Modeling soil erosion by water using SWAT in northern Ethiopia

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Abstract

This study was designed to evaluate the performance of Soil and Water Assessment Tool (SWAT) model for estimating runoff, sediment and nutrient yields in Mai-Negus catchment, northern Ethiopia and suggest model applicability for management planning. The SWAT model was selected after hydrological models were reviewed using predefined criteria. The extrapolation of response information from similar areas was used to prepare observed data for model calibration and validation for the ungauged study catchment. Following sensitivity analysis, the SWAT model was calibrated, validated and assessed for evaluation model uncertainty using Nash–Sutcliffe coefficient (N_{SE}) and coefficient of determination (R^2). The model was calibrated from 1992 to 2000 periods and validated from 2001 to 2009 for flow. The annual flow calibration (N_{SE} = 0.67, R^2 = 0.81) and validation (N_{SE} = 0.73, R^2 = 0.84) values were higher than the daily and monthly basis. For sediment yield and nutrient losses, the calibration and validation periods were from 2001 to 2004 and 2005 to 2009, respectively. This study shows model efficiency > 0.50 and 0.60 for N_{SE} and R^2, respectively, which are adequate for SWAT model application for management planning. Such successful evaluation of SWAT model as illustrated in this study can widen model applicability into other ungauged basins.

Keywords: *SWAT model, Model evaluation, Runoff, Sediment yield, Nutrient losses, Mai-Negus catchment*

1. INTRODUCTION

Soil erosion is a serious global issue because of its severe adverse economic and environmental impacts. Economic impacts on productivity may be due to direct effects on crops/plants both on-site and off-site, and environmental consequences are primarily off-site related to the damage to civil structure, siltation of water ways and reservoirs, and additional costs involved in water treatment (Lal, 1998; Scherr, 1999). Globally, Oldeman (1994) approximated a land area of 1094 million ha to be affected by water erosion while El-Swaify et al. (1985) found that soil erosion within tropical environments was the most serious and least reversible form of land degradation. Dejene (1990) and Admassie (1995) reported that there was nowhere in the world where erosion was as destructive to the environment as in the Ethiopia highlands.

Even though the adverse influences of soil erosion on soil degradation have long been recognized as a key problem for human sustainability (Lal, 1998; Scherr, 1999; Tamene, 2005), estimation of soil erosion is often difficult due to the complex interplay of many factors such as climate, land cover, soil, topography, lithology and human activities. In addition to this, social, economic, political, and methodological components influence the rate of estimated soil erosion (Lal, 1998; Ananda and Herath, 2003). In support to the above facts, previous studies showed that average soil loss rates within croplands is estimated at 42 t ha^{-1} y^{-1} but may reach 300 t ha^{-1} y^{-1} in some fields in Ethiopia (Hurni, 1993). Erosion rates are also estimated at 130 t ha^{-1} y^{-1} within croplands and 35 t ha^{-1} y^{-1} averaged over all land use types in the Ethiopian highlands (FAO, 1986). Similarly, studies in Tigray region, northern Ethiopia have indicated that the mean rate of soil erosion varies from 7 t ha^{-1} y^{-1} (Nyssen, 2001) to more than 24 t ha^{-1} y^{-1} (Tamene, 2005) and 80 t ha^{-1} y^{-1} (Tekeste and Paul, 1989).

Past studies on soil erosion in Ethiopia were mainly based on plot level or empirical model such as Universal Soil Loss Equation (USLE). Although such studies provided good insight into the relationships between soil loss under different cover, soils and slopes (Tamene and Vlek, 2008; Setegn et al., 2009), the results cannot be extrapolated for an entire catchment directly, as such approaches possess many limitations in terms of representation, and reliability of the resulting data (Lal, 1998). The decisions made based on such results could be part of the reasons for the less effectiveness of the soil and water conservation programs that have been practiced in Ethiopia in the past four decades. Modeling soil erosion using physical models can thus provide an alternative and sophisticated tool for investigating the processes and mechanisms of soil erosion for targeted implementation of appropriate management measures at catchment or larger scales (Boggs et al., 2001).

Considerable progress has been made in soil erosion model development, though field evaluation of these models remains to be tested for many eco-regions. Even if there are numerous models intended to predict erosion, the application of these models is not always an easy task since they need large amount of information which often is just experimental or simply not available. However, models are the only current tools that enable an approximate quantification of soil erosion processes, facilitating the recognition of high-risk areas and consequently the development of an efficient planning to prevent future soil degradation (Santhi et al., 2001). Careful selection of appropriate models is thus crucial to achieve the intended goal.

In predicting soil erosion many erosion models have been developed and used over many years, for example, USLE (Wischmeier and Smith, 1978), Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), Water Erosion Prediction Project (WEPP) (Flanagan and Nearing, 1995), European Soil Erosion Model (EUROSEM) (Morgan et al., 1998), and AnnAGNPS (Bingner and Theurer, 2001). Among these models, the USLE has remained the most practical method of estimating soil erosion for over 40 years (Dennis and Rorke, 1999; Kinnell, 2000), whereas other process-based erosion models developed afterward have limitation in applicability due to intensive data and computation requirements (Lim et al., 2005). However, studies that applied the USLE model do not consider the sediment delivery ratio when estimating the sediment delivered to the downstream to the point of interest (Lim et al. 2005).

As a result, scientists have been involved in soil erosion research for a long time, and many physical based models for soil erosion estimation that take into account the sediment delivery have been developed. However, before applying any of the models developed elsewhere for natural resource management and decision making, evaluation of model performance from the context of the new environment is very crucial. Few case studies (e.g., Chekol, 2006; Setegn et al., 2008; Tibebe and Bewket, 2010; van Griensven et al., 2012) have already shown that SWAT model was evaluated with adequate level of accuracy in gauged catchments in some parts of Ethiopia. However, the lack of appropriate decision support tools and limitation of data concerning weather, hydrological, topographic, soil and land use are some of the factors that significantly hinder research and development efforts, as many of the catchments have very little or no monitoring data available in the country. With regard to this, little or no information is documented in evaluating the performance of erosion models interfaced in geographical information system (GIS) such as SWAT model for ungauged catchment in Ethiopia condition.

This study employs the SWAT model to take advantage of its integration with GIS and locally available data and data from similar areas that can be used to calibrate and validate the model. The objective of this study are thus to (1) evaluate the performance of the SWAT model by comparing its predicted stream flow, sediment yield and soil nutrient loadings with the corresponding measured values at the study catchment, and (2) suggest the applicability of the model in management planning and decision making processes for the conditions of Mai-Negus catchment, northern Ethiopia. Evaluation the SWAT model to such condition will also be a contribution for the scientific community to expand a well-refined research against the processes of soil degradation due to soil erosion.

2. MATERIALS AND METHODS

2.1. Study area

This study was conducted at the Mai-Negus catchment in Tigray regional state, northern Ethiopia (Fig. 1). The catchment area is about 1240 ha, with an altitude that varies over short distance within the range of 2060 to 2650 m above sea level. The catchment is part of the northern highlands of Ethiopia comprising of high and low mountains, hilly-lands, and Valleys. The study catchment has a mean annual temperature of 22^{o}C and precipitation of 700 mm, with unimodal rainy season of July-September. An annual rainfall is erratic in distribution and also highly variable over a single main rainy season. The dominant soil type in the catchment is Cambisols. Soils in the mountains, hilly-land and piedmont areas are generally shallow and are normally deep in the valleys. The farming system is principally crop oriented with supplement from livestock. Natural vegetation has been almost cleared due to deforestation. Forest covers small area in the catchment and classified as deciduous and dry forest with medium and small trees including bushes dominated, and some scattered trees showing evidence of former natural forest (Ministry of Water Resources, MWR, 2002; personal observation). Recently, trees such as *Eucalyptus globulus* and *Acacia species* have been planted on protected areas. Apart from forest, other land use types include rainfed annual crops (*Zea mays*, *Eragrostis tef*, pulses /e.g., *Vicia faba*, etc.). However, *Eragrostis tef* covered larger (> 80%) proportion of the cultivated land in the study catchment.

2.2.The SWAT model

The Soil and Water Assessment Tool (SWAT) is a river basin scale, continuous time and spatially distributed physically based model developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in complex catchments with varying soils, land use and management conditions over long periods of time (Arnold et al., 1998; Setegn et al., 2009). In this study, the ArcSWAT 2009 version of the SWAT model was applied to predict flow, sediment yield and nutrient losses. The model was selected after hydrological models were reviewed using predefined criteria like meeting the objectives of the study, data availability (DEM, land use-cover, soil, weather), model sensitivity and uncertainty analysis, applicability for complex catchment, spatial continuity, interface with geographic information system (GIS) and its potential for continuous review and improvements. The SWAT-CUP interfaced program for calibration and uncertainty analysis procedures (CUP) also made the SWAT model more preferable than others for this study.

As a physically based model, SWAT uses Hydrologic Response Units (HRUs) to describe spatial heterogeneity in terms of land cover, soil type and slope within a catchment. The SWAT model uses two steps for the simulation of hydrology: the land phase and routing phase. The land phase controls the amount of sediment, nutrient and pesticides loading to the main channel in each sub-basin. Routing phase defines the movement of water, sediments, and nutrients through the channel network of the catchment to the outlet. The land phase of the hydrologic processes is simulated by the model based on the water balance equation in Setegn et al. (2009) defined as:

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{seep}\ Q_{gw})i \qquad (1)$$

where SW_t is the final soil water content (mm), SW_0 is the initial soil water content on day i (mm), t is the time (days), R_{day} is the amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_a is the amount of evapotranspiration on day i (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm) and Q_{gw} is the amount of return flow on day i (mm).

SWAT offers two methods for estimating surface runoff: the Soil Conservation Service (SCS) curve number (CN) procedure (SCS, 1972) and the Green and Ampt infiltration method (Green and Ampt, 1911). Using daily or sub-daily rainfall amounts, SWAT simulates surface runoff volumes and peak runoff rates for each HRU. SCS curve number method is less data intensive than the Green-Ampt method (Fontaine, 2002). In this study, the SCS curve number method was used to estimate surface runoff volumes because of the unavailability of sub-daily data for the Green and Ampt method. The SCS curve-number surface runoff equation (SCS, 1972) is:

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

where Q_{surf} is the daily accumulated surface runoff or rainfall excess (mm), R_{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:

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

where CN is the curve number for the day. Runoff will only occur when $R_{day} > I_a$ *(=0.2S).* The hydrological model component estimates the runoff volume and peak runoff rate that are in turn used to calculate the runoff erosive energy variable. SWAT calculates the peak runoff rate using a modified rational method. Additional information about runoff calculation can be found in SWAT2005 theoretical documentation (Neitsch et al., 2005).

The SWAT model calculates the surface erosion caused by rainfall and runoff within each HRUs using the Modified Universal Soil Loss Equation (MUSLE) (equation 4) (Williams, 1975; Betrie et al., 2011).

The modified universal soil loss equation is:

$$Sed = 11.8.(Q_{surf}.q_{peak}.area_{hru})^{0.56}.K_{USLE}.C_{USLE}.P_{USLE}.LS_{USLE}.CFRG \quad (4)$$

where *sed* is the sediment yield on a given day (metric tons), Q_{surf} is the surface runoff volume (mm ha^{-1}), q_{peak} is the peak runoff rate (m^3 s^{-1}), $area_{hru}$ is the area of the HRU (ha), K_{USLE} is the USLE soil erodibility factor (metric ton m^2 hr (m^3-metric ton cm)$^{-1}$), C_{USLE} is the USLE cover and management factor, P_{USLE} is the USLE support practice factor, LS_{USLE} is the USLE topographic factor and *CFRG* is the coarse fragment factor. The sediment routing model (Arnold et al., 1995) that simulates the sediment transport in the channel network consists of two components operating simultaneously: deposition and degradation. The details of the USLE factors and the descriptions of the different model components can be found in SWAT theoretical documentation (Neitsch et al., 2005).

The SWAT model also allows the computations of soil nutrient losses such as nitrogen (N) and phosphorus (P) through runoff flows and attached to sediment from the sub-basins to the basin outlet (Tripathi et al., 2003; Neitsch et al., 2005). Runoff transported NO_3-N is estimated by considering the top-layer (10 mm) only. The loading function estimates the daily organic N runoff loss based on the concentration of organic N in the topsoil layer, the sediment yield and enrichment ratio for individual runoff events. The amount of organic and mineral P transported with sediment is also calculated using the loading function in the model (Tripathi et al., 2003; Neitsch et al., 2005). Details about the processes of the soil nutrients and sediment routing simulation by the SWAT model can be found in SWAT theoretical documentation (Neitsch et al., 2005).

2.3.Model input

The spatial databases needed for the ArcSWAT 2009 model include digital elevation model (DEM), land use-cover, and soils. Daily observed weather data also required for the model. The data required for the SWAT model are determined following the information given in Neitsch et al. (2005). Digital Elevation Model (DEM): A 10 m by 10 m cell size DEM was developed from the topographical map of the area. After DEM was created, pits/sinks were filled before any processing was undertaken in order to “route” runoff to the catchment outlet. The DEM was used to delineate the catchment and analyze the drainage patterns of the land surface as well as derive slope parameter. The clipped DEM for the study catchment is shown in Fig. 2A.

Land use-cover and soil data: Land use is one of the most important factors that affect runoff, evapo-transpiration and surface erosion in a catchment. The land use and cover was derived for the study catchment (Fig. 2B) from a Landsat image of November/December 2007. Since SWAT has pre-defined land use types which identified by four-letter codes, these codes were used to link with the study catchment land use map, and made it compatible with the requirements of the model. The SWAT model is capable of splitting the land use-cover into different proportions based on the information from the user. The frequently noted tree species as forest-mixed include: seraw (*Acacia etbaica*), chea’ (*Acacia abyssinica*), Awhi (*Cordia africana*), momona (*Acacia albida*), tambock (*Croton machostachys*), tahsus, (*Dodonaea euquistifolia*), Awlie (*Olea europaea*), lahai (*Acacia lahai*), Kulkual (*Euphorbia candelabrum*) and

Kulieo (*Dovyelis abyssinica*). The soil map for the catchment (Fig. 2C) was also derived from the NEDECO database (NEDECO, Netherlands Engineering Consultants, 1998). The vector soil map was grid in 10 m by 10 m grid size, matching the DEM. The SWAT model requires soil properties such as soil texture, available water content, bulk density and organic carbon content for the soil layers in each soil types. These data were collected from the field for each of the soil types, besides to the data in the NEDECO (1998).

Weather data: The weather variables required by the model for driving the hydrological balance include daily rainfall, minimum and maximum air temperature, solar radiation, wind speed and relative humidity. These data were obtained for the period of 1992-2009 from Ethiopian National Meteorological Agency, Mekelle branch for a station located near the catchment. Missed data for daily rainfall, temperature, solar radiation, wind speed and relative humidity were estimated using the weather generator in the SWAT model.

2.4. Model setup

The model setup involved five steps: (1) data preparation, (2) sub-basin discretization, (3) hydrologic Response Units (HRUs) definition, (4) parameter sensitivity analysis, (5) calibration and uncertainty analysis. The SWAT model interfaced within GIS integrates the spatial data inputs of soil, land cover, topography and weather. The DEM was utilized by ArcSWAT to automatically delineate the basin (or catchment) into 16 sub-basins boundaries, calculate sub-basin average slopes and delineate the stream network. By overlaying the slope map along with the reclassified land use and soil datasets, all those three map inputs were used to determine HRUs that define the level of spatial detail to include in the model. Within each sub-basin, the HRUs were created by ArcSWAT when the option to create multiple HRUs per sub-basin was enabled. The multiple slope option (an option for considering different slope classes for HRU definition) was used in this study. The land use, soils and slope threshold values used in this application were 4%, 4% and 2%, respectively. These were selected in order to keep the number of HRUs to a reasonable number of 369. The model calculates unique runoff and sediment transport to each HRU.

2.5.Observed data preparation

The SWAT model does not use observed data values of flow, sediment and soil nutrients in calculations but instead they are used for comparing the simulated values during model calibration and validation. Nevertheless, the SWAT model was originally developed to operate in ungauged basins with little or no calibration efforts (Arnold et al., 1998). This is because the applicability of the SWAT model can be improved by *a priori* parameter estimation from the physical catchment characteristics (Atkinson et al., 2003). This implies that given appropriate spatial input data, SWAT can provide a satisfactory simulation. To improve the actual result of simulation in this study, first hand catchment characteristics such as curve number, Manning's coefficients, soil erodibility, management practices, land cover, terrain and weather factors, were collected and used as model input.

Model calibration and validation requires sufficiently long, quality observations of stream flow and the other variables, but observed data on both spatial and temporal scales of interest are very limited, especially in ungauged catchments such as Mai-Negus catchment in Ethiopia. In such situation, different methods have been suggested to build hydrologic modeling systems in ungauged basins, including the extrapolation of response information from gauged to ungauged basins, measurements by remote sensing, the application of process based hydrological models in which climate inputs are specified or measured, and the application of combined meteorological-hydrological models that do not require the user to specify precipitation inputs (Sivapalan et al., 2003).

In this study, the extrapolation of response information from gauged to ungauged basins with similar situation (averages based on expected similarities in catchment response variables) was adopted to prepare the observed data for model calibration and validation for the study catchment. In doing so, the measured (observed) runoff (Q) was found from the runoff coefficient (RC) method (Neitsch et al., 2005; equation 5) that multiplies the daily rainfall of 1992-2009 (18 years) by the mean RC obtained from studies conducted in different parts of Tigray region in northern Ethiopia having similar farming system (dominated by cereal cultivation), climate, topography and soil conditions (Table 1). This is because there is no short and long-term measured stream flow and other parameters for the study catchment or similar areas in the region. A mean RC of 0.20 was thus adopted in this study, which was assumed representative for the real situation of the study catchment, since it is an average of different sites having many aspects in common. Generally, reports for RC in the region are in the range of 15-30%.

$$Q = RC * R_{day} \tag{5}$$

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where Q is runoff (mm), RC is runoff coefficient (-) and R_{day} is the rainfall for the day (mm).

The sediment thickness in the reservoir of the study catchment was collected using pit-based survey in June 2009 when large part of the reservoir bed was almost without water. Number of points (pits) sampled depends on size and shape of the reservoir as well as pattern of sediment deposition based on judgment and visual observation. Then, the Thiessen interpolation method was used to estimate sediment deposition in the reservoir (Tamene, 2005). Soil total nitrogen (TN) and mineral phosphorus (P) were also determined from the sediment exported to the reservoir following the standard procedures. In addition to the sediment and soil nutrient observed at the reservoir of the study catchment, data from previous studies in the region which has similar catchment characteristics were also used for model calibration and validation (Table 2).

2.6. Model sensitivity analysis, calibration and validation

SWAT Model is one of the complex catchment models relying on numerous parameters. This creates problems when attempting to calibrate the model for specific study area due to the number of parameters and possible correlations between each other (Vandenberghe et al., 2001). Therefore, a sensitivity analysis was performed before model calibration to determine the influence of model parameters when predicting annual stream flow, sediment, nitrogen and phosphorus. Model sensitivity is defined as the change in model output per unit change in parameter input. The analysis was conducted for the whole study catchment to determine the parameters needed to improve simulation results and understand better the behavior of the hydrologic system, but it could also be useful to interpret results during the calibration phase (Kleijnen, 2005). The parameters for sensitivity analysis were selected by reviewed previously used calibration parameters and SWAT model documentation (e.g., Neitsch et al., 2005; Chekol, 2006; Ashagre, 2009).

In this study, sensitivity analysis was conducted for flow, sediment and the soil nutrients (N and P) using 29 model parameters. The parameters associated with flow, sediment and the soil nutrients were analyzed with a Latin Hypercube interval value of 10 and so the sensitivity analysis required 290 simulations. Parameters that have high sensitivity were chosen with care because small variations in their values can cause large variations in model output. Sensitivity analysis was run for the period 1992 to 1995. The 1992 was used as a 'warm-up' period for the model and the rest of the years (1993 to 1995) were considered in the sensitivity analysis. Relative sensitivity (absolute value) was categorized by Lenhart et al. (2002) as 0-0.05, 0.05-0.2, 0.2-1.0 and > 1 for small to negligible, medium, high and very high sensitivity, respectively. This is adopted to rank the sensitivity of model parameters in this study.

Following the sensitivity analysis, the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) version 3.1.3 was applied to calibrate, validate, and assess model uncertainty (Abbaspour et al., 2007). Calibration and uncertainty analysis was performed using SUFI-2 (sequential uncertainty fitting version 2) algorithm, which is a semi-automated inverse modeling procedure for a combined calibration-uncertainty analysis (Abbaspour et al., 2004, 2007).

In order to utilize any predictive catchment model for estimating the effectiveness of future potential management practices, the model must be first calibrated to measured data and should then be tested (without further parameter adjustment) against an independent set of measured data (model validation). Model calibration determines the best or at least a reasonable parameter set while validation ensures that the calibrated parameters set performs reasonably well under an independent dataset.

The SWAT was calibrated and validated based on daily, monthly and yearly basis for flow; whereas sediment and soil nutrients yields were calibrated on an annual basis. The constraint to calibrate and validate sediment and soil nutrients on a daily and monthly basis is that no measured data existed for the catchment or similar areas. Flow data from 1992 to 2000 were used for calibration using the 1992 data as 'warm-up' period for the model. The 2001 to 2009 data were used for model validation using the 2000 year as the 'warm-up' period. The model was next calibrated for sediment and then for soil nutrients. Observed sediment and nutrient data from 2001 to 2004 was used for calibration. The period 2001 was used for model 'warm-up' during calibration. For model validation of sediment and soil nutrients, the observed data from 2005 to 2009 were used, with the 2005 year as the 'warm-up' period.

2.7.Model evaluation

For using the model with confidence for future predictions under different scenarios, the model predictive capability is demonstrated for being reasonable in the calibration and validation phase using model evaluation criteria. The goodness-of-fit of SWAT model was evaluated by the coefficient of determination (R^2) and Nash–Sutcliff coefficient (N_{SE}) (Nash and Sutcliffe, 1970) between the observations and the final best simulation. The R^2 is the square of the Pearson's product-moment correlation coefficient and describes the proportion of the total variance in the observed data that can be explained by the model. It ranges from 0.0 to 1.0 with higher R^2 values indicating better agreement (Legate and McCabe, 1999). The N_{SE} ranges between −∞ and 1.0 (1 inclusive), with N_{SE} = 1 being the optimal value (Nash and Sutcliffe, 1970). Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance (but N_{SE} > 0.50 is accepted as satisfactory), whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance of model. The R^2 and N_{SE} can be calculated as:

$$R^2 = \left[\frac{\sum_{i=1}^{N} (O_i - \overline{O})(P_i - \overline{P})}{\left[\sum_{i=1}^{N} (O_i - \overline{O})^2 \right]^{0.5} \left[\sum_{i=1}^{N} (P_i - \overline{P})^2 \right]^{0.5}} \right]^2 \qquad (6)$$

$$E_{NS} = 1.0 - \left[\frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (O_i - \overline{O})^2} \right] \qquad (7)$$

where O_i is the measured data at time i, $\overline{O}$ is the mean of measured data, P_i is the predicted data at time i, $\overline{P}$ is the mean of the predicted data and N is the number of compared values.

3. RESULTS AND DISCUSSION

3.1.Model sensitivity analysis

The relative sensitivity value, category and rank of 12 parameters with respect to each SWAT output variable is shown in Table 3. This table shows that among the parameters, the relative sensitivity ranged from medium to very high for flow, sediment and soil nutrient simulation and also ranked from first (most important) to the least. For example, the most top sensitive parameters for flow simulation are CN2, slope, Esco, Sol_Awc, Gwqmn, Slsubbsn, Sol_k and Sol_BD. The CN2 determines the amount of precipitation that becomes runoff as well as the amount that infiltrates into soil profile. The Esco is used for modifying the depth distribution for meeting soil evaporative demand to account mainly for the effect of capillary action, and the Gwqmn is used for regulating the return flow and groundwater storage.

In the study catchment, the very high sensitive parameters for sediment included Usle_C, Spcon, Usle_P and slope. Soil nutrient such as N was highly sensitive to ErorgN, Surlag, Nperco and Usle_C whereas P was very highly sensitive to Usle_K, Usle_P, Usle_C and Erorgp. There are common parameters which show high sensitivity to flow, sediment and soil nutrients, regardless of the differences in the sensitivity values. An example of this is that the Usle_K, Usle_C, Usle_P, slope, Slsubbsn are sensitive to change these model outputs. In general, the obtained sensitivities show consistency with results determined in other studies for most of the parameters (e.g., Chekol, 2006; Ashagre, 2009).

3.2.Flow calibration and validation

After the sensitive parameters had been identified, the calibration process focused on adjusting model-sensitive input parameters determined from the sensitivity analysis to obtain best fit between simulated and observed data. Model calibration is an important step in catchment modeling studies that helps to reduce uncertainties in model predictions (Abbaspour et al., 2007). Twelve (12) sensitive parameters were considered during model stream flow calibration processes. The final fitted values of these parameters were included in the SWAT model (Table 4) so as to fine tune the simulation to the observed data during validation and other applications. The effect of each parameter on model result is given in SWAT user manual (Neitsch et al., 2005).

The calibration and validation result of the simulated stream flow on daily, monthly, and an annual basis perform well for the Mai-Negus catchment as shown by the model goodness-of-fit (Table 5). The N_{SE} for stream flow calibration and validation on daily basis was 0.55 and 0.53, respectively. An R^2 of 0.67 for daily flow calibration and 0.64 for daily flow validation was achieved. The model calibration efficiency value for monthly stream flow was N_{SE} = 0.59 and R^2 = 0.72, whereas the monthly flow validation statistics was N_{SE} = 0.61 and R^2 = 0.79. This indicates that model statistical values for daily flow validation were slightly lower than the calibration result while the opposite was found for the monthly values. But the model calibration and validation statistics results are within the acceptable or satisfactory levels in both periods. On the other hand, the annual flow calibration (N_{SE} = 0.67, R^2 = 0.81) and validation (N_{SE} = 0.73, R^2 = 0.84) model goodness-of-fits values were higher than the daily and monthly basis (Table 5).

Generally, efficiency values $\geq$ 0.50 for N_{SE} and $\geq$ 0.60 for R^2 are considered adequate for SWAT model applications in management planning as it captures the variability of simulated and observed values well (Santhi et al., 2001). Considering the model statistics (N_{SE} and R^2) for flow calibration and validation, SWAT model was thus calibrated and validated successfully on an annual, monthly and daily basis. This indicates that the final values of the model-sensitive parameters selected during the calibration represent those parameters in the study area.

In addition to the statistical measures (R^2, N_{SE}), the visual comparison of graphs also indicate the model performance during calibration and validation for stream flows (Fig. 3). This is used to identify model bias and differences in the timing and magnitude of peak flows simulated. The SWAT model underestimated daily peak flow for a number of days in the main rainy season (June to Sep.) during calibration, whereas overestimated for daily flow for the validation period (Fig. 3A and B). This is could be attributed to the fact that the model was unable to simulate the daily low flows well enough. But the monthly and annually cumulative value of such low flows can be well simulated. Literature also show that ‘‘The underestimation of the low flows could be due to more than one aquifer contributing to deep groundwater recharge in the basin, a situation not handled in SWAT at present’’ (Obuobie, 2008).

In general, the monthly peak stream flow during calibration and validation showed similar trend to that of daily flows. The SWAT model underestimated high flows 6 out of 8 peaks for monthly calibration and overestimated 6 out of 9 peak flows during monthly validation (Fig. 3C and D). Generally, the peak runoff value predicted by the model in the dry dates and months (Oct, Nov., Dec., Jan., Feb. and Mar.) during calibration and validation were slightly higher than that of the observed value. This could be associated with the sub-surface flows simulated by the model in such conditions. The SWAT model overestimated the high flows 5 out of 8 years during annual calibration and overestimated 6 out of 9 years during validation (Fig. 3E and F). The model under or over estimation is ranged from 2-15%. Nevertheless, the SWAT model well tracked most of the peak flow events that occurred in the study catchment as indicated by the model statistics values and Fig. 3.

In general, the SWAT model in this study provides an acceptable and better prediction efficiency of stream flow that can use in further analysis to identify and prioritize critical runoff source sites and simulate alternative management strategies than using the observed mean values. In addition, the results show how well spatially distributed models are able to produce acceptable results using readily available and observed input parameters in ungauged small catchments. Given further information about the catchment's characteristics and the availability of measured flow data using gauged stations, it is expected that better simulation results than in this study could be obtained. In support to this view past studies (e.g., Chekol, 2006; Setegn et al., 2008; Tibebe and Bewket, 2010) found a higher SWAT model simulation performance in a gauged catchment in the country as compared to the model efficiencies achieved in this study. However, since most of the catchments in Ethiopia are ungauged, the application of SWAT model as a decision supporting tool after evaluation through similar approach is encourageable.

3.3.Calibration and validation of sediment and soil nutrients

The parameters and the fitted values considered during sediment and soil nutrients model calibration processes are presented in Table 4 (section 3.2). The SWAT model calibration and validation statistics for the annual sediment yield and soil nutrients show an adequate level of accuracy (Table 6). The R^2 and N_{SE} model statistic computed between the simulated and observed annual sediment yield for the calibration period were 0.73 and 0.57, respectively. The validation of annual sediment yield showed an R^2 of 0.85 and N_{SE} of 0.76, which is higher than the calibration values. The calibration of annual TN gave an R^2 of 0.72 and N_{SE} of 0.54, while the annual mineral phosphorus (P) calibration had an R^2 0.72 and N_{SE} 0.81. The efficiency for P calibration is higher than for sediment and TN (Table 6). The reason may be attributed to the uncertainty in the observed data used, and also to the use of best fit parameters during calibration. Similarly, in the model validation R^2 and N_{SE} were higher for sediment and P than TN (Table 6). These model efficiencies improved during validation for sediment, TN and P as compared to calibration. The improvement for sediment was from 0.57 to 0.76 for N_{SE} and from 0.73 to 0.85 for R^2, whereas for TN from 0.54 to 0.67 for N_{SE} and from 0.72 to 0.83 for R^2. Phosphorus prediction efficiency also increased during validation from 0.72 to 0.76 and 0.81 to 0.87 for N_{SE} and R^2, respectively.

The higher annual validation statistics for sediment yield and P indicated a close agreement between the measured and predicted values on an annual basis, which was explained comprehensively by N_{SE} and R^2 for P and sediment yield than TN. The best fit between simulated and measured values for P and sediment other than TN is likely associated with the quality of input data used in this study. The sources of TN were included in the model; however, it was difficult to obtain or measure all possible nitrogen sources and losses. In addition, errors in sediment loads were less than errors in soil nutrients such as nitrogen because sediment mass is not subject to post-collection transformation. Higher model efficiency can also be associated with the inclusion of best-fit parameters during calibration processes.

Overall model prediction capacity for the sediment yield and soil nutrients is acceptable for the study catchment as it is greater than 0.50 for N_{SE} and 0. 60 for R^2.

With regard to the observed versus simulated data for sediment during calibration and validation, results of this study reveal that the model overestimated in all the simulation years (Table 6). The overestimation of sediment by the model ranged from 4-10% for calibration whereas 9-13% for validation periods. The model also overpredicted for TN and P by 5-15% during validation. However, TN was overestimated (5-8%) during calibration for two years (2002 and 2004) and underestimated in the 2003 year by about 5%. Similarly, P was overestimated for 2002 and 2003 and underestimated in 2004 within an acceptable range of deviation. It is therefore important to estimate soil erosion and soil nutrient losses using the verified SWAT model that captured well the complex catchment characteristics during the simulation periods. The model can support to introduce targeted anti-degradation management intervention by prioritizing the most erosion vulnerable landscapes of the catchment.

3.4.SWAT model application for management planning

The SWAT model is a complex catchment model relying on numerous parameters. This creates problem when attempting to access data for modeling in a specific study area due to the high number of parameters and their possible correlations between each other (Vandenberghe et al., 2001). The application of SWAT model for suggesting management planning on large catchment in Ethiopia is difficult as this attributed to the possibility of data scarcity or not getting data at all for model verification and application. This indicates that model evaluation and application in the context of small catchment such as the present study area which has relatively sufficient data for model verification and running is too crucial in order to extrapolate the values of model parameters to similar catchments with data scarcity for SWAT model evaluation and running. In addition, knowledge on the parameters that influence model outputs in the condition of the study catchment can be used for suggesting management options that reduce soil erosion-related problems in similar catchments with insufficient data during management planning. This study can contribute in narrowing the limitations and research gaps related to soil degradation due to soil erosion using the SWAT model as a supporting tool for management planning and decision making processes in large catchments with limited or no measured data. Identification of erosion-hotspot areas using a physical model that estimates soil erosion rates and soil nutrient losses with sufficient accuracy will have great importance for implementing appropriate erosion control practices. SWAT model simulation using possible management scenarios that influence mainly the sensitive model parameters identified during model calibration is crucial in order to select the best-bet intervention while reducing losses by erosion. Such model results are also important for prioritizing sub-catchments with severe erosion sources as a basis for decision making and planning processes.

After SWAT model evaluation, the model can be applied for identifying and prioritising critical hotspots of runoff, soil and soil nutrient losses in the study catchment conditions. The ranges of erosion rates and their classes suggested by Tamene (2005) can be set as thresholds for identification of critical soil loss sub-catchments using SWAT model simulation result. The sub-catchments can be prioritized for the implementation of best management practices that reduce the runoff, sediment yield and nutrient losses. Priorities can be fixed on the basis of rank assigned to each critical sub-catchment according to ranges of soil erosion classes described by Tamene (2005) (Table 7). For nutrient losses a threshold value of 10 mg l^{-1} for nitrate nitrogen and 0.5 mg l^{-1} for dissolved phosphorous as described by Environmental Protection Agency (EPA) can be adopted as criterion for identifying the critical sub-catchments (EPA, 1976). Evaluation the effectiveness of management options in reducing soil loss (sediment yield), runoff and nutrient losses for targeted sub-catchments should be executed in order to increase their practical application (efficiency) in the study area conditions. This is because studies have shown in many catchments that, a few critical areas are responsible for a disproportionate amount of sediment yields (Mati et al., 2000; Tripathi et al., 2003; Tamene, 2005).

4. CONCLUSION

Calibration and validation of the SWAT model is a key factor in reducing uncertainty and increasing user confidence in its predicative abilities, which makes the application of the model for decision making more effective. This study has shown that a set of important parameters were identified for calibration based on the sensitivity analysis using the SWAT model. The model was successfully calibrated and validated (N_{SE} > 0.5 and R^2 > 0.6) for flow, sediment yield and soil nutrients losses in the Mai-Negus catchment, northern Ethiopia. Such model evaluation generally shows that the model simulated data are better than the mean observed value for management planning, and decision making processes. In general, this study shows that it is possible to calibrate and validate SWAT model in catchments by use of average values that are based on the expected similarities of gauged catchments hydrologic responses, especially where no monitoring data exist. The successful evaluation of SWAT model in northern Ethiopia catchment as illustrated in this study can provide the opportunity for extending the model application to other ungauged basins in the country. This analysis suggests that SWAT has the potential to be a powerful model once calibrated and validated effectively. It can also produce useful catchment hydrologic and erosion predictions that aid for designing future management strategies. The model evaluation results thus confirm that the SWAT model can be applied to simulate runoff, sediment yield and nutrient losses from the study catchment condition so as to identify erosion hotspot areas (the source of disproportionately large amount of erosion). Therefore, the model simulation results can support planners and decision makers to answer *where* land management measures should be implemented to bring the best benefit through reducing soil degradation problems. However, it is suggested that a wider validation effort is needed before adopting the model for decision making purpose throughout the Tigray region of northern Ethiopia which has diverse environmental settings.

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List of Tables

Table 1. Annual rainfall (P) and runoff (R) measured data from different scales in different catchments of Tigray region, northern Ethiopia

Location /catchment	°N	°E	SG (%)	Elevation (m)	A(km^2)	n	years	P (mm)	R (mm)	RC (%)	Land use	source
Adi Gudum	13°14`	39°32`	3	2000-2500	9.5 x10^{-5}	2		422	65.3	15.5	cultivation	Gebreegziabher et al. (2009)
May Zeg Zeg (before catchment management)	13°39`	39°11`	Flat to > 30	2100–2650	1.65		1	629	95	15	Cultivated, grazing, exclosure	Nyssen et al. (2010)
May Zeg Zeg (after catchment management)	13°39`	39°11`	Flat to > 30	2100–2650	1.65		1	629	51	8.1	Cultivated, grazing, exclosure	Nyssen et al. (2010)
Giba (with out soil conservation)	13°30`	39°29`	2	2550	2 x10^{-5}	3	4	600	96-180	16-30	cultivation	Araya and Stroosnijder (2010)
Giba (with soil conservation)	13°30`	39°29`	2		2.4 x10^{-5}	3	4	600	30-45	5-9	cultivation	Araya and Stroosnijder (2010)
Maileba	13°14`	39°15`	Flat to 470	2300-2935	17.3	8	2	588	188	32	Cultivated	Grimay et al. (2009)
						4	2	588	106	18	Grazing	
						4	2	588	53	9	Plantation	
						3	2	588	47	8	Exclosure	
Gum Selasa	13°15`	39°32`	Flat to 80	2000-2500	23.5	8	2	452	136	30	cultivated	Grimay et al. (2009)
						4	2	452	81	18	Grazing	
Hagere Selam	13°39`	39°10`	15-110	2650	1 x10^{-5}	28	2	700	12-245	1.7-35	Degraded grazing, young to old exclosure	Descheemaeker et al. (2006)
Mean								650	130	20		

Note: SG, slope gradient; A, area; n, replication; P, rainfall; RC, runoff coefficient; years, duration of the study

Table 2: Measured sediment, total nitrogen (TN) and Phosphorus (P) at the outlet of the study catchment and other similar areas in Tigray region, northern Ethiopia

Sediment yield (t ha^{-1} Y^{-1})	TN (kg ha^{-1} y^{-1})	P (kg ha^{-1} y^{-1})	Year	source
14.3	18	0.094	2002	Haregeweyn et al. (2006)
18.2	21	0.099	2003	Haregeweyn et al. (2006)
16.1	19.5	0.097	2004	Mean of 2002 and 2003
20.2	11.0	0.08	2006	Girmay et al. (2009)
16.7	12.7	0.145	2007	Girmay et al. (2009)
18.5	11.85	0.112	2008	Mean of 2006 and 2007
19.6	17.74	0.135	2009	Author (from the study area)

Table 3. Most sensitive parameters for flow, sediment and soil nutrient loadings in Mai-Negus catchment, northern Ethiopia

Flow			**Sediment**			**Nitrogen (N)**			**Phosphorus (P)**			Rank[1]
Parameter	RS	category	parameter	RS	category	parameter	RS	category	parameter	RS	category	
CN2	2.02	v. high	Usle_C	2.34	v. high	ErorgN	0.89	high	Usle_K	1.32	v. high	1
Slope	1.33	v. high	Spcon	2.12	v. high	Surlag	0.87	high	Usle_P	1.10	v. high	2
Esco	0.84	high	Usle_P	1.84	v. high	Nperco	0.75	high	Usle_C	0.97	high	3
Sol_Awc	0.75	high	Slope	0.89	high	Usle_C	0.73	high	Erorgp	0.92	high	4
Gwqmn	0.56	high	Ch_N2	0.68	high	CN2	0.70	high	Slope	0.86	high	5
Slsubbsn	0.47	high	Ch_Erod	0.53	high	Slope	0.62	high	Ch_N2	0.78	high	6
Sol_K	0.42	high	Usle_K	0.37	high	Ubn	0.57	high	Ch_Erod	0.73	high	7
Sol_BD	0.22	high	Spexp	0.33	high	Epco	0.18	medium	Psp	0.56	high	8
Ch_K2	0.18	medium	Ch_Cov	0.28	high	Usle_P	0.15	medium	Pperco	0.49	high	9
Surlag	0.13	medium	Canmx	0.19	medium	Sol_Z	0.11	medium	Slsubbsn	0.17	medium	10
Sol_Z	0.10	medium	Slsubbsn	0.14	medium	Slsubbsn	0.08	medium	Epco	0.13	medium	11
Alpha_Bf	0.06	medium	Prf	0.10	medium	GwNO3	0.06	medium	Prf	0.09	medium	12

[1]Ranking of 1 is the highest relative sensitivity (RS) decreasing up to 12 for flow, sediment and soil nutrients simulation.

RS, relative sensitivity; CN2, Initial SCS curve number II; Slope, Average slope steepness (m m^{-1}); Esco, Soil evaporation compensation factor; Sol_Awc, Available water capacity (mm mm^{-1}); Gwqmn, Threshold water depth in the shallow aquifer for flow (mm); Surlag, Surface runoff lag time (days); Sol_K, Saturated hydraulic conductivity (mm hr^{-1}); Sol_BD, soil moist bulk density (g cm^{-3}); Ch_K2, Channel effective hydraulic conductivity (mm hr^{-1}); Ch_N2, Manning's n value for main channel; Ch_Cov, channel cover factor; Alpha_Bf, Base flow alpha factor (days); Sol_Z, Soil depth (mm); Spcon, maximum amount of sediment that can be re-entrained during channel sediment routing; Erorgp, P enrichment ratio with sediment loading; Usle_C, Universal soil loss equation cover factor; Usle_P, Universal soil loss equation management factor; Canmx, Maximum canopy storage (mm); Spexp, Sediment channel re-entrained exponent parameter; Slsubbsn, Prf, Sediment routing factor in main channels; Slsubsn, Average slope length (m); Usle_K, Universal soil loss equation soil factor; Ch_Erod, channel erodibility; Epco, plant uptake compensation factor; Nperco, Nitrate percolation coefficient(10 m^3 Mg^{-1}); Pperco, P percolation(10 m^3 Mg^{-1}); Ubn, N uptake distribution parameter; ErorgN, Organic N enrichment for sediment; Erorgp, Organic P enrichment for sediment; GwNO3, Concentration of NO_3 in groundwater; Psp, P availability index.

Table 4. Calibrated flow, sediment and soil nutrient parameter values[u] for Mai-Negus catchment, northern Ethiopia

Flow		Sediment		Total nitrogen (TN)		Mineral phosphorus (P)	
Parameter	value	parameter	value	parameter	value	parameter	value
CN2	-0.2[r]	Usle_C	0.27[v]	ErorgN	2.35[v]	Usle_K	0.15[r]
Slope	1.50[r]	Spcon	0.003[v]	Surlag	0.10[v]	Usle_P	0.8[v]
Esco	0.53[v]	Usle_P	0.8[v]	Nperco	0.12[v]	Usle_C	0.35[v]
Sol_Awc	-0.11[r]	Slope	1.20[r]	Usle_C	0.27[v]	Erorgp	3.5[v]
Gwqmn	53[v]	Usle_K	0.12[r]	Ch_N2	0.03[v]	Slope	1.20[r]
Slsubbsn	0.25[r]	Ch_Erod	0.42[v]	Slope	1.20[r]	Ch_N2	0.03[v]
Sol_K	0.15[r]	Ch_N2	0.03[v]	Ubn	3[v]	Ch_Erod	0.42
Sol_BD	0.15[a]	Spexp	1.25[v]	Epco	0.03[v]	Epco	0.14[v]
Ch_K2	1.2[v]	Ch_Cov	0.45[v]	Usle_P	0.6[v]	Pperco	-0.10[r]
Surlag	0.10[v]	Canmx	0.13[v]	Sol_Z	-0.10[r]	slsubbsn	0.20[r]
Sol_Z	-0.10[r]	Slsubbsn	0.20[r]	Slsubbsn	0.20[r]	Psp	0.2[v]
Alpha_Bf	0.12[v]	Prf	1.10[v]	GwNO3	-0.10[r]	Prf	1.1[v]

[u] Lower and upper parameter values are based on recommendations given in the SWAT User's Manual (Neitsch et al. 2005).
[r] relative change in the existing parameter where the current value is multiplied by 1 plus a given value.
[v] substitution of the existing parameter value by the given value.
[a] given value is added to the existing parameter value.
For description of parameters see Table 3.

Table 5. Model evaluation statistics for stream flow calibration and validation at Mai-Negus catchment, northern Ethiopia

	Nash-Sutcliffe model efficiency (N_{SE})			Coefficient of determination (R^2)		
	Daily	Monthly	Annual	Daily	Monthly	Annual
Cal	0.55	0.59	0.67	0.67	0.72	0.81
Val	0.53	0.61	0.73	0.64	0.79	0.84

Cal, calibration; Val, validation.

Table 6. Observed, simulated and model statistics during calibration and validation of annual sediment yield, total nitrogen (TN) and mineral phosphorus (P) at the outlet of the Mai-Negus catchment, northern Ethiopia

	Calibration (2002-2004)							**Validation (2006-2009)**					
	Sediment (ton)		TN (kg)		P (kg)			Sediment (ton)		TN (kg)		P (kg)	
Year	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.	Year	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
2002	17732	19540	22320	23460	109	110	2006	25048	28400	13640	17060	99	118
2003	22568	23500	26040	25010	115	115	2007	20708	24720	15748	15810	180	169
2004	19964	21080	24180	25072	113	111	2008	22940	25480	14694	14802	139	150
N_{SE}	0.57		0.54		0.72		2009	24304	26680	21998	23426	167	185
R^2	0.73		0.72		0.81		N_{SE} (R^2)	0.76 (0.85)		0.67 (0.83)		0.76 (0.87)	

Obs., observed; Sim., Simulated; N_{SE}, Nash-Sutcliffe model efficiency; R^2, coefficient of determination.

Table 7. Classification of soil erosion into different categories based on the soil loss rate for northern Ethiopia

Soil loss range (t ha^{-1} y^{-1})	Category
0-5	Very low
5-15	Low
15-30	Medium
30-50	High
> 50	Very high

Source: Tamene (2005)

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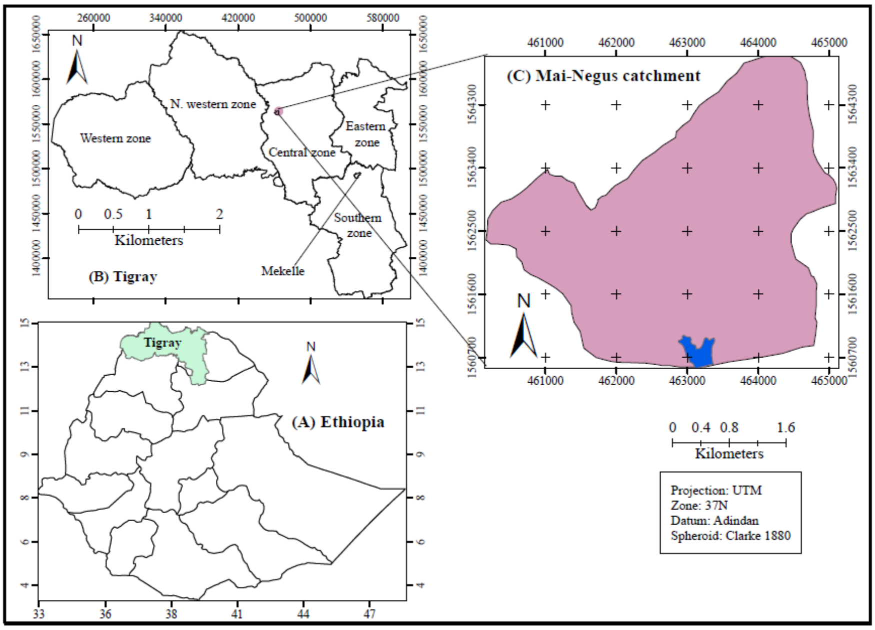
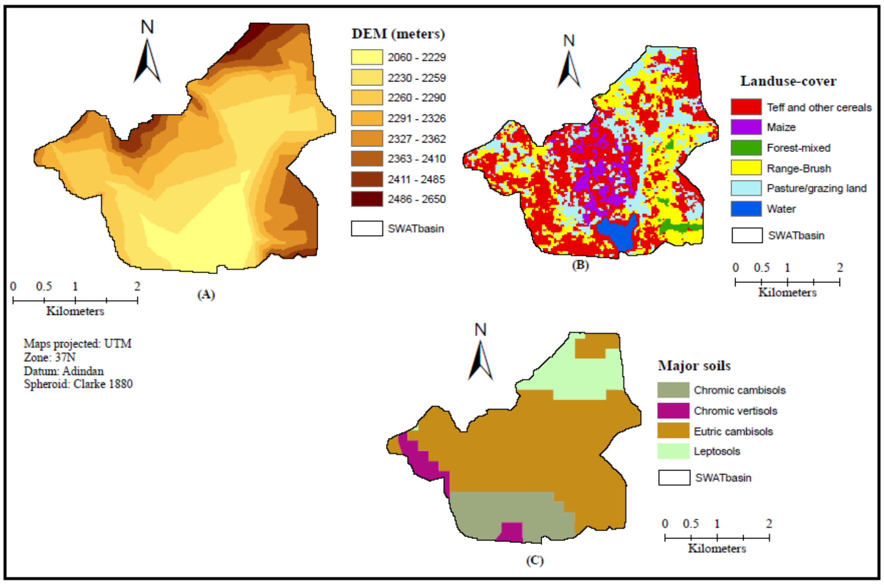


Figure 1



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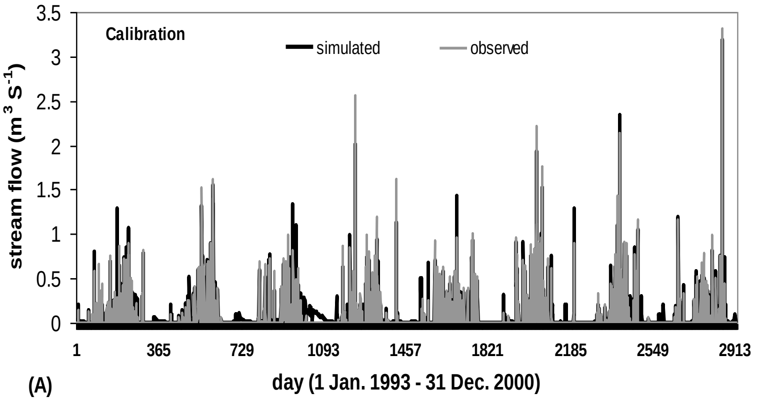

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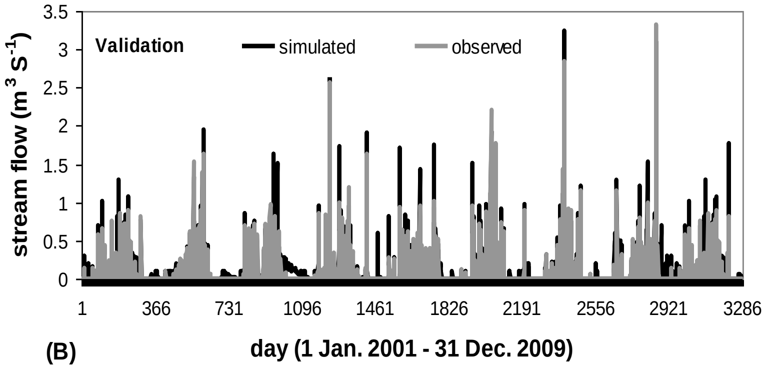

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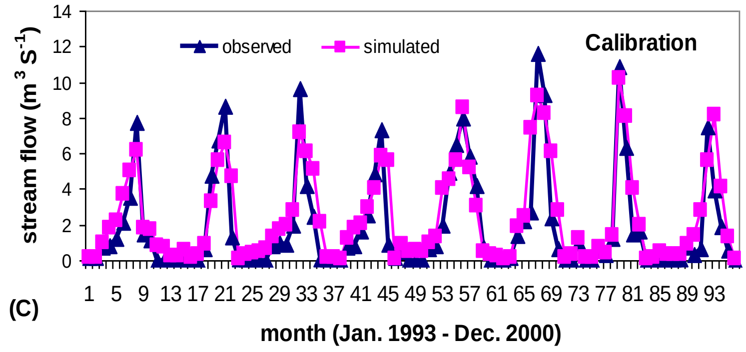

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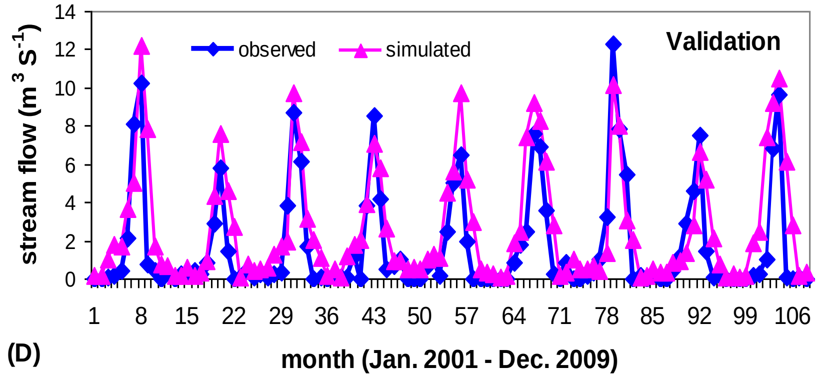

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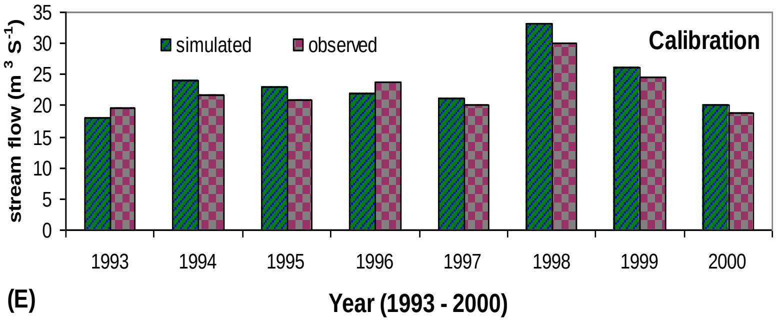

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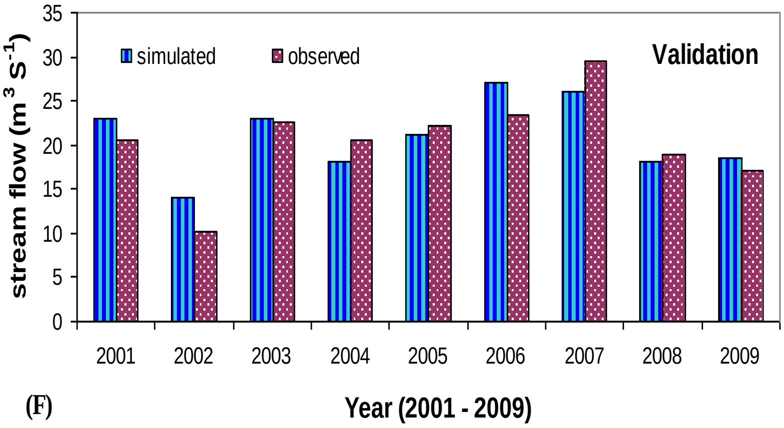

Figure 3F

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