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Full Length Research Paper

Assessment of Surface Water Potential Based On Watershed Modeling : A Case of Sor Watershed, Ethiopia

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Abstract
The successful understanding of surface water resources is fundamental to a country like Ethiopia for the growth of the national economy. Because, Surface water is the main source of water with only minimal dependence on utility. Knowing the potential, availability and use of surface water in Sor River would help to increase the productivity of agriculture. Consequently, this study is aimed to estimate total surface water potential at the outlet of the Sor watershed and examine the associated uncertainty that can affect the accuracy in estimation of the surface water potential of a River. Sor River is one of the tributaries of Baro-Akobo River basin. According to watershed delineation using SWAT hydrological model an area of Sor watershed is about 1963.512 km². For assessing the surface water potential of Sor watershed, the Geographic Information System (GIS) based Soil and Water Assessment Tool (SWAT) has been used to assess surface water potential of Sor sub-basin. The calibration and validation of the model was found verygood as performance rating criteria value of coefficient of correlation (R^2) and Nash-Sutcliffe simulation efficiency (E_{NS}) is found to be 0.80 and 0.74for calibration and 0.79and 0.70 for validationrespectively.In the equivalent order from the model uncertainties analysis the percentage of the simulated data within the uncertainty bound is just 49% for calibration and 44% for validation, which shows that there is uncertainty in the process. The result obtained from SWAT model, the watershed receives a mean annual rainfall 1700.7mm,Surface water runoff of the watershed 338.84 mm, and lateral soil flow is 143.73 mm. From total watershed area of 1963.512 km², 665.32MCm runoff was generated by the model from catchment annually.

Key words*: Sor watershed, surface Runoff, SWAT-CUP,SWAT Model, Uncertainties analysis.*

Introduction

Water is necessary for all forms of human, animal and plant life. It is essential for overall human well being and supports all aspects of human living. Furthermore, water plays an important role in supporting productive human activities such as agricultural, energy and industrial production, sanitation, transportation services, fishing and tourism (UNEP, 2009). The global water demand will primarily grow due to population and economic growth, rapid urbanization and the increasing demand for food and energy (GWP, 2009).Therefore, assessing water resource availability at relevant spatial and temporal scales is of importance (Yang,*et al*., 2007)as well as an ability to assess the availability of freshwater resources has been an issue of importance in most countries for many decades (WMO, 2012).

The successful realization of any water resources activity is vital to a country like Ethiopia for the development of the national economy. The proper planning, design, construction and operation of water resource uses are therefore, essential. Among the twelve river basins in Ethiopia, the Baro Akobo basin has abundant water resources, which up to now have not been developed to any significant level. The Baro Akobo basin has great unrealized potential, under populated by Ethiopian standards, and with plenty of land and water. Knowing the potential, availability and use of surface water would help to increase the productivity of agriculture, to improve ways and means of the traditional water management system, to increase drinking water supply and to increase the hydroelectric power generation of the country in the coming future. Sor River is one of the tributaries Baro-Akobo basins, which provides resources for livelihoods of the living population. The Sor River is used as a source of drinking water for livestock, agricultural and as hydropower energy. This makes the issue of surface water potential very crucial for effective surface water potential management and improves livelihoods.

Ethiopia has important water resources, but is unevenly distributed across the territory and varies substantially between years. At the same time water, demand for both domestic and productive uses is expected to grow rapidly in the near future (Nata, 2006).
Currently utilization of water resources is very limited including domestic and minor agricultural activities, mainly through rain fed cultivation. However, knowledge and understanding of surface water and their interactions with spatial and temporal variability are

essential for the present and future assessment of water resource availability. For sustainable allocation of surface water and conflict management between beneficiaries, determination of the surface water potential is fundamental. This implies that detail assessment of surface water potential of river is very important.

General Objective of the study is to assess the surface water potential of Sor River catchment using Soil and Water Assessment Tool (SWAT) hydrological model and to analyses the uncertainty associated with it.

Specific Objectives

1. To Calibrate, validate and undertake sensitivity analysis using Soil and Water Assessment Tool- Calibration and Uncertainty Programs (SWAT-CUP)model
   On Sor watershed for assessment of surface water potential;
2. To identify the most prone sub basins to surface runoff.
3. To estimate total surface water potential of the Sor River using SWAT model.
4. This research is undertaken with an aim to Surface Water Potential Based On Watershed Modeling

Materials and methods

Study Area

Sor watershed, drained by Sor Rivers, is located in Illubabor zone of the Oromia National Regional State near Metu town. This watershed is part of the BaroAkobobasin.Baro-Akobo Basin lies in the southwest of Ethiopia between latitudes of 5° 31` and 10° 54` N, and longitudes of 33° 0` and 36° 17` E. The basin area is about 76,000 km^2 and is bordered by the Sudan in the West, northwest and southwest, Abbay and Omo-Ghibe Basins in the east. The major rivers within the Baro-Akobo basin are Sor, GebbaandBaro. These rivers, which arise in the eastern part of the highlands, flow westward to join the White Nile in Sudan. The Sor river catchment area is located at 7^{O}55'N, 35^{O}52'E to 8^{O}28'N, 35^{O}21'E. The elevation of the study sites ranges from 1544 to 2500 m a.s.l. It has a total drainage area of approximately 1963.512 Km^2.

Hydrological modeling

A physically based hydrological model was used for So watershed to assess theater resource potential of Sor river catchment. Soil and Water Assessment tool (SWAT) was selected as the best modeling tool owing to many reasons. First and for most it is a public domain model and it is used for free. Secondly, in countries like Ethiopia, there is a shortage of long term observational data series to use sophisticated models; however, SWAT is computationally efficient and requires minimum data. Besides SWAT was checked in the highlands of Ethiopia and gave satisfactory results (Setegn, 2007). SWAT model was developed to predict the effect of land management practices onagricultural chemical yields, sediment and water. But, this study concentrated on the watershed hydrology. The explanations of the model inputs are discussed in detail in the lateral sections.

Soil and Water Assessment Tool (SWAT)

US Department of Agriculture, Agriculture Research Service (USDA-ARS), developed the Soil and Water Assessment Tool (SWAT) model. It is a conceptual model that functions on a continuous time step. Model components include weather, hydrology, erosion/sedimentation, plant growth, nutrients, pesticides, agricultural management, channel routing, and pond/reservoir routing. Agricultural components in the model include fertilizer, crops, tillage options, and grazing and have the capability to include point source loads.

SWAT is a physically based river basin scale model developed by Dr. Jeff Arnold to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time (Neitsch, 2005).The main model components include hydrology, soil temperature and properties, weather, plant growth, land management, bacteria and pathogens, nutrients and pesticides.

G- Soil heat flux density ($\frac{MJ}{m^2\, day}$)

T-mean daily air temperature at 2m height(0_c)

U_2 – wind speed at 2m height ($\frac{m}{s}$)

es – Saturation vapor pressure (Kpa)

ea – actual vapor pressure(Kpa)

es - ea - saturation vapor pressure deficit(Kpa)

Δ = Slope vapor pressure curve ($\frac{Kpa}{0_c}$)

$\gamma = \ Psychometrics\ constant\ (\frac{Kpa}{0_c})$

Methods of Filling Missed Data

Missing data is a known problem in hydrology. Before using hydro meteorology records of a station, it is necessary first to check the data for continuity. The continuity of a record may be broken with missing data due to many reasons such as absence of the observer and broken or failure of instrument. It is often necessary to carry out hydrological analysis and simulation using data of long time series, filling in missing data is extremely important. The missing data can be estimated by using the data of the neighboring station.

There are different methods of filling the missing data such as arithmetic average method, normal ratio method, linear regression method or other approximation methods. The station average method for filling missing data is conceptually the same as the arithmetic average method for estimating a mean precipitation. This method may not be accurate when the total annual rainfall at any of the n region gauges differs from the annual rainfall at the point of interest by more than 10%. The normal-ratio method is conceptually simple; it differs from the station average method of that the average annual rainfall is used in deriving weights. If the total annual rainfall at any of the n region gauges differs from the annual rainfall at the point of interest by more than 10%, the normal ratio method is preferable (Richard, 1989).

SWAT model setup

Watershed delineation

SWAT uses digital elevation model (DEM) data to calculate the flow accumulation, Stream networks and automatically delineate the watershed into several hierologically connected sub watersheds. The model setup steps in the watershed delineation; the first step was loading the properly projected DEM. Next, a mask of the catchments was used to focus the watershed area. This is however such not necessary step if catchments are known, The stream definition and the size of sub-basins were carefully determined by selecting threshold area or minimum drainage area required to form the origin of the streams, next to stream definition defining the inlet of draining watershed and outlet point of discharge for the sub-basin added, deleted or redefined manually. For this study, the outlet and inlet definition was chosen by using sub basin outlet and manually adding the out let for the Sor river catchment particularly at the gauging station. The watershed delineation activity was completed by calculating the geomorphic sub basin parameter.

Hydrologic response unit analysis

The sub basin delineation was followed by the determination of Hydrologic response units (HRUs)that dividing the basins into smaller pieces each of which has a unique land cover, soil and management combinations that are used by SWAT. HRUs enable the model to reflect differences Evapotranspiration and other hydrologic conditions for different land covers and soils. The runoff is estimated separately for each HRU and the total runoff depends on the actual hydrologic condition of each land cover/land use and soil present in the watershed. Land cover/land Use and soil are factors greatly influencing the hydrological properties of a watershed that are required by SWAT to explain a sub basin or Hydrologic response units. This increases the accuracy in flow prediction and provides a much better physical description of the water balance.

The soil and the land use data in a projected shape file format were loaded into the Arc SWAT interface to determine the area and hydrologic parameters of each land soil category simulated within each sub basin. This distribution of land use, soil and slope characteristics within each HRU have the maximum impact on the calculating stream flow. After the land use and soil SWAT code assigned , the land use/ land cover and soil maps of the study area were also imported into the model and overlaid to obtain a unique combination of land use, soil and slope within the watershed. After the overlay of the land-use, soil maps and slope, the distributions of the Hydrological Response Units within the watershed were determined and reclassification was done.(Alkasim, 2016).

The final Step was now reported as done and now available a variety of reports regarding the sub basin land use, soil and slope distribution, topographic and HRUs properties. As per the final report the watershed was divided into 26 sub-basins which were further divided into 47 hydrologic response units were created within the Sorwatershed and sub-basin HRU report has been generated composed of homogeneous

Weather Generator

The SWAT model has an automatic weather data generator. However, it needs some input data to run the model. The model can be run if the following data are available. Daily precipitation, maximum daily temperature, minimum daily temperature, sunshine hour, daily relative humidity and daily wind run data. If no data are available at the same time for all stations, the model can generate all the remaining data from daily precipitation and temperature data. For this purpose the model needs some main stations with full data and from that it can generate for the remaining stations (Alkasim, 2016). To conduct these research four stations were used to run the SWAT model for estimation of surface runoff. Among the four stations, one station with full data was used to run the model and generate the missed data for the other station. The station with full data was Gore meteorological stations. For these Principal stations the SWAT model needs the following input data.

- Precipitation data
- Maximum temperature
- Minimum temperature
- Standard deviation for temperature
- Dew point data
- Average solar radiation data

- Average wind run data

Edit SWAT Input

The edit SWAT input menu allows editing the SWAT model databases and the watershed databases files containing the current inputs for the SWAT model. The edits made to the parameters using the Arc-SWAT interface are reflected only in the current SWAT project.

SWAT Simulation

The SWAT Simulation menu allows conclude the setup of input for the SWAT model, to run the SWAT model and to read the SWAT output by importing files to database and saving to the importance place or by opening the output. At the end Running SWAT check take Place for output visualization.

Finally, the other key aspects of the SWAT simulation performed for the watershed were:

- Output time step: Monthly and annually.
- Simulation period: generally thirty years (1986–2015) but for calibration and validation individually.

Following this sensitivity analysis, calibration , validation and uncertainty analysis has been done using SWAT-CUP.

Base Flow Separation

Base flow is the ground water contribution to stream flow. Base flow is an important component of stream flow, which comes from ground water storage or other delayed sources (Shallow subsurface storage, lakes, etc). It is a portion of stream flow that is not directly generated from the excess rainfall during storm event. or the sake of comparisons of water balance statistics of simulated and observed flows, the total gauged stream flow data should be separated into surface and base flow components. Thus, base flow was separated from stream flow using an automated base flow separation and recession analysis techniques (Arnold et al, 1996).

Determination of the base flow component of stream flow is necessary to understand the hydrologic budgets of surface and ground water basins. Especially for SCS model of runoff estimation it is essential first to separate the base flow from the surface runoff component The catchment size, soil type, geology, landscape, vegetation covers, climate etc., can be considered as the major catchment characteristics that influence the amount of the base flow contribution to the total stream flow. The automated base flow separation and recession analysis technique uses software called Base flow separator-program found from the SWAT website.

Sensitivity Analysis

Sensitivity analysis was performed to limit the number of optimized parameters to obtain a good fit between the simulated and measured data. Sensitivity analysis helps to determine the relative ranking of which parameters most affect the output variance due to input variability which reduces uncertainty and provides parameter estimation guidance for the calibration step of the model(BELAY, 2013). Therefore sensitivity analysis as an instrument for the assessment of the input parameters with respect to their impact on model output is useful not only for model development, but also for model validation and reduction of uncertainty (Lenhart *et al*, 2002).

Using the tool in SWAT model, sensitivity analysis has been performed on 16runoff parameters and the most sensitive parameters were identified using Global sensitivity analysis method in SWAT-CUP SUFI2 on stream flow of the watershed and the result is found in result and discussion section of this paper.

Calibration and Validation of SWAT Model

Calibration

Model calibration is a means of adjusting or fine tuning model parameter to match with the observed data as much as possible, but with acceptable limited range of deviation. Similarly, model validation is testing of calibrated model results with independent data set without any further adjustment (Neitsch, 2005). There are three calibration approaches widely used by the scientific community. These are the manual calibration, automatic calibration and a combination of the two. Manual calibration is the most widely used approach. However it is tedious, time consuming, and success of it depends on the experience of the modeler and knowledge of the watershed being modeled (Eckhardt, 2001). For this research work the measured stream flow data automatic calibration was performed from a period of 1990-2005at outlet of Sor River. The calibration was done for surface runoff at the outlet of the River by adjusting sensitive parameters that affect surface runoff which were identified during sensitivity analysis, until a satisfactory objective function was attained (i.e.R^2 >0.6 and ENS> 0.5).

Model Validation

In order to utilize the calibrated model for estimating the total surface water potential of Sor River, the model tested against an independent set of measured data. This testing of a model on an independent set of data set is commonly referred to as model validation. As the model predictive capability was demonstrated as being reasonable in both the calibration and validation phases, the model was used for future predictions. Sor River flows data set were Validated an independently without making further adjustments of the calibration parameters. To make sure that the simulated values are still within the accuracy limits, statistical criteria (R^2 and NSE) used during the calibration procedure were also checked here. Therefore Validation for the year 2006-2014 was done on daily average monthly basis.

SUFI-2

In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables (e.g., rainfall), conceptual model, parameters, and measured data. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the P-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). As all the processes and model inputs such as rainfall and temperature distributions are correctly manifested in the model output (which is measured with some error) the degree to which we cannot account for the measurements the model is in error; hence uncertain in its prediction. Therefore, the percentage of data captured (bracketed) by the prediction uncertainty is a good measure to assess the strength of our uncertainty analysis. As parameter uncertainty increases, the output uncertainty also increases. Hence, SUFI-2 starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially falls within the 95PPU, then decreases this uncertainty in steps while monitoring the P-factor and the R-factor. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centered on the best simulation (Abbaspour, 2009).

Evaluation of Model Performance

The performance of SWAT was evaluated using statistical measures to determine the quality and reliability of predictions when compared to observed values. Coefficient of determination (R^2) and Nash-Sutcliffe simulation efficiency (ENS) were the goodness of fit measures used to evaluate model prediction. The R^2value is an indicator of strength of relationship between the observed and simulated values. The Nash-Sutcliffe simulation efficiency (ENS) indicates how well the plot of observed versus simulated value fits the 1:1 line. If the measured value is the same as all predictions, ENS is 1. If the ENS is between 0 and 1, it indicates deviations between measured and predicted values. If ENS is negative, predictions are very poor, and the average value of output is a better estimate than the model prediction (Nash and Sutcliffe, 1970).The performance of a model must be evaluated on the extent of its accuracy, consistency and adaptability (Goswami*et al.*, 2005). A forecast efficiency criterion is therefore necessary to judge the performance of the model. Assessing performance of a hydrologic model requires subjective and/or objective estimates of the closeness of the simulated behavior of the model to observations (Krause *et al.,* 2006).

The goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. Theoretically, the value for P-factor ranges between 0 and 100%, while that of R-factor ranges between 0 and infinity. A P-factor of 1and R-factor of zero is a simulation that exactly corresponds to measured data. The degree to which we are away from these numbers can be used to judge the strength of our calibration. A larger P-factor can be achieved at the expense of a larger R-factor. Hence, often a balance must be reached between the two. When acceptable values of R-factor and P-factor are reached, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the R^2 and/or Nash-Sutcliff (NS) coefficient between the observations and the final "best" simulation (Alkasim, 2016). SWAT developers assume an acceptable calibration for hydrology at $r^2 > 0.6$ and ENS > 0.5 these values were also considered in this study as adequate statistical values for acceptable calibration. The detailed description of $R^2$and ENS is presented below. The r^2coefficient and ENS simulation efficiency measure how well trends in the measured data are reproduced by the simulated results over a specified time period and for a specified time step (Santhi*et al.*,

2001).$$r^2 = \frac{\sum_{i=1}^{n}(q_{si}-q_s^{-})(q_{oi}-q_o^{-})^2}{\sum_{i=1}^{n}(q_{si}-q_s^{-})^2\sum_{i=i}^{n}((q_{oi}-q_o^{-})^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.8$$

Where: q_{si} is the simulated value
q_{oi} is the measured values
$q_s$is the average simulated value
$q_o$is the average measured value

The ENS simulation efficiency for n time steps is calculated as:

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(q_{oi}-q_{si})^2}{\sum_{i=i}^{n}((q_{oi}-q_o^{-})^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.9$$

Where: qsi is the simulated value
qoiis the measured value

To evaluate the models performance during calibration and validation processes coefficient (R^2) and Nash and Sutcliffe simulation efficiency (E_{NS}) (Nash and Suttcliffe, 1970) correlation were used for this specified research. And the result is offered in result and discussion section of this paper.

Results and discussions

SWAT Hydrological Model: Under this section all the results of the study obtained from the SWAT model analysis is covered.

Land use/Cover

The Sor watershed land use/cover was classified as Grassland, Agriculture Crop, Broad Leaf Deciduous Forest and Broad Leaf ever green Forest types and Broad Leaf ever green Forest types covering the largest (59.97%) and Grassland covering smallest (0.8%) portion of it respectively.

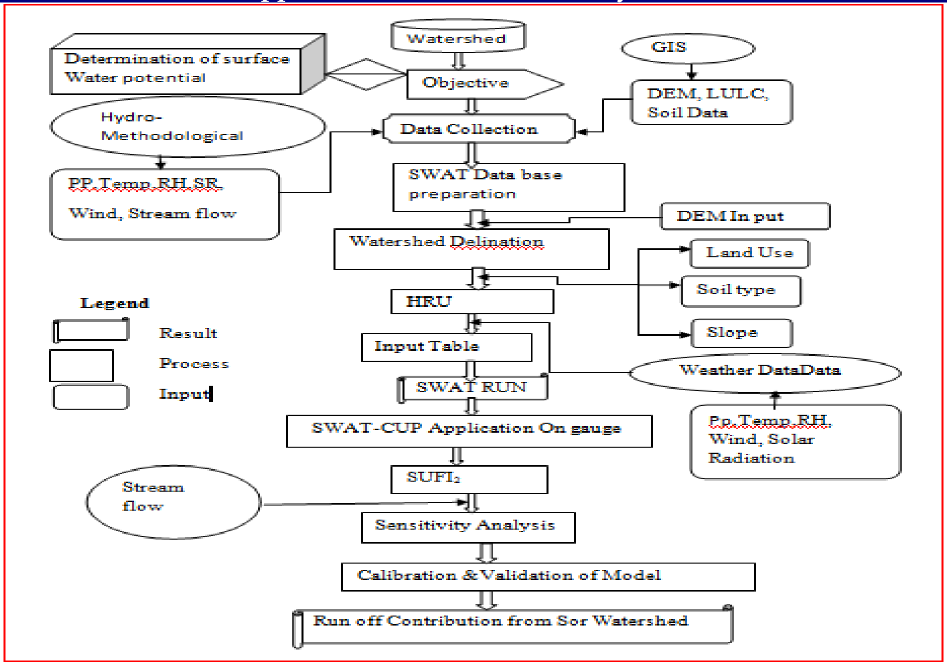

Fig 1: Simplified flow chart of the methodology

Table 1: Land use/cover classification of Sor catchment

Redefined land use according to SWAT database	SWAT code	Area [ha]	%Wat.Area
Range-Grassland	RNGE	1575.8531	0.80
Agriculture Crop/cultivated	AGRR	66866.1871	34.05
Broad Leaf Deciduous Forest	FRSD	10155.4192	5.17
Broad Leaf ever green Forest	FRSE	117753.7357	59.97

Soil Data

The FAO soil classification, result that the most dominant soils in the watershed are Eutric Nitisols, Orthic Acrisols, Eutric Cambisols ,Haplic Alisols, Haplicnitisols and Humic Cambisols respectively.

Table 2: The main FAO Soil classification system in Sor Watershed used for SWAT input

Major Soil Type	Area (ha)	% Watershed Area
HumicCambisols	598.4466	0.30
EutricCambisols	18402.1210	9.37
OrthicAcrisols	27798.1133	14.16
EutricNitisols	138979.3083	70.78
HaplicNitisols	968.8080	0.49
HumicAcrisols	9604.3981	4.89

Slope

The catchment area has multiple types of slopes and the whole catchment area coverage about the 87.28% dominated with 5-35% types of slope. The common types of slope obtained by SWAT of the software were found in table 3 and figure 4.3 This illustrate that the catchment in nature is steep and used for agricultural cultivation purpose that lead to effect on the surface water potential availability of the river.

Table3: Sor watershed Multiple Slope

Classes	Slope Interval (%)	Land form	Area (ha)	% of Total Area
Classes 1	0-10	Flat or almost Flat	58725.1509	29.91
Classes 2	10-25	Gentle Sloping	109859.6662	55.95
Classes 3	25-35	Undulating, Steep hills	20702.0316	10.54
Classes 4	>35	Very steep slopes	7064.3466	3.60

Sensitivity analysis

Sensitivity analysis was carried out on 16 runoff parameters and for a sixteen years, that include period of calibration (January 1st, 1990 to December 31st, 2005). Global sensitivity analysis method in SWAT-CUP SUFI2 was used to identify the most sensitive parameters.

t-test and p-values

The t-stat is the coefficient of a parameter divided by its standard error. It is a measure of the precision with which the regression coefficient is measured. If a coefficient is “large” compared to its standard error, then it is probably different from 0 and the parameter is sensitive.

The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low p-value (< 0.05) indicates that you can reject the null hypothesis. In other words, a predictor that has a low p-value is likely to be a meaningful addition to your model because changes in the predictor's value are related to changes in the response variable. Conversely, a larger p-value suggests that changes in the predictor are not associated with changes in the response. So that parameter is not very sensitive. A p-value of < 0.05 is the generally accepted point at which to reject the null hypothesis (i.e. the coefficient of that parameter is different from 0). With a p-value of 0.05, there is only a 5% chance that results you are seeing would have come up in a random distribution, so you can say with a 95% probability of being correct that the variable is having some effect(Alkasim, 2016).

Table 5: Results of most sensitivity analysis parameters

Parameter Name	t-Stat	P-Value	Sensitivity rank
13:R__CANMX.hru	0.225659098	0.824975446	12
6:V__ESCO.hru	-0.271023109	0.790628928	11
9:R__SURLAG.bsn	-0.478795505	0.640036903	10
11:R__REVAPMN.gw	0.521571278	0.610740109	9
8:V__CH_K2.rte	0.649762826	0.527160592	8
15:R__EPCO.hru	-1.002358851	0.334463557	7
7:V__CH_N2.rte	-1.869524739	0.084238498	6
1:R__CN2.mgt	-1.904977455	0.079143325	5
12:R__SOL_AWC(..).sol	2.076504877	0.058240411	4
5:V__GW_REVAP.gw	-2.492896828	0.026947245	3
2:V__ALPHA_BF.gw	-2.500646328	0.026556395	2
3:V__GW_DELAY.gw	-4.499571235	0.000597759	1

As shown in table 5: a p-value close to zero and t-test value larger in absolute value is most significant sensitive parameter. From the model output, the first two most sensitive parameters are Groundwater delay and Base flow alpha factor.

Model Calibration and Validation

SUFI2Using for model calibration and validation with the objective function of NS and R^2 for more than 500 simulations and the outcome are summarized below.

Model calibration

The SWAT model analysis of daily and monthly runoff of the chosen gauging stations obtained through trial and error was calibrated by SWAT-CUP against the observed discharge. The gauging station, which was chosen for calibration and validation, is or near Metu gauging station. For calibration and validation of flow twenty five years from January 1st, 1990 to December 31st, 20014 were taken. From these years, nine- year data (2006-2014) was used for validation and sixteen- year data (1990-2005) was used for calibration.

Figure 4.1: illustrate that the Coefficient of determination is best if R^2> 0.60 and Nash-Sutcliff Efficient (NSE) Nash is NS>0.5. Therefore the Sor catchment satisfies these criteria. Since coefficients of efficiency is NS=0.74 and coefficient of determination is R^2=0.80.The calibration results show that model performance evaluation indicated a high-quality correlation and agreement between the daily measured data and simulated flow.

Table 6: Calibration and validation model efficiencies parameters

No. sub basin	Period of simulation	Parameter	Period	Monthly
26(Sor Nr. Metu)	1990-2005	R^2	Calibration	0.80
		E_{NS}	Calibration	0.74
	2006-2014	R^2	Validation	0.79
		E_{NS}	Validation	0.70

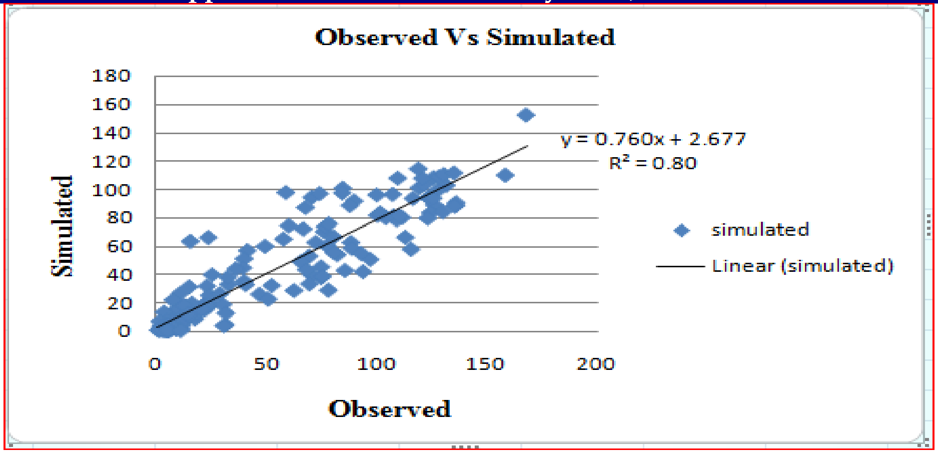

Fig 2: Model calibration periods (1990-2005)

Model validation

Calibrated model parameters can result in simulations that indicate a high-quality of correlation and agreement between the daily measured data and simulated flow. After model calibration has been done, the model was validated using observed stream flow of Sor hydrological station from January 2006 to December 2014was used for validation of model. For validation nine-year daily data was used.

After validating the following result was obtained .The Nash-Sutcliff efficient (NSE) and coefficient of determination (R^2) are 0.70 and 0.79respectively. The validation graph is shown below in the figure 4.2.The model performance assessment indicates a high-quality of correlation and agreement between the daily measured data and simulated flow.

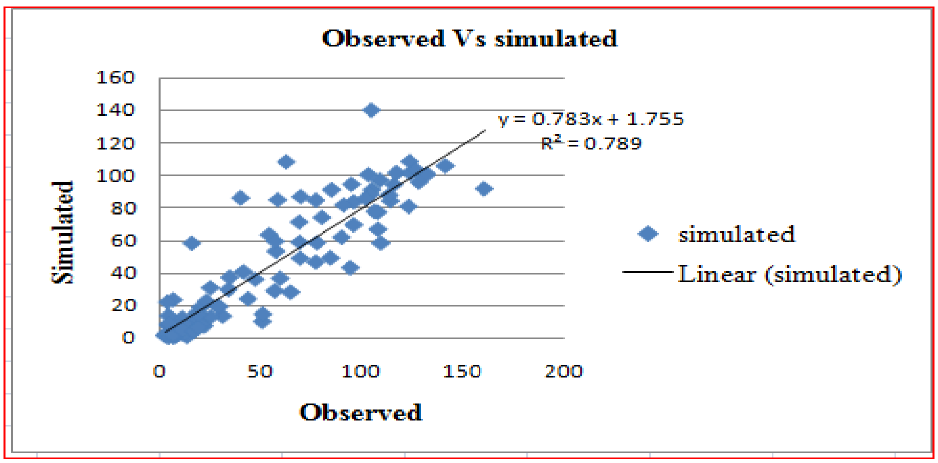

Fig 3: Model validation graph

Uncertainty analysis

SWAT was calibrated based on the daily average value of monthly measured flow, at the outlets for each catchment using the automatic calibration method embedded in Arc Swat. A split sample procedure 60 and 40 percent was used for calibration and validation respectively. For most of the selected catchments data from the period of 1990–2005 were used for calibration, and data from 2006–2014 were used to validate the model. It should be noted that a watershed model can never be fully calibrated and validated. Calibration of models at a watershed scale is a challenging task because of the possible uncertainties that may exist. Sources of uncertainties in distributed models are due to inputs such as rainfall and temperature. Rainfall and temperature data are measured at local stations and regionalization of these data may introduce large errors. In SWAT, climate data for every sub basin is furnished by the station nearest to the centroid of the sub basin. Direct accounting of rainfall or temperature distribution error is quite difficult as information from many stations would be required.

Therefore, carrying out uncertainty analysis for the prediction of the hydrological model is crucial to decide the calibrated parameters to transfer to other homogenous catchments and also using for further predictions. In SUFI-2, parameter uncertainty accounts for all sources of uncertainty, e.g., input uncertainty, conceptual model uncertainty, and parameter uncertainty, because disaggregation of the error into its source components is difficult, particularly in cases common to hydrology where the model is nonlinear and different sources of error may interact to produce the measured deviation (Gupta et al., 2005 cited SWAT-CUP User Manual).

At the end calibration of flow of the catchment the value of the uncertainty is determined using SUFI-2 (Abbaspour *et al*., 2009) interface and the result show below were obtained.

Uncertainty Analysis Results

The SWAT simulated flow was initially calibrated based on the observed stream flow at the watershed outlet near Metu. This calibrated model produced satisfactory results of variable for calibration and validation periods. The results of calibration and validation are graphically shown in above for daily averaged stream flow in months. The parameter ranges were selected based on the calibrated parameter ranges of SWAT model.

Table 7: Sor watershed after uncertainty analysis using SUFI-2, performance index

	P factor	R factor	R^2	E_{NS}
Calibration (1990-2005)	0.49	0.24	0.80	0.74
Validation(2006-2014)	0.44	0.22	0.79	0.70

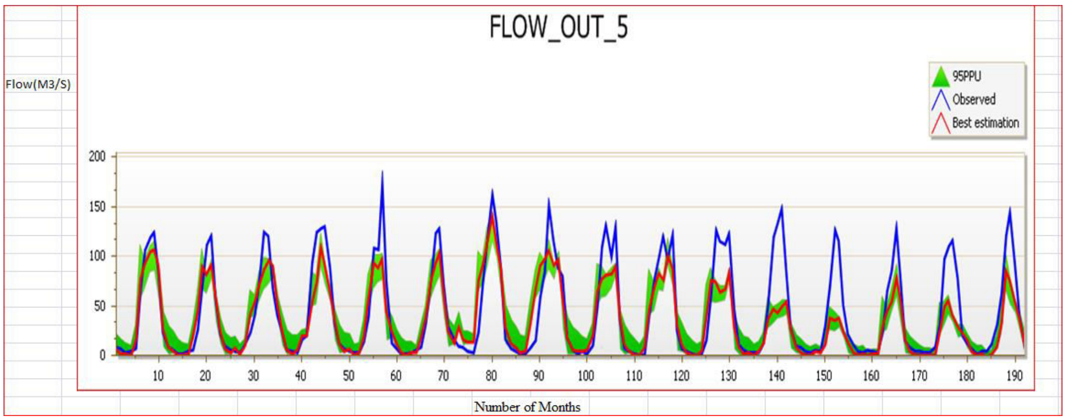

Fig 4: The 95% prediction uncertainty (95PPU) for Sor River for calibration

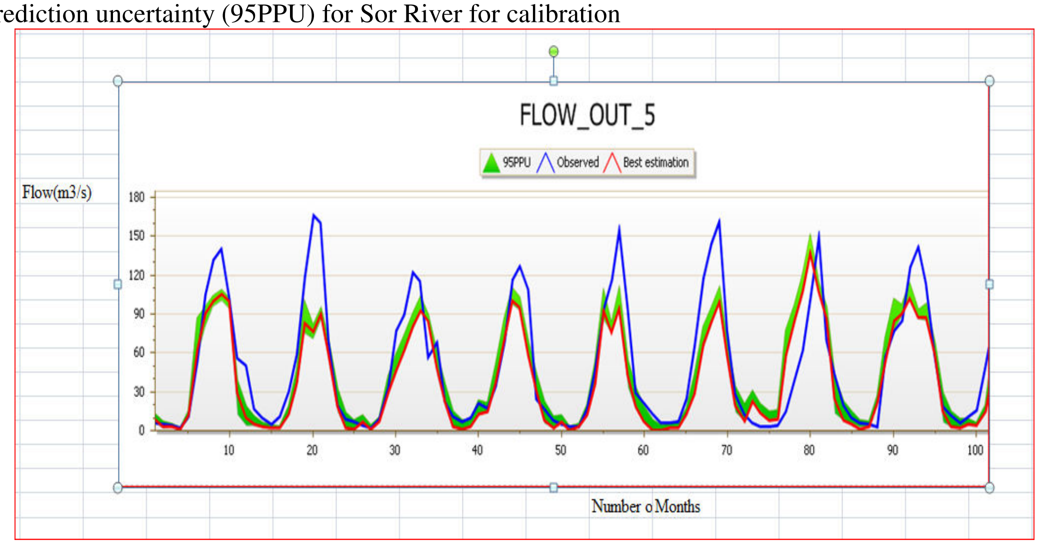

Fig 5: The 95% prediction uncertainty (95PPU) for Sor River for validation

P-factor shows the percentage of observations covered by the 95PPU and as a result the value of p factor in the above table 4.9. Accordingly, the result for the Stream flow calibration shows that 49% of the observed data is bracketed by the 95PPU (p-factor) and r-factor had a value of 0.22, which are quite fair results. The validation results were also quite fair with 44% of the data bracketed with r-factor equal to 0.24.The smaller the r-factor, which quantifies the thickness of the 95PPU, the smaller the uncertainties and the better calibration work. A value close to 1 is highly desirable for r-factor with a p-factor also close to1.On behalf of the above possible errors, calibration and validation results of the watershed could be qualified as ‘‘quite fair’’ in this study. This indicates a fair quality of the input data as well as small conceptual model errors in the dominant processes in the watershed.

Surface Water potential

To determine the surface water potential of the Sor river catchment, running the SWAT model and SWAT-CUP for calibration of the model is important. After running the SWAT model and SWAT-CUP for calibration of the model, the next results were obtained. Surface water runoff of the watershed 338.84 mm, rainfall is 1700.7mm and lateral soil flow is 143.73 mm. From total watershed area of 1963.512 km^2, 665.32million m^3 runoff was generated by the model from catchment annually. The annual and monthly values of the model output are shown in table 8. Average annual watershed values and table 4.8. Average monthly watershed values respectively.

Table 8: Average monthly watershed values.

MON	Rain (mm)	SURF Q (mm)	LAT Q (mm)	WATER YIELD (mm	ET (mm)	PET (mm)
1	26.83	3.41	0.68	17.12	28.81	102.59
2	24.06	2.05	0.43	6.09	29.21	103.18
3	63.37	6.24	1.06	9.27	78.93	122.74
4	106.33	13.54	2.43	18.22	92.01	117.27
5	224.41	39.18	11.02	54.97	92.14	103.04
6	252.93	59.52	21.85	99.86	73.1	81.81
7	253.48	68.06	26.03	139.84	61.06	78.77
8	274	80.54	27.61	178.2	62.94	84.75
9	244.16	62.88	25.01	171.28	71.16	91.62
10	142.25	33.45	13.01	131.52	64.34	104.47
11	62.35	11.78	3.92	76.54	46.22	97.85
12	26.31	3.19	1.23	40.65	33.49	99.72

Table 9: Average annual watershed values

Average annual values	
PRECIP	1700.7 mm
SURFACE RUNOFF Q	383.87mm
LATERAL SOIL Q	134.28mm
GROUNDWATER (SHAL AQ) Q	402.93mm
GROUNDWATER (DEEP AQ) Q	22.52mm
REVAP (SHAL AQ => SOIL/PLANTS)	23.77mm
DEEP AQ RECHARGE	22.47 mm
TOTAL AQ RECHARGE	449.33mm
TOTAL WATER YLD	943.6 mm
PERCOLATION OUT OF SOIL	449.18mm
ET	733.7 mm
PET	1188.70 mm

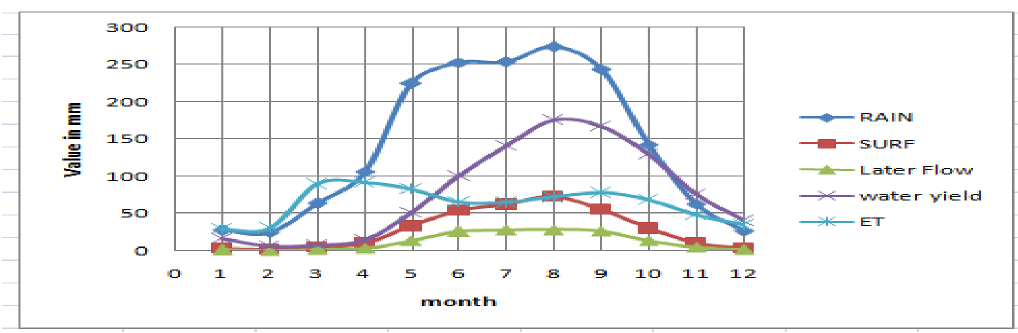

Fig 6:.Average monthly watershed values.

Spatial Variation of Surface Runoff in Sub basins

After Calibration and validation, the model was run for a period25 years. From the model simulation output, surface runoff source areas were identified in the Watershed. The assessment of the spatial variability of surface runoff is useful for catchment management planning.

The spatial distribution of runoff indicated that, out of the total 26 sub-basins, sub-basins 16 and 18 contribute highest average annual surface runoff. The SWAT model simulation shows that the average surface runoff extent varies from negligible to over1800 mm per year. The extreme surface runoff was observed in the cultivated land and low surface runoff was observed in the forest land. Sub basins number 1,3,5,6,7,16 and 21 have average annual surface runoff greater than 1200 mm and sub-basins 9, 18, 22, 23 and 24 have average annual surface runoff below 600 mm. The spatial distribution of surface runoff generation for the Sor river watershed is presented in Figure 4.6.

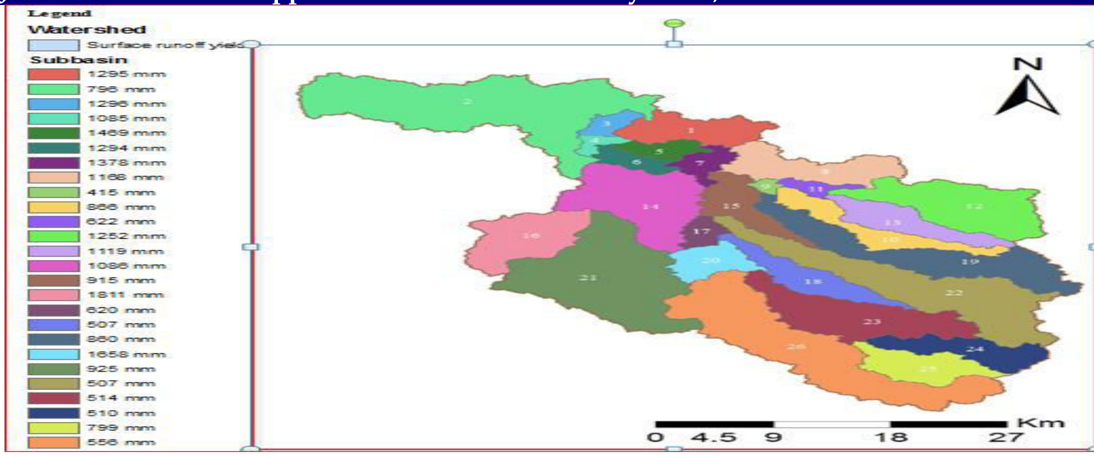

Fig 7: Spatial Distribution of annual surface runoff in each sub basins

Conclusion

In this particular study, physically based, spatially distributed and public domain Soil and Water Assessment Tool (SWAT) was successfully used to simulate and determine surface water potential, based on some model parameters required to determine surface water potential of Sor River watershed. Thus, based on the applied methods and results acquired, the following conclusions were made: surface runoff quantity has been determined by using rainfall amount, slope, land use, soil type, of the watershed and other factors of the watershed. The above listed parameters are the inputs of the model and affect the surface runoff of the watershed. Finally SWAT model were tested for its performance at a watershed in to examine the hydrological response of the watershed.

The sensitivity analysis parameters using SWAT-CUP SUFI-2 model has been identified as sixteen most significant parameters that control the surface runoff of under studied catchment. Also the SWAT model was calibrated from 1990 to 2005 and validated from 2006 to 2014 for sensitivity analysis. Performance of the model for both calibration and validation of watershed at Metu gauging station during calibration and validation was evaluated by correlation coefficient (R^2 = 0.80) and Nash-Sutcliffe model efficiency (E_{NS}=0.74) for calibration period and correlation coefficient (R^2 = 0.79) and Nash-Sutcliffe model efficiency (E_{NS} = 0.70) for validation periods. Therefore, it is possible to conclude that SWAT is able to fairly describe the hydrological characteristic of the catchments. Hence, simulation efficiency was found to be satisfactory.

The uncertainty analysis was performed by using SUFI2 in SWAT-CUP. In general the calibration and validation of the model for specified catchment was satisfactory. Since the model uncertainties analysis indicates the percentage of the simulated flow for specified catchment was within an uncertainty limit is more than 40%.Generally, this study was attempted to reply the stated objectives, which were determining and quantifying the total surface water potential of the watershed. This assessment results the total watershed area was estimated as1 1963.512 Km^2 and the annual surface water potential of the basin is about 665.32MmC.

Recommendations

The SWAT model requires more efforts to find best estimation of the surface water potential. Since model is very sensitive and needs accurate input data to simulate good result, which fits the observed stream flow data. In addition to this up to date land use and management data is essential for SWAT model.

Quality and quantity the weather stations data should be improved in the catchment, in order to improve the model performance. Hence, it is highly recommended to establish a good network of both hydrometric and meteorological stations. Because, SWAT model calibrated using observed flow data at gauging station but with significant uncertainty. To decrease model uncertainty the best description of the climate data, water management, and water use would be essential .Hence the reliability of the water resources decreases as the uncertainties increase.

The objective of this particular study is to estimate the runoff contribution from Sor watershed based on a semi distributed modeling methods. On the other hand, in water balance components, the sub-surface condition for the Sor watershed was not considered. Therefore, detail investigation work, which integrates ground water, is suggested to understand the interaction of surface and sub-surface condition and River water balance.

The numbers of beneficiaries for different purpose like hydropower, water supply, local irrigation practice and etc are increasing from time to timefrom a River.But,the waterdemands of available surface water potential of the Sor River are not identified in detail.Thereforefor future study, it is betterif the waterdemand assessment ofRiver was performed for sustainable allocation of available surface water potential of the Sor River.

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