). The mean annual rainfall of the catchment area is about 1280 mm. The annual mean ac-

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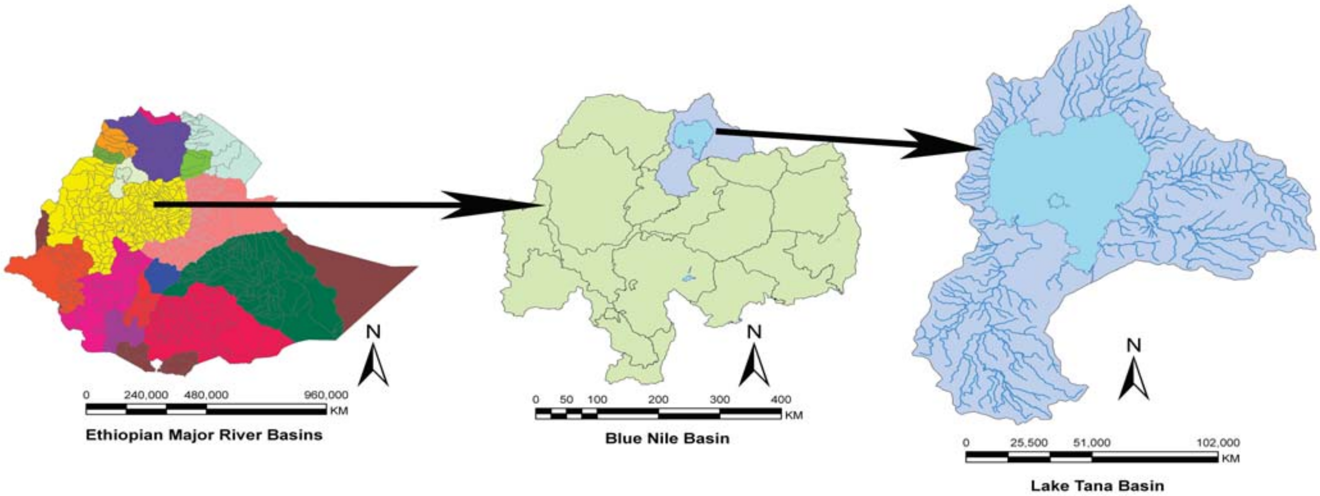


Fig. (1). Location Map of the study area.

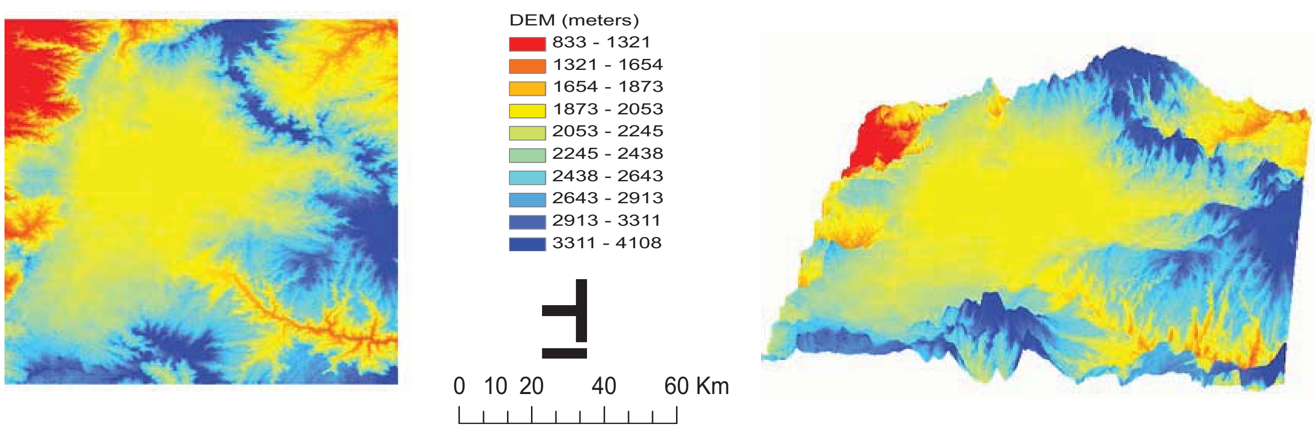


Fig. (2). DEM of the Lake Tana Basin (meter above see level).

tual evapotranspiration and water yield of the catchment area is estimated to be 773 mm and 392 mm, respectively. The climate of the region is 'tropical highland monsoon' with main rainy season between June and September. The air temperature shows large diurnal but small seasonal changes with an annual average of 20 °C. The mean annual relative humidity (1961–2004) at Bahr Dar gauge station (Fig. **4**) is 0.65. The basin has significance national importance due to its high potentials for irrigation, hydroelectric power development, high value crops and livestock production, and ecotourism. Lake Tana, the main source of the Blue Nile River, is the largest lake in Ethiopia and the third largest in the Nile Basin. It is approximately 84 km long, 66 km wide and is located in the country's north-west highlands (Lat 12° 0' North, Lon 37° 15' East). The lake is a natural freshwater lake which covers 3000 - 3600 km^2 area at an elevation of 1800 m. The lake is shallow with a maximum depth of 15 m. The main tributaries of the Lake Tana are GilgelAbay, Gumera, Ribb and Megech rivers. The present study shows that these four inflow rivers contribute to more than 45% of the annual Lake water budget. The only surface outflow is the Blue Nile (Abba) River with an annual flow volume of 4 billion cubic meters measured at Bahir Dar gauge station.

3. METHODS

The present study concerns the application of a physically based watershed model SWAT2005 in the Lake Tana Basin to examine the influence of topographic, landuse, soil and climatic condition on stream flow. The impact of subbasin discretization and hydrologic response units (HRU) definition on stream flow were also studied. The application of the model involved calibration, sensitivity and uncertainty analysis. For this purpose SUFI-2, ParaSol and GLUE calibration and uncertainty analysis algorithms were used. To get converged solutions 2000, 3000, and 10000 iterations were needed for each method, respectively. A converged solution is reached when the objective functions such as Nash Sutcliffe efficiency, reach constant values.

3.1. Description of SWAT Model

SWAT (Soil Water Assessment Tool) is continuous time, spatially distributed model designed to simulate water, sedi-

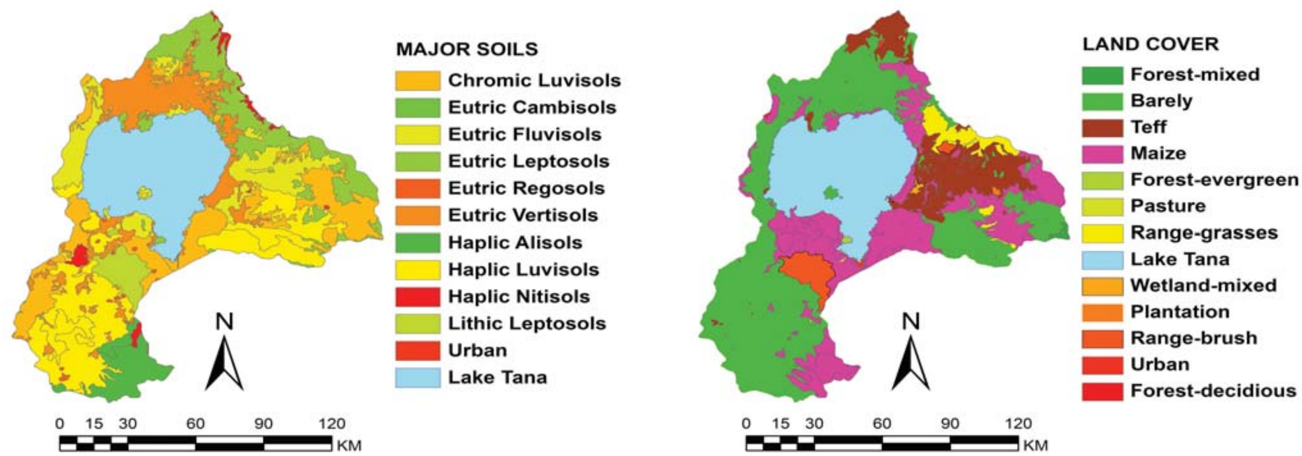


Fig. (3). Soil types (a) and land cover (b) maps in Lake Tana Basin.

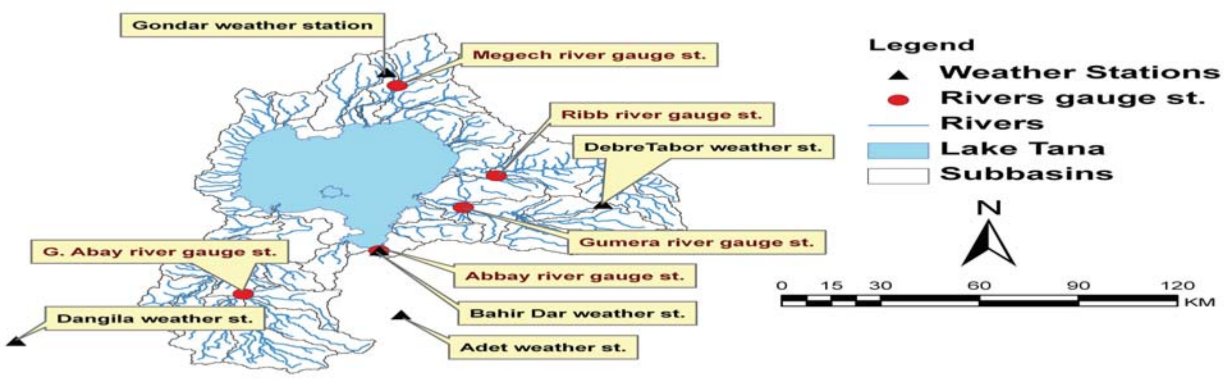


Fig. (4). Weather and streamflow gauge stations, subbasins and river layers in Lake Tana Basin.

ment, nutrient and pesticide transport at a catchments scale on a daily time step. It uses hydrologic response units (HRUs) that consist of specific land use, soil and slope characteristics. The HRUs are used to describe spatial heterogeneity in terms of land cover, soil type and slope class within a watershed. The model estimates relevant hydrologic components such as evapotranspiration, surface runoff and peak rate of runoff, groundwater flow and sediment yield for each HRUs unit. SWAT is imbedded in a GIS interface. ArcSWAT ArcGIS extension is a graphical user interface for the SWAT2005 which is evolved from AVSWAT which is an ArcView extension developed for an earlier version of SWAT. The hydrologic cycle simulated by SWAT is based on the water balance equation (1).

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{qw} \right)_i \tag{1}$$

In which, SW_t is the final soil water content (mm water), SW_o is the initial soil water content in day i (mm water), t is the time (days), R_{day} is the amount of precipitation in day i (mm water), Q_{surf} is the amount of surface runoff in day i (mm water), E_a is the amount of evapotranspiration in day i (mm water), W_{seep} is the amount of water entering the vadose zone from the soil profile in day i (mm water), and Q_{gw} is the amount of return flow in day i (mm water). To estimate surface runoff two methods are available. These are the SCS curve number procedure USDA Soil Conservation Service [26] and the Green & Ampt infiltration method [27]. In this study, the SCS curve number method was used to estimate surface runoff. Hargreaves method was used for estimation of potential evapotranspiration (PET) [28]. The SCS curve number is described by equation 2.

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

In which, Q_{surf} is the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm), S is the retention parameter (mm). The retention parameter is defined by equation 3.

$$S = 25.4\left(\frac{100}{CN} - 10\right) \tag{3}$$

The SCS curve number is a function of the soil's permeability, landuse and antecedent soil water conditions. SCS defines three antecedent moisture conditions: 1 – dry (wilting point), 2 – average moisture, and 3 – wet (field capacity).

The moisture condition 1 curve number is the lowest value that the daily curve number can assume in dry conditions. The curve numbers for moisture conditions 2 and 3 are calculated from equations 4 and 5.

$$CN_1 = CN_2 - \frac{20 \cdot (100 - CN_2)}{(100 - CN_2 + \exp[2.533 - 0.0636 \cdot (100 - CN_2)])} \quad (4)$$

$$CN_3 = CN_2 \cdot \exp[0.00673 \cdot (100 - CN_2)] \quad (5)$$

In which CN_1 is the moisture condition 1 curve number, CN_2 is the moisture condition 2 curve number, and CN_3 is the moisture condition 3 curve number.

Typical curve numbers for moisture condition 2 are listed in various tables [29] which are appropriate to slope less than 5%. But in the Lake Tana basin there are areas with slopes greater than 5%. To adjust the curve number for higher slopes an equation developed by [2] was used (equation 6).

$$CN_{2S} = \frac{(CN_3 - CN_2)}{3} \cdot [1 - 2 \cdot \exp(-13.86 \cdot slp)] + CN_2 \quad (6)$$

In which CN_{2S} is the moisture condition 2 curve number adjusted for slope, CN_3 is the moisture condition 3 curve number for the default 5% slope, CN_2 is the moisture condition 2 curve number for the default 5% slope, and *slp* is the average percent slope of the subbasin.

3.2. Model Input

The spatially distributed data (GIS input) needed for the ArcSWAT interface include the Digital Elevation Model (DEM), soil data, land use and stream network layers. Data on weather and river discharge were also used for prediction of streamflow and calibration purposes.

Digital Elevation Model

Topography was defined by a DEM that describes the elevation of any point in a given area at a specific spatial resolution. A 90 m by 90 m resolution DEM (Fig. **2**) was downloaded from SRTM (Shuttle Radar Topography Mission) website on 20 September 2007 [30]. The DEM was used to delineate the watershed and to analyze the drainage patterns of the land surface terrain. Subbasin parameters such as slope gradient, slope length of the terrain, and the stream network characteristics such as channel slope, length, and width were derived from the DEM.

Soil Data

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. These data were obtained mainly from the following sources: Soil and Terrain Database for northeastern Africa CD-ROM (Food and Agriculture Organization of the United Nations [31], Major Soils of the world CD-ROM [32], Digital Soil Map of the World and Derived Soil Properties CD-ROM [33], Properties and Management of Soils of the Tropics CD-ROM [34], Abbay River basin Integrated Development Master Plan Project - Semi detailed Soil Survey and the Soils of Anjeni Area, Ethiopia (SCRP report). Major soil types in the basin are Chromic Luvisols, Eutric Cambisols,Eutric Fluvisols, Eutric Leptosols, Eutric Regosols, Eutric Vertisols, Haplic Alisols, Haplic Luvisols, Haplic Nitisols and Lithic Leptosols (Fig. **3a**).

Land Use

Land use is one of the most important factors that affects surface erosion, runoff, and evapotranspiration in a watershed. The land use map of the study area was obtained from ministry of water resources Ethiopia. We have reclassified the land use map of the area based on the available topographic map (1:50,000), aerial photographs and satellite images. The reclassification of the land use map was done to represent the landuse according to the specific land cover types such as type of crop, pasture and forest. Fig. (**3b**) shows that more than 50% of the Lake Tana watershed is used for agriculture.

Weather Data

SWAT requires daily meteorological data that can either be read from a measured data set or be generated by a weather generator model. The weather variables used in this study for driving the hydrological balance are daily precipitation, minimum and maximum air temperature for the period 1978 – 2004. These data were obtained from Ethiopian National Meteorological Agency (NMA) for stations located within and around the watershed (Fig. **4**). We have used a weather generator developed by [35] to fill the gaps due to missing data.

River Discharge

Daily river discharge values for Ribb, Gumera, GilgelAbay, Megech rivers and the outflow river Blue Nile (Abbay) were obtained from the Hydrology Department of the Ministry of Water Resources of Ethiopia. These daily river discharges at four tributaries of Lake Tana; Gumera, GilgelAbay, Megech and Ribb rivers gauging stations (Fig. **4**) were used for model calibration and validation. Fig. (**5**) indicated that the peak flows for all inflow rivers occur in August. But the outflow river gets its peak flow at the month of September. There is a one month delay of peak flow for outflow river. This is due to the influence of the lake which retards the flow before it reach the outlet. The record of the outflow river (Abbay) at BahirDar gauge station was not used for model calibration and validation. This is because we have seen a significant difference between the default simulated and measured stream flow data at this gauge station. There is abstraction of water from the lake for irrigation and other purposes. But there is no available information on the amount of water losses from the lake. The outflow river measured data was used to study the water balance of the lake and understand the amount of unknown losses of water from the lake.

3.3. Model Setup

The model setup involved five steps: (1) data preparation; (2) subbasin discretization: (3) HRU definition; (4) parameter sensitivity analysis; (5) calibration and uncertainty analysis.

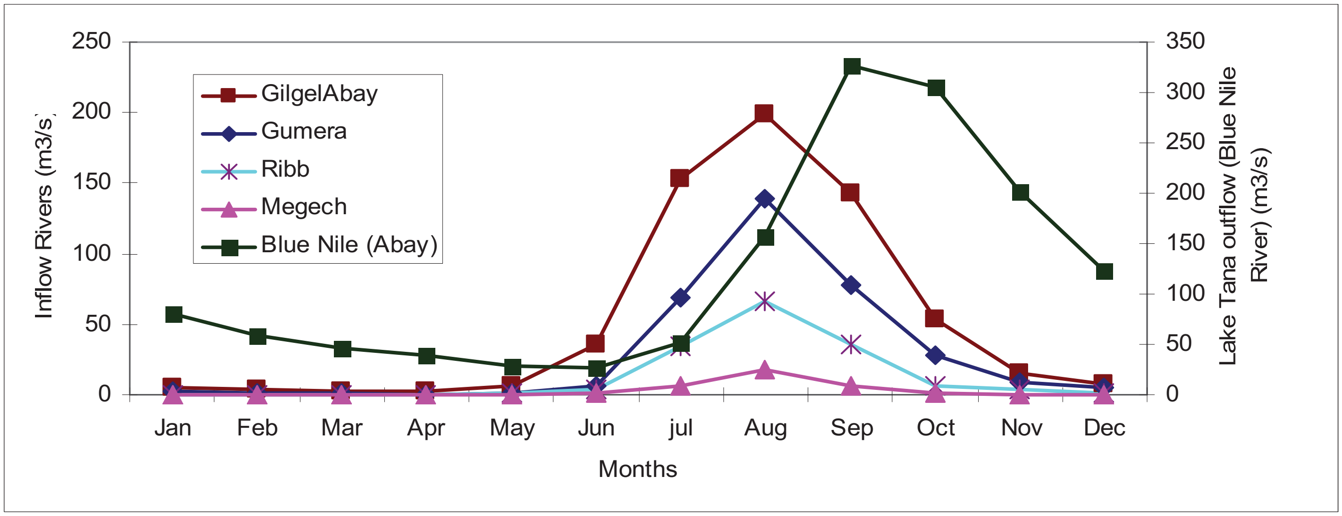


Fig. (5). Average monthly flows for the major tributary rivers of Lake Tana and Outflow river.

The required spatial datasets were projected to the same projection called Adindan UTM Zone 37N, which is the transverse mercator projection parameters for Ethiopia, using ArcGIS 9.1. The DEM was used to delineate the watershed and to analyze the drainage patterns of the land surface terrain. DEM mask was used that was superimposed on the DEM. The ArcSWAT interface uses only the masked area for stream delineation. A predefined digital stream network layer was imported and superimposed onto the DEM to accurately delineate the location of the streams. The Land use/Land cover spatial data were reclassified into SWAT land cover/plant types. A user look up table was created to identify the SWAT code for the different categories of land cover/land use on the map as per the required format. The soil map was linked with the soil database which is a soil database designed to hold data for soils not included in the U.S. The watershed and subwatershed delineation was done using DEM data. The watershed delineation process include five major steps, DEM setup, stream definition, outlet and inlet definition, watershed outlets selection and definition and calculation of subbasin parameters. For the stream definition the threshold based stream definition option was used to define the minimum size of the subbasin. The ArcSWAT interface allows the user to fix the number of subbasins by deciding the initial threshold area (TA). The threshold area defines the minimum drainage area required to form the origin of a stream. To explore the sensitivity of SWAT2005 model flow predictions to threshold area values for subbasin delineation eight different scenarios were tested in the Lake Tana Basin using the same DEM. The first scenario was the threshold area suggested by the interface (49954 hectares). Other seven scenarios were cases below (1/4, 1/3, 1/2 and 3/4) and above (5/4, 3/2, and 7/4) the suggested threshold area (12488, 15000, 24977, 37465, 62442, 74931 and 87419 hectares).

Subdividing the sub watershed into areas having unique land use, soil and slope combinations makes it possible to study the differences in evapotranspiration and other hydrologic conditions for different land covers, soils and slopes. The landuse, soil and slope datasets were imported overlaid and linked with the SWAT2005 databases. To define the distributions of HRUs both single and multiple HRU definition options were tested. For multiple HRU definition the ArcSWAT user's manual suggests that a 20 percent land use, a 10 percent soil and 20% slope threshold are adequate for most applications. To identify the most reasonable threshold level in the area the suggested threshold and other landuse, soil and slope combinations scenarios were tested in Lake Tana Basin. These were 20% - 10% - 20%, 10% - 20% - 10%, 10% - 10% - 20%, 20% - 20% - 10%, and 25% - 30% - 20%. Each scenario was arranged in order of land use percentage over subbasin area, soil class percentage over land use area and slope class percentage over soil area. For example, if a 20% soil area is defined in HRU distribution, only soils that occupy more than 20% of a subwatershed area are considered in HRU distributions. Land uses, soils or slope that cover a percentage of the subbasin area less than the threshold level were eliminated. After the elimination processes the area of the land use, soil or slope is reallocated so that 100 percent of the land area, soil or slope in the subbasin is included in the simulation.

The parameter sensitivity analysis was done using the ArcSWAT interface [36] for the whole catchment area. Twenty six hydrological parameters were tested for sensitivity analysis for the simulation of the stream flow in the study area. Here, we used the default lower and upper bound parameter values. The details of all hydrological parameters are found in the ArcSWAT interface for SWAT user's manual [37].

The calibration and uncertainty analysis were done using three different algorithms, i.e., Sequential Uncertainty Fitting (SUFI-2) [22, 11], Parameter Solution (ParaSol) [38] and Generalized Likelihood Uncertainty Estimation (GLUE) [39]. These methods are chosen for their applicability from simple to complex hydrological models. SUFI-2 and GLUE algorithms account for several sources of uncertainties such as uncertainty in driving variables (e.g., rainfall), conceptual model, parameters, and measured data. But ParaSol assesses only model parameter uncertainty. The degree to which uncertainties are accounted for is quantified by a *P-factor* which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). 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 [11]. Another measure quantifying the strength of a calibration or uncertainty analysis is the r-*factor* which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. The goodness of calibration and prediction uncertainty is judged on the basis of the closeness of the *p-factor* to 100% (i.e., all observations bracketed by the prediction uncertainty) and the *r-factor* to 1. The average thickness of the 95PPU band ($\bar{r}$) and the r-factor are calculated by Equation 7 and 8.

$$\bar{r} = \frac{1}{n}\sum_{t_i}^{n}(y^M_{t_i,97.5\%} - y^M_{t_i,2.5\%}) \tag{7}$$

$$r - factor = \frac{p - factor}{\sigma_{obs}} \tag{8}$$

In which $y^M_{t_i,97.5\%}$ and $y^M_{t_i,2.5\%}$ represent the upper and lower boundaries of the 95PPU, and σ_{obs} is the standard deviation of the measured data.

The other factor is the goodness of fit that can be quantified by the coefficient of determination (R^2) and Nash-Sutcliff efficiency (NSE) [40] between the observations and the final best simulations. Coefficient of determination (R^2) and Nash-Sutcliffe coefficient (NSE) are calculated by equation 9 and 10.

$$R^2 \frac{\left[\sum_i\left(Q_{m,i}-\overline{Q_m}\right)\left(Q_{s,j}-\overline{Q_s}\right)\right]^2}{\sum_i\left(Q_{m,j}-\overline{Q_m}\right)^2\sum_i\left(Q_{s,i}-\overline{Q_s}\right)^2} \tag{9}$$

$$NSE = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2} \tag{10}$$

In which Q_m is the measured discharge, Q_s is the simulated discharge, $\overline{Q}_m$ is the average measured discharge and $\overline{Q}_s$ is the average simulated discharge

After setting up of the model, the default simulations of stream flow, using the default parameter values, were done in the Lake Tana Basin for the calibration period (1978-1992). The default simulation outputs were compared with the observed streamflow data on four tributaries of Lake Tana. In this study the automatic calibration was done after the model was manually calibrated and reached to stage that the differences between observed and simulated flows were minimized and shown improved objective function values. The data for period 1981 to 1992 were used for calibration. An independent precipitation, temperature and streamflow dataset (1993 to 2004) was used for validation of the model in the four river basins. Periods 1978 to 1980 and 1990 to 1992 were used as "warm-up" periods for calibration and validation purposes, respectively. The warm-up period allows the model to get the hydrologic cycle fully operational.

4. RESULT AND DISCUSSION

The results and discussion include five components: (i) the analysis of SWAT2005 model sensitivity to the level of subbasin discretization, (ii) effect of land use, soil and slope threshold in defining HRU on SWAT2005 model performance, (iii) flow parameter sensitivity analysis (iv) SWAT2005 model calibration and validation for flow at GilgelAbay, Gumera, Ribb and Megech rivers of Lake Tana Basin using manual and automatic calibration methods and (v) analysis of base flow and other hydrological components.

4.1. Impact of Subbasin Discretization

The model efficiency was computed using the default simulation result and the measured flow data. It was observed that the threshold area of 15000 hectares resulted in 34 subbasins that accounts for the main drainage lines within the watershed. This resulted in a better representation of the hydrological processes and produced streamflow yield which had a better model efficiency in comparison to the measured streamflow. Number of subbasins above this threshold has brought no significant changes in the simulation of streamflow. The overall results indicated that the simulation of streamflow is not significantly affected by increasing the size of threshold area from 1/3 to 7/3 of suggested threshold area. The streamflow increased by less than 10 percent as the number of subwatershed increased by 26 percent. This is due to an increase in transmission gains (subsurface flow). The results have shown that subbasin discretization on SWAT2005 model has limited impact on streamflow prediction in the study area. This is mainly due to the fact that prediction of surface runoff is highly related to curve number which is not affected significantly by the size of the subbasin. Generally, there are many factors that affect runoff such as climatic and watershed or physiographic factors. SWAT model uses SCS curve number method (i.e., equation 2) to calculate the surface runoff that accounts for the precipitation and the retention parameter. The latter parameter is calculated with the value of curve number (i.e., equation 3). Curve number depends primarily on the soil type, landuse and to the lesser extent on slope. The calculation of CN in the Lake Tana basin was adjusted for slope greater than 5%. Thus making runoff to be less dependent on subbasin discretization.

4.2. Effect of Landuse, Soil and Slope Thresholds

The analysis of HRU definition indicated that dominant type of HRU definition resulted in a single HRU for each subbasin where the dominant land use, soil and slope within the basin was considered to be the land use, soil and slope of each subbasin. This single HRU with in each subbasin was not able to properly represent the characteristics of the subbasins. Accordingly the simulated streamflow shows unsatisfactory result as compared to the measured stream flows in the four river basins of the study area. The multiple scenarios that accounts for 10% landuse, 20% soil and 10% slope threshold combination gives a better estimation of streamflow in the Lake Tana Basin. It resulted in 214 HRUs in the

Table 1. Stream Flow Calibration and Validation Result for GilgelAbay, Gumera, Megech and Ribb Rivers Using SUFI-2, GLUE and ParaSol Methods

Objective Function		Rivers							
		GilgelAbay		Gumera		Megech		Ribb	
		Cal	Val	Cal	Val	Cal	Val	Cal	Val
NSE	SUFI-2	0.71	0.69	0.62	0.60	0.18	0.04	0.51	0.48
	GLUE	0.58	0.69	0.60	0.60	0.20	0.04	0.50	0.48
	PARASOL	0.73	0.71	0.61	0.61	0.22	0.20	0.55	0.45
R^2	SUFI-2	0.80	0.80	0.69	0.70	0.19	0.32	0.59	0.55
	GLUE	0.79	0.80	0.71	0.70	0.25	0.32	0.58	0.55
	PARASOL	0.80	0.78	0.71	0.70	0.20	0.31	0.59	0.57
p-factor	SUFI-2	83%	79%	79%	73%	53%	57%	73%	65%
	GLUE	76%	75%	73%	64%	55%	46%	66%	61%
	PARASOL	21%	19%	19%	17%	15%	15%	17%	16%
r-factor	SUFI-2	0.81	0.77	0.75	0.72	0.39	0.33	0.58	0.54
	GLUE	0.65	0.69	0.62	0.65	0.11	0.13	0.45	0.49
	PARASOL	0.10	0.08	0.08	0.05	0.02	0.02	0.06	0.05

Cal= Calibration, Val=Validation

whole basin. This scenario resulted in detailed land use, slope and soil database, containing many HRUS, which in turn represent the heterogeneity of the study area. The comparison between the default model predictions and measured discharge produced the highest Nash-Suttcliffe efficiency (NSE). The distribution of landuse, soil and slope characteristics with in each HRU have the greatest impact on the predicted streamflow. As the percentage of land use, slope and soil threshold increases the actual evapotranspiration decreases due to eliminated land use classes. Hence, the characteristics of HRUs are the key factor affecting streamflow.

4.3. Parameter Sensitivity Analysis

In this study we have evaluated the relative sensitivity values found in the parameter estimation process. Nineteen parameters were found to be sensitive with the relative sensitivity values ranges from 0.001 to 0.45. Among which the most sensitive parameters were: soil evaporation compensation factor (ESCO), initial SCS Curve Number II value (CN2), base flow alpha factor (Alpha_Bf) [days], threshold depth of water in the shallow aquifer for "revap" to occur (REVAPMN.gw) [mm H_2O], [days], available water capacity (Sol_Awc) [mm WATER/mm soil], groundwater "revap" coefficient (Gw_Revap), channel effective hydraulic conductivity (Ch_K2) [mm/hr] and threshold depth of water in the shallow aquifer for return flow to occur (GWQMN.gw) [mm H_2O]. These sensitive parameters were considered for model calibration. The remaining parameters had no significant effect on streamflow simulations. Changes in their values do not cause significant changes in the model output.

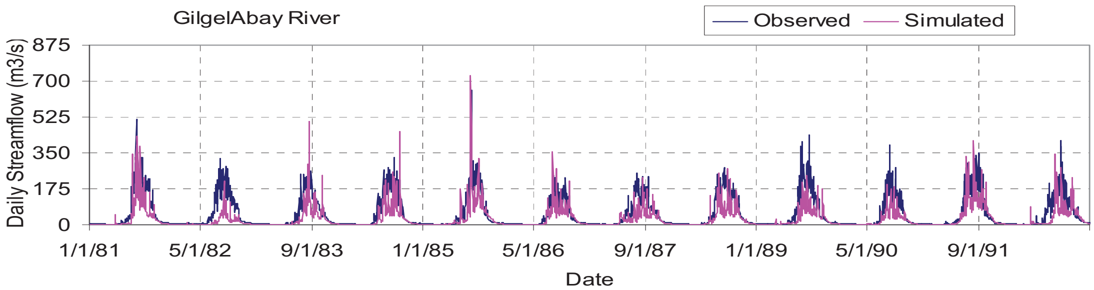
4.4. Default Simulation and Manual Calibration

The comparison of default simulation output with the observed streamflow data on four tributaries of Lake Tana showed a clear difference between the observed and simulated flow results. For manual calibration the model was run in order of yearly, monthly and daily bases. Parameters manually adjusted were evaporation compensation factor (ESCO), curve number (CN), available water holding capacity of the soil layer (Sol_AWC, mm/mm), saturated hydraulic conductivity (Sol_K, mm/hr), and surface runoff lag time. The manual calibration was time intensive but it helped to get better automatic calibration results.

4.5. Flow Calibration Using SUFI-2 Algorithm

The comparison between the observed and calibrated flow discharge values for twelve years of simulations indicated that there is a good agreement between the observed and simulated flows using SUFI-2 algorithms with higher values of coefficient of determination and Nash Sutcliffe efficiency (NSE) for Gilgel Abay, Gumera and Ribb rivers. [41-43] suggested that model simulation can be judged as satisfactory if R^2 is greater than 0.6 and NSE is greater than 0.5. Hence our results agree reasonably well with these values. Calibrated model predictive performance for all rivers on daily flows is summarized in Table **1**. Fig. (**6**) shows the time series of measured and simulated daily flow at GilgelAbay river gauge station during calibration period.

The p-factor, which is the percentage of observations bracketed by the 95% prediction uncertainty (95PPU), brackets 83% of the observation and r-factor equals 0.81 for GilgelAbay river. The 95PPU brackets only 53% of the observations and r-factor equals 0.39 for Megech river. This shows that the SUFI-2 did not capture the observations well during calibration period for Megech river. This problem coupled with the lower values of NSE and R^2 for Megech river indicate that there is high uncertainty of simulated flow due to errors in inputs data such as rainfall and temperature



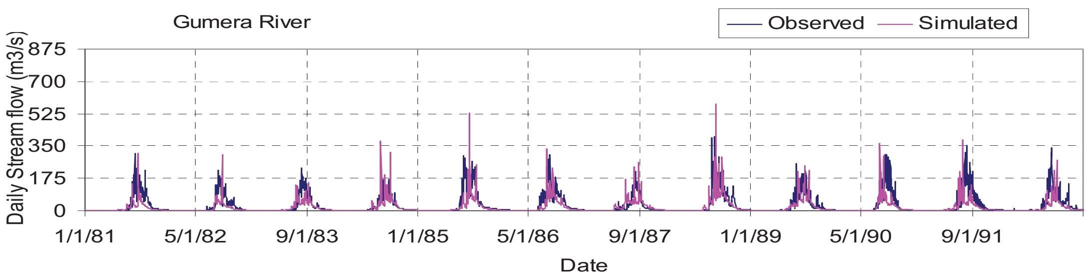


Fig. (6). Observed and simulated discharge in GilgelAbay and Gumera rivers for the calibration period.

Table 2. Daily Flow Calibration Result for all Rivers for Each Year of Calibration Period (1981 – 1992)

Year	GilgelAbay River		Gumera River		Ribb River		Megech River	
	NS	R2	NS	R2	NS	R2	NS	R2
1981	0.82	0.89	0.35	0.44	0.68	0.72	0.28	0.36
1982	0.62	0.67	0.44	0.61	0.72	0.76	0.64	0.66
1983	0.70	0.79	0.61	0.66	0.76	0.61	0.31	0.31
1984	0.67	0.78	0.66	0.56	0.61	0.51	0.24	0.32
1985	0.78	0.82	0.56	0.48	0.51	0.50	0.48	0.52
1986	0.79	0.85	0.48	0.69	0.50	0.57	0.58	0.67
1987	0.50	0.67	0.69	0.55	0.57	0.55	0.36	0.47
1988	0.64	0.81	0.55	0.57	0.55	0.78	0.79	0.89
1989	0.54	0.77	0.57	0.71	0.78	0.78	0.10	0.54
1990	0.58	0.78	0.71	0.53	0.78	0.72	1.00	0.66
1991	0.83	0.89	0.53	0.41	0.72	0.64	-0.63	0.21
1992	0.54	0.63	0.41	0.58	0.64	0.58	0.59	0.64

and/or other sources of uncertainties such as upstream dam construction for town water supply, diversion of streams for irrigation, and other unknown activities in the subbasins. However, the uncertainties may not only depend on rainfall and temperature. We have used the Hargreaves method to calculate evapotranspiration that depends on minimum and maximum temperatures. Thus, the main inputs used in the model are rainfall and temperature. The lack of meteorological data did not allow to consider additional factors. We have assumed that the model deficiency in Megech watershed could be due to the input uncertainty as well as construction of infrastructures in the upstream of the watershed. However, we cannot rule out the possibility of an error in the type of soil and the corresponding soil properties in the area. This can create some uncertainty on the simulated result. Another issue is the soil erosion that affects the structure, infililtration capacity and other properties of the soil. Since the model does not consider the effect of soil erosion on runoff, the predictions can be uncertain. Hargreaves method does not include the effect of wind on evapotranspiration. In cases where the wind is a predominating factor the method can introduce some errors.

Table **2** lists various performance statistics for each calibration year. For GilgelAbay, Gumera and Ribb river basins, the NSE and R^2 values are good for all calibration years whereas the evaluation statistics for Megech river shows lower values for the years 1981, 1983, 1984, 1987, 1989 and 1991. This might show that there might be input (precipitation and temperature) or measured streamflow data uncer-

Table 3. Breakdown of Different Hydrological Components for GilgelAbay River at Wet and Dry Years

Year		Rainfall (mm)	ET (mm)	SW (mm)	PERC (mm)	SURQ (mm)	GW_Q (mm)	LAT_Q (mm)	WYLD (mm)
Calibration period									
1982	Dry	902	699	142	120	25	17	54	96
1991	Wet	1799	813	138	580	280	421	118	819
Validation period									
1994	Dry	1085	741	132	235	55	100	69	224
2003	Wet	1658	700	137	562	278	390	110	778

ET=Actual Evapotranspiration from HRU, SW=Soil water content, PERC=water that percolates past the root zone during the time step
SURQ=Surface runoff contribution to streamflow during time step, TLOSS= Transmisson losses, water lost from tributary channels in the HRU via , transmission through the bed, GW_Q= Ground water contribution to streamflow, LAT_Q= Lateral floe contribution to streamflow
WYLD=water yield (water yield=SURQ+LATQ+GWQ-TLOSS-pond abstractions)

Table 4. SWAT Flow Sensitive Parameters and Fitted Values After Calibration Using SUFI-2

No.	Sensitive Parameters	Lower and Upper Bound	Final Fitted Value			
			GilgelAbay River	Megech River	Ribb River	Gumera River
1	ESCO	0 - 1	0.8	0.8	0.8	0.8
2	CN2	±25%	-10	-9	-10	-8
3	ALPHA_BF	0 - 1	0.1	0.1	0.1	0
4	REVAPMN	0 - 500	300	289	372	446
5	SOL_AWC	±25%	0.2	-0.2	-0.1	0.2
6	GW_REVAP	±0.036	0	0.1	0	0.1
7	CH_K2	0 - 5	4.6	3.2	1.9	0.7
8	GWQMN	0 - 5000	108	17	333	98

tainty during the mentioned years. Moreover, NSE is more sensitive to extreme values hence in such years there is a high variability between the whole observed flow data and their average. In year 1990 the NSE value for Megech river is one. This shows that the ratio between the mean square error to the variance in the observed data is zero. It shows that the peak flows of the measured and observed flows matches very well. But for the year 1991 the negative NSE value indicate that observed mean is a better predictor than the model. There is a higher variability between the observed and measured peak flows.

To understand the prediction performance of SWAT2005 model for different rainfall conditions we have compared the annual average rainfall and other hydrological components for each year of the calibration and validation periods for GilgelAbay river. Table **3** shows that year 1982 was a dry year and 1991 was a wet year for calibration period and 1994 and 2003 were driest and wettest years, respectively during the validation period for GilgelAbay river. The use of the term ‘dry’ is relative as the rainfall is greater than 900mm. The wet years produce a larger water yield than the dry years. The water fluxes in Table **3** indicate that in a wet year surface runoff dominates water yield which is the total amount of water leaving the HRU and entering main channel during the time step. However, in dry year, lateral flow contribution makes up a larger part of the water yield. As indicated in Fig. (**7**) in a dry year the simulated streamflow is lower than the observed flow. It resulted is some degree of prediction uncertainties. However, in wet year condition the simulated flow fits the observed stream flow. This indicates that the model efficiency differs between wet and dry years conditions in the study area.

Based on the above result we can assume that the model can better predict the surface runoff than the groundwater contribution to stream flow during wet season. One reason could be due to the soil data quality and estimation of the curve number at dry moisture condition. Since the SCS curve number is a function of the soil’s permeability, landuse and antecedent soil water conditions the estimation of curve number at dry moisture condition (wilting point) might not be efficient in that watershed.

The calibration process using SUFI-2 algorithm gave the final fitted parameters for each river basin (Table **4**). The final values for CN2, Soil_AWC includes the amount adjusted during the manual calibration. These final fitted parameter values were incorporated into the SWAT2005 model for validation and further applications.

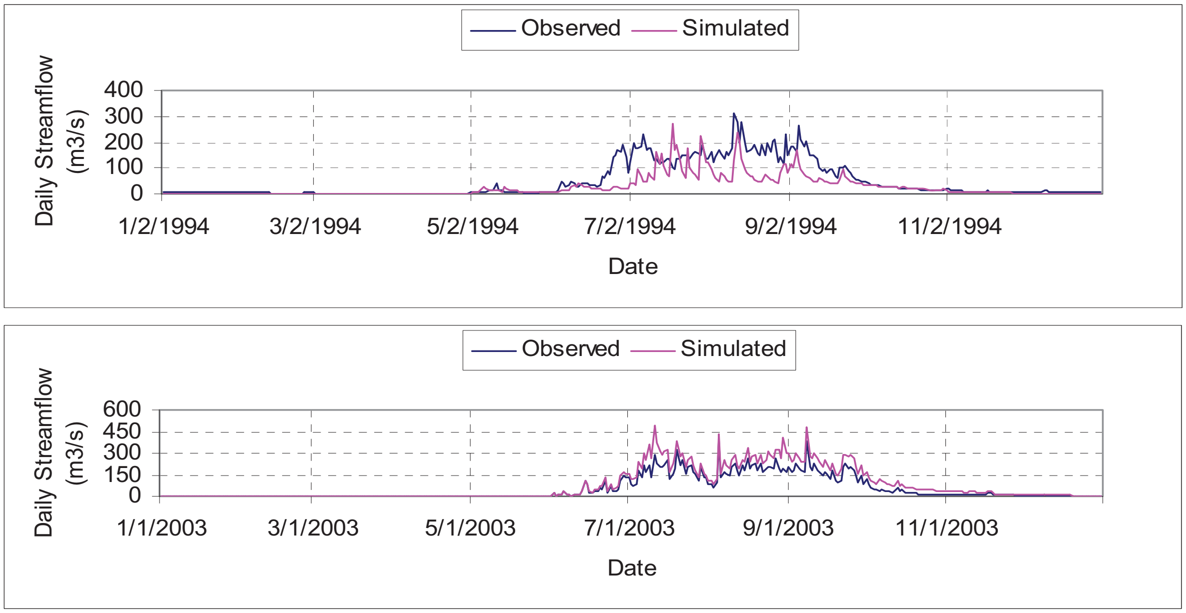


Fig. (7). Low flow (top) and high flow (middle) condition in GilgelAbay river for Validation period.

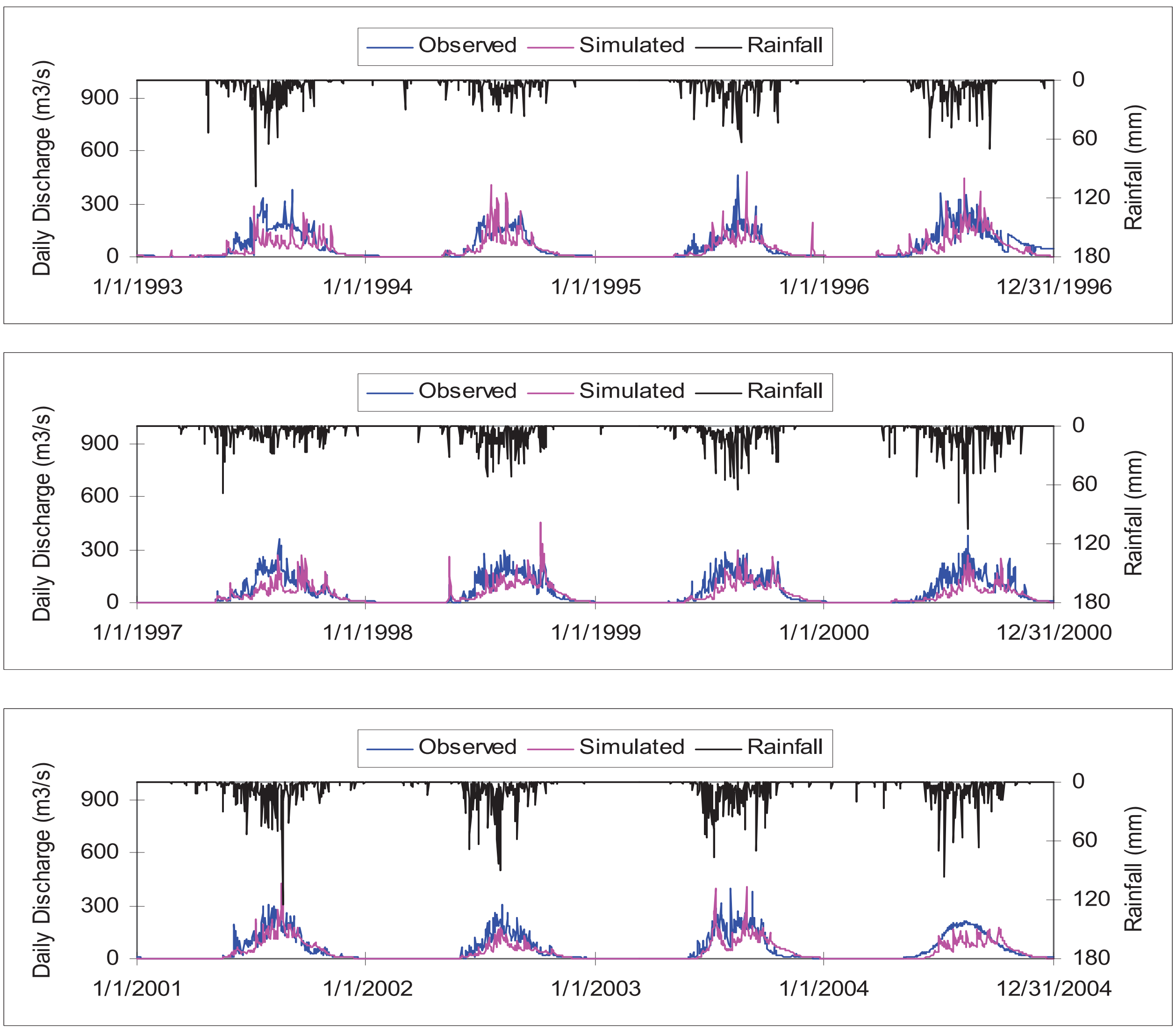


Fig. (8). Time series of measured and simulated daily flow validation results at GilgelAbay river gauge station.

4.6. Flow Validation Using SUFI-2 Algorithm

The validation result was good for GilgelAbay, Gumera and Ribb rivers with high values of R^2 and NSE (Table **1**). Further more 79% of the observed data bracketed by 95PPU for GilgelAbay river, 73% for Gumera and 65 for Ribb rivers. Time series of measured and simulated daily flows with respect to the depth of rainfall in Gilgel Abay river basin indicated that both the observed and simulated flow discharge follows the rainfall pattern of the area. The higher discharge occurs during the months of June to September. This high flow corresponds to the longer rainy season. Above 75% percent of annual flow occurs in this period. Fig. (**8**) shows the time series of measured and simulated daily flow at GilgelAbay river gauge station during validation period.

The monthly calibration results of SUFI-2 algorithm has also shown a good agreement between monthly observed and simulated flows in all river basins both during calibration and validation processes which is shown by the coefficient of determinations (R^2) and the Nash-Sutcliffe simulation efficiency (NSE) greater than 0.8. Fig. (**9**) shows the monthly calibration result for GilgelAbay River Basin.

4.7. Calibration and Validation Using GLUE and ParaSol Algorithms

In GLUE method four iteration levels were tested with simulations sample sizes of 1000, 2000, 5000 and 10000 for four river basins. The comparison showed that there are differences in the simulation results for different levels of iterations. Good results were found at 10000 iteration level for each river basin. The NSE and R^2 values showed that there is a good agreement between the measured and simulated flows both for calibration and validation periods. Moreover most of the observations are bracketed by the 95PPUs for GilgelAbay and Gumera rivers. Table **1** lists NSE, R^2, p-factor and r-factor for all rivers computed by comparing the measured flow with the best simulation streamflow. According to [44] the disadvantage of GLUE method is its excessive computational burden due to its random sampling strategy. ParaSol calibration process converges within 2000 to 3000 iterations. This is because the model was already calibrated manually and the minimum and maximum parameters boundary ranges were narrowed for automatic calibration. In ParaSol method the best simulation result matches the observation quite well during both calibration and validation periods for all the rivers (Table **1**). But the method was not able to bracket the observed flow. For instance only 21%, 19%, 15% and 17% of measurements were bracketed by 95PPU during the calibration period for GilgelAbay, Gumera, Megech and Ribb rivers, respectively. This is because ParaSol doesn't consider the error in the model structure, measured input and measured response.

4.8. Hydrological Water Balance

The baseflows were evaluated on an annual basis for Gilgelabay, Gumera, Megech, and Ribb river basins (Table **5**). The baseflow filter program by [45] generates a range of predicted baseflow volumes. On an annual basis, the measured flow at GilgelAbay river gauge station is estimated as 59% baseflow over the calibration period. In comparison, the simulated flow at GilgelAbay is estimated as 54% baseflow

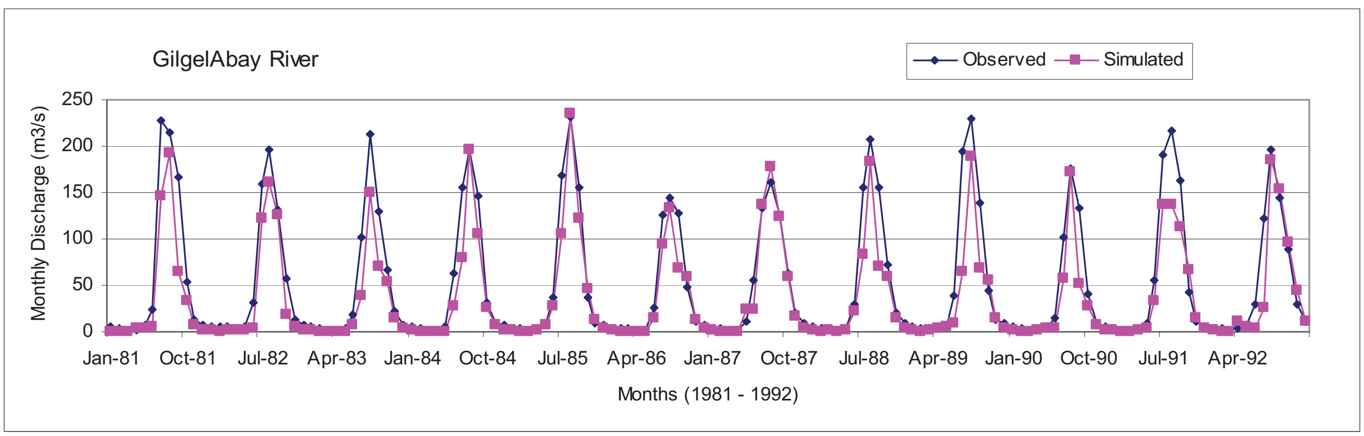


Fig. (9). Time series of monthly calibration result for GilgelAbay river.

Table 5. Baseflow Contribution at four River Gauge Stations for the Calibration Period

Station	Mean Measured Flow (m3/s)	Mean Simulated Flow (m3/s)	Observed Mean Baseflow Contribution (%)	Simulated Mean Baseflow Contribution (%)
GilgelAbay	53	47	59	54
Megech	3.9	3.6	49	60
Gumera	29	22	58	64
Ribb	13	12	60	65

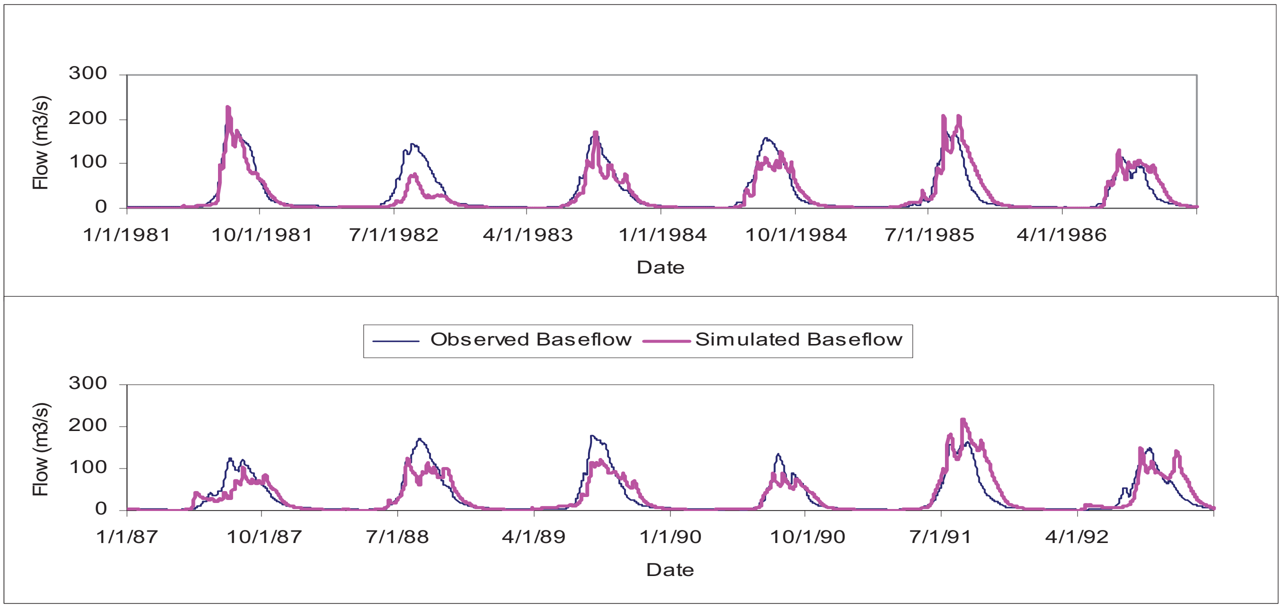


Fig. (10). Time series graph showing Baseflow separated from Observed and simulated flow for Gilgelabay River.

Table 6. Water Balance Components on an Annual Average Basis Over the Calibration and Validation Periods for the Lake Tana Basin

Period		Rainfall	ET	SurQ	LatQ	GW_Q	WYLD	SW	PERC	TLOSS
Calibration	(mm)	1168	758	95	73	137	305	217	251	12
	(%)	100.0	64.9	8.1	6.2	11.7	26.1	18.6	21.5	1.0
Validation	(mm)	1394	782	120	101	254	474	227	400	13
	(%)	100.0	56.1	8.6	7.2	18.2	34.0	16.3	28.7	1.0

ET = evapotranspiration, SURQ = surface runoff, LATQ = lateral flow into stream, GW_Q = groundwater contribution to stream flow, WYLD = SURQ + LATQ + GW_Q - LOSSES, SW = soil water, PERC = percolation below root zone (groundwater recharge).

Table 7. Inflow and Outflow Components of Lake Tana Water Balance

Water Balance Components	Annual Budget	
	(BM3)	(%) Over Total Input
Direct rainfall over the Lake	4.3	51
Inflow from main rivers and small streams	3.7	44
Surface runoff from unmonitored sub-watershed (runoff coefficient of 0.22 (Shahin, 1988).)	0.4	5
Total Input to the Lake	8.4	
Lake evaporation	3.9	46
Out flow from the Lake	4.0	48
Total losses from the Lake	7.9	
Change in water balance (unknown losses)	0.5	6

over the calibration period. Therefore the calibrated model was considered to generate acceptable predictions of base-flow on an annual basis.

The main water balance components of the four river basins includes: the total amount of precipitation falling on the subbasin during the time step, actual evapotranspiration from the basin and the net amount of water that leaves the basin and contributes to streamflow in the reach (water yield). The water yield includes surface runoff contribution to stream-flow, lateral flow contribution to streamflow (water flowing laterally within the soil profile that enters the main channel), groundwater contribution to streamflow (water from the shallow aquifer that returns to the reach) minus the transmission losses (water lost from tributary channels in the HRU via transmission through the bed and becomes recharge for the shallow aquifer during the time step). Table **6** lists the simulated water balance components on an annual average basis for the Lake Tana Basin over the calibration and validation period. The results indicated that 65% of the annual precipitation is lost by evapotranspiration in the basin during calibration as compared to 56% during validation period. Surface runoff contributes 31% and 25% of the water yield during calibration and validation period respectively. Where as the ground water contribute 45% and 54% of the water yield during calibration and validation period respectively. Fig. (**10**) shows time series graph showing Baseflow separated from Observed and simulated flow for Gilgelabay River.

Water Balance of Lake Tana

The water balance components of the Lake Tana includes the direct rainfall over the lake surface (P), inflow from main rivers and small streams (Q_{inflow}), surface runoff inflow from unmonitored sub-watershed (Q_{surq},), Out flow from the Lake (($Q_{outflow}$), Lake evaporation (E_L), change in water balance (unidentified losses) (ΔS). We can assume the following water balance equation to the Lake (equation 11).

$$P + \sum Q_{\inf low} + Q_{surq} = \sum Q_{outflow} + E_L + \Delta S \quad (11)$$

The prediction of Lake Tana water balance is based on the simulation result from 1978 to 2004. The estimated annual precipitation falling on the lake is 1375 mm and the evaporation loss from the Lake is about 1248 mm. The Estimation of the input and output water fluxes, in billion cubic meter and percentage with respect to the total water inputs to the lake, are indicated in Table **7**. Components such as groundwater loss or recharge are difficult to estimate. The analysis of the Lake Tana water balance has shown that there is an annual surplus of 0.5 BM3 of water. Part of this excess water can be used for irrigation practices by the surrounding local farmers, groundwater and other unidentified abstractions.

5. CONCLUSION

The SWAT2005 model was successfully calibrated and validated in the Lake Tana Basin using different algorithm. It was applied to the Lake Tana Basin for the modeling of the hydrological water balance. The sensitivity analysis of the model to subbasin delineation and HRU definition thresholds showed that the flow is more sensitive to the HRU definition thresholds than subbasin discretization effect. SUFI-2, GLUE and ParaSol algorithms gave good results in minimizing the differences between observed and simulated flow in the Lake Tana Basin. The p-factor and r-factor computed using SUFI-2 and GLUE gave good result by bracketing more than 60% of the observed data. A SUFI-2 algorithm is an effective method but it requires additional iterations as well as the need for the adjustment of the parameter ranges. ParaSol method doesn't consider all sources of uncertainty thus it gave lower p-factor and r-factor. The hydrological water balance analysis showed that baseflow (40% - 60%) is an important component of the total discharge within the study area that contributes more than the surface runoff. More than 60% of losses in the watershed are through evapotranspiration. Despite data uncertainity, the SWAT model produced good simulation results for daily and monthly time steps. The calibrated model can be used for further analysis of the effect of climate and land use change as well as other different management scenarios on stream flow and of soil erosion.

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REFERENCES

[1] Knisel WG. CREAMS, a field scale model for chemicals, runoff, and erosion from agricultural management systems. USDA Conservation Research Report Washington, D.C.: USDA, 1980; No. 26.

[2] Williams JR. The EPIC model. In Singh VP. (Ed). Computer models of watershed hydrology. Water resources Publications, Highlands Ranch, CO, 1995, Chapter 25, pp. 909-1000.

[3] Young RA, Onstad CA, Bosch DD, Anderson WP. Agnps - a Non-point-Source Pollution Model for Evaluating Agricultural Watersheds. J Soil Water Conserv 1989; 44(2): 168-173.

[4] Arnold JG, Srinivason R, Muttiah RR, Williams JR. Large Area Hydrologic Modeling and Assessment Part I: Model Development. J Am Water Resour Assoc 1998; 34(1): 73-89.

[5] Bicknell BR, Imhoff JC, Kittle JL, Jobes TH, Donigian AS. Hydrologic Simulation Program – FORTRAN (HSPF), user's manual for version 12.0, 2001; USEPA.

[6] Morgan RPC. A simple approach to soil loss prediction: a revised Morgan–Morgan–Finney model. Catena 2001; 44: 305-322.

[7] Srinivasan R, Ramanarayanan TS, Arnold JG, Bednarz ST. Large Area Hydrologic Modeling and Assessment. Part II:Model Application. J Am Water Resour Assoc 1998; 34(1): 91-101.

[8] Grønsten HA, Lundekvam H. Prediction of surface runoff and soil loss in south eastern Norway using the WEPP Hillslope model. Soil Tillage Res 2006; 85: 186-199.

[9] Debele B, Srinivasan R, Yves Parlange J. Coupling upland watershed and downstream waterbody hydrodynamic and water quality models (SWAT and CE-QUAL-W2) for better water resources management in complex river basins. Environ Model Assess 2006; DOI 10.1007/s10666-006-9075-1.

[10] Santhi C, Srinivasan R, Arnold JG, Williams JR. A modeling approach to evaluate the impacts of water quality management plans implemented in a watershed in Texas. Environ Model Softw 2006; 21: 1141-1157.

[11] Abbaspour KC, Yang J, Maximov I, *et al.* Modelling hydrology and water quality in the pre-alpine/alpine Thur watershed using SWAT. J Hydrol 2007; 333: 413-430.

[12] Sheng XB, Sun JZ, Liu YX. Effect of land-use and land-cover change on nutrients in soil in Bashang area, China. J Environ Sci 2003; 15 (4): 548-553.

[13] Claessens L, Hopkinson C, Rastetter E, Vallino J. Effect of historical changes in land use and climate on the water budget of an urbanizing watershed. Water Resour Res 2006; 42(3): W03426.

[14] Wu W, Hall CAS, Scatena FN. Modelling the impact of recent land-cover changes on the stream flows in northeastern Puerto Rico. Hydrol Process 2007; 21: 2944-2956.

[15] Andersson L, Wilk J, Todd MC, *et al.* Impact of climate change and development scenarios on flow patterns in the Okavango River. J Hydrol 2006; 331 (1): 43-57.
[16] Huang YF, Zou Y, Huang GH, Maqsood I, Chakma A. Flood vulnerability to climate change through hydrological modeling - A case study of the swift current creek watershed in western Canada. Water Int 2005; 30(1): 31-39.
[17] Zhang X, Srinivasan R, Hao F. Predicting Hydrologic Response to Climate Change in the Luohe River Basin Using the SWAT Model. Trans ASABE 2007; 50(3): 901-910.
[18] Gassman PW, Reyes MR, Green CH, Arnold JG. The soil and water assessment tool: Historical development, applications, and future research directions. Trans ASABE 2007; 50(4): 1211-1250.
[19] Alamirew CD. Modeling of Hydrology and Soil Erosion in Upper Awash River Basin. University of Bonn, Institut für Städtebau, Bodenordnung und Kulturtechnik 2006; pp. 235.
[20] Kassa T, Foerch G. Impacts of Land use/cover dynamics on streamflow: The case of Hare watershed, Ethiopia. In the proceedings of the 4th International SWAT2005 Conference 2007.
[21] Shimelis GS, Srinivasan R. Calibration and Validation of SWAT2005/ArcSWAT in Anjeni Gauged Watershed, Northern Highlands of Ethiopia. In the proceedings of the 4th International SWAT Conference 2007.
[22] Abbaspour KC, Johnson CA, van Genuchten MT. Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone J 2004; 3(4): 1340-1352.
[23] Abbaspour KC. Calibration of hydrologic models: when is a model calibrated? In Zerger A, Argent RM. (Eds) MODSIM 2005 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand, December 2005, pp. 2449-12455.
[24] Eckhardt K, Arnold J. Automatic calibration of a distributed catchment model. J Hydrol 2001; 251: 103-109.
[25] Yang J, Reichert P, Abbaspour KC, Yang H. Hydrological modelling of the chaohe basin in China: Statistical model formulation and bayesian inference. J Hydrol 2007; 340: 167-182.
[26] USDA Soil Conservation Service. National Engineering Handbook Section 4 Hydrology, 1972; Chapters 4-10.
[27] Green WH, Ampt GA. Studies on soil physics, 1. The flow of air and water through soils. J Agric Sci 1911; 4: 11-24.
[28] Hargreaves GL, Hargreaves GH, Riley JP. Agricultural benefits for Senegal River basin. J Irrig Drain Eng 1985; 111(2): 113-124.
[29] Neitsch SL, Arnold JG, Kiniry JR, Williams JR. Soil and Water Assessment Tool, Theoretical Documentation: Version 2005. Temple, TX. USDA Agricultural Research Service and Texas A&M Blackland Research Center, 2005.
[30] Jarvis A, Reuter HI, Nelson A, Guevara E. Hole-filled seamless SRTM data V3, International Centre for Tropical Agriculture (CIAT) 2006, available from http://srtm.csi.cgiar.org.
[31] FAO. The Soil and Terrain Database for northeastern Africa (CDROM) FAO, Rome, 1998.
[32] FAO, Major Soils of the World. Land and Water Digital Media Series Food and Agricultural Organization of the United Nations, Rome. CD-ROM, 2002.
[33] FAO. Digital Soil Map of the World and Derived Soil Properties (CDROM) Food and Agriculture Organization of the United Nations. FAO, 1995.
[34] Van Wambeke, A. Properties and management of soils of the tropics. FAO Land and Water Digital Media Series No. 24, FAO, Rome, 2003.
[35] Schuol J, Abbaspour KC. Using monthly weather statistics to generate daily data in a SWAT model application to West Africa. Ecol Model 2007; 201: 301-311.
[36] Van Griensven A, Meixner T, Grunwald S, Bishop T, Diluzio M, Srinivasan R. A global sensitivity analysis tool for the parameters of multi-variable catchment models. J Hydrol 2006; 324(1-4): 10-23.
[37] Winchell M, Srinivasan R, Di Luzio M, Arnold J. ArcSWAT Interface for SWAT User's Guide. Blackland Research Center, Texas Agricultural Experiment station and USDA Agricultural Research Service 2007.
[38] Van Griensven A, Meixner T. Methods to quantify and identify the sources of uncertainty for river basin water quality models. Water Sci Technol 2006; 53(1): 51-59.
[39] Beven K, Binley A. The future of distributed models: model calibration and uncertainty prediction. Hydrol Process 1992; 6: 279-298.
[40] Nash JE, Sutcliffe JV. River flow forecasting through conceptual models. Part I –A discussion of principles. J Hydrol 1970; 10: 282-290.
[41] Benaman J, Christine AS, Douglas AH. Calibration and validation of soil and water assessment tool on an agricultural watershed in upstate New York. J Hydrol Eng, ASCE 2005; 10(5): 363-374.
[42] Moriasi DN, Arnold JG, Van Liew MW, Binger RL, Harmel RD, Veith T. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 2007; 50(3): 885-900.
[43] Santhi C, Arnold JG, Williams JR, Dugas WA, Srinivasan R, Hauck LM. Validation of the SWAT model on a large river basin with point and nonpoint sources: J Am Water Resour Assoc 2001; 37(5): 1169-1188.
[44] Hossain F, Anagnostou EN, Lee KH. A non-linear and stochastic response surface method for Bayesian estimation of uncertainty in soil moisture simulation from a land surface model. Nonlinear Process Geophys 2004; 11(4): 427-440.
[45] Arnold JG, Allen PM. Automated methods for estimating baseflow and ground water recharge from streamflow records. J Am Water Resour Assoc 1999; 35(2): 411-424.

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