ZIBELINE INTERNATIONAL™ PUBLISHING

ISSN: 2523-5664 (Print)
ISSN: 2523-5672 (Online)
CODEN: WCMABD

Water Conservation & Management (WCM)

DOI: http://doi.org/10.26480/wcm.01.2022.22.29

RESEARCH ARTICLE

RAINFALL-RUNOFF MODELING AND ITS PRIORITIZATION AT SUB-WATERSHED LEVEL USING SWAT MODEL: A CASE OF FINCA'AA, OROMIA, WESTERN ETHIOPIA

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ARTICLE DETAILS

Article History:

Received 22 December 2021
Accepted 25 January 2022
Available online 03 February 2022

ABSTRACT

Rainfall-runoff modeling is essential for soil and water conservation and for watershed management. The Soil and Water Assessment Tool, SWAT, model was used to predict average annual stream flow and identify vulnerable areas in the Finca'aa watershed at the sub-basin level. Meteorological, land use land cover, LULC, soil, 30 m resolution digital elevation model (DEM), and hydrological data were used as inputs for the model. There were 21 sub-basins and 205 HRUs in the simulated watershed. The sequential uncertainty fitting (SUFI-2) technique in the SWAT- calibration uncertainty program package was used for the sensitivity analysis, the calibration, and the validation of the model. The base flow alpha factor (ALPHA BF) and SCS runoff curve number (CN2) were the most sensitive stream flow parameters. The coefficient of determination, R^2, and Nash-Sutcliffe, E_{NS}, values for the calibration and the validation were 0.81 and 0.79, and 0.76 and 0.74, respectively. These values indicate the good fit between the observed and simulated stream flow data. The surface runoff during the rainy, the intermediate, and the dry seasons were 328.25, 77.525, and 39.31 mm, respectively. The average and maximum annual simulated surface runoff values were 449.81 and 567.4 mm, respectively. Agriculture was the main factor that caused high surface runoff in the watershed. Sub-basins 4 and 5 were runoff prone areas. The findings of the study call for the implementation of appropriate water management practices to conserve the soil and water resources of the watershed.

KEYWORDS

Annual runoff; Finca'aa watershed; Hydrological modeling; Stream flow simulation; SWAT model

1. INTRODUCTION

For soil and water management, understanding of rainfall, runoff, and their interactions, and variation in time and area, is critical issue at worldwide and at a local level. Hydrologic modeling can aid in decision-making at the global and local levels, which can help meet a key requirement in a variety of water-related applications, such as food security, climate change, and risk reduction (Souffront et al., 2019). Modeling of the hydrological system is representations of the real-world system. Modeling of rainfall-runoff processes is required for a variety of reasons, such as a limited range of hydrological measuring techniques and observations in space and time (Blöschl, 2006). There are various hydrological models, including lumped, semi-distributed and distributed models. The models, by discretizing the catchment into several elements, solve the governing equations for the state variables associated with each element (Beven, 1990; Souffront et al., 2019; Suanj et al., 2015).

For hydrological modeling, there are several integrated physical-based approaches (Amin et al., 2017; Cardoso et al., 2019; Souffront et al., 2019). The main factors that influence hydrological modeling include climate and catchment characteristics change, land use land cover changes, phsico-chemical parameters nutrients delivered from agricultural areas and local determinants (natural and anthropogenic) are some of the main factors that influence (Li et al., 2016; Mebrahtu et al., 2021; Legesse et al., 2010; Lv et al., 2019; Ahearn et al., 2005; Petersen et al., 2017; Sharpley and Syers, 1979; Sharma et al., 2016). Hydrologic modeling is used to answer environmental transport concerns, including water shortage, excess, or dissolved or solid content (Burges, 1986). In many hydrologic evaluations, soil water infiltration, conductivity, storage, and plant-water linkages are evaluated (Saxton and Rawls, 2006).

For flood control, disaster mitigation, hydraulic engineering construction, water resource exploitation, and pollution evaluation has all benefited from hydrological models (Amin et al., 2017). Early-warning systems have been identified as one of the most important solutions for reducing environmental risks, particularly those caused by hydrological disasters (Alfieri et al., 2013; Hallegatte, 2012; Suanj et al., 2015). Mountainous watersheds are mostly the source of rainfall-high runoff and of the world's largest rivers sources (Jain et al., 2010). Rainfall-runoff or hydraulic models have many applications in operational hydrology, water resource management and in research (Jeníček, 2006). Investigation of seasonal variability of rainfall and runoff using SWAT model is used to alleviate challenges, integrated water resources management, and effective water allocation system for different purposes (Tibebe et al., 2017).

Modeling of rainfall runoff using SWAT model is an important for the possibilities of combining/extending gage rainfall data with satellite rainfall (Dessu and Melesse, 2012). Estimation of rainfall-runoff is vital to calculate the required quantities of water storage in reservoirs and to determine the likelihood of flooding (Hamdan et al., 2021). Rainfall runoff models play an important role in hydrological predictions, especially for automatic flood prediction (Sir et al., 2015). The purpose of rainfall-runoff modeling includes estimating stream flow in ungauged catchments, flood forecasting, urban hydrology, water resources assessment and

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Cite The Article: Seifu Kebede Debela, Fekadu Fufa Feyessa (2022). Rainfall-Runoff Modeling and Its Prioritization At Sub-Watershed Level Using Swat Model: A Case of Finca'aa, Oromia, Western Ethiopia. *Water Conservation & Management, 6(1): 22-29.*

hydrological research (Peel and McMahon, 2020). To understand the hydrological phenomena of the catchment regarding change in time and space, study of rainfall-runoff using SWAT software is important that indicates effective and safe water structure designs (Kurbah and Jain, 2017a).

Some researcher agreed that, modeling of rainfall-runoff at a watershed-scale level is the complement of the national assessment by analyzing conservation benefits and used as tools to compensate the lack of measurements (Muke and Prof, 2016). The SWAT model is one of the hydrologic model with good capacity to predict rainfall-runoff interaction from the catchment at sub-watershed level (Blöschl, 2006; Gastesi et al., 2014; Kurbah and Jain, 2017b; Lv et al., 2020; Muke and Prof, 2016; Sir et al., 2015; Tibebe et al., 2017). The aim of the study is to determine the rainfall-runoff interaction of Finca'aa watershed and identify the surface runoff vulnerable areas of the watershed at sub-basin level using SWAT model.

2. Material and Methods

2.1 Study area

The Finca'aa watershed is in the Horro Guduru Wollega Zone of Oromia National Regional State, Ethiopia (Figure 1). It is located between latitudes 9°9′53′′ N and 10°1′00′′ N and longitudes 37°00′25′′ E and 37°33′17′′ E. The watershed covers sections of six districts: Jimma Geneti, Horro, Abbay Comen, Ababo Guduru, Guduru, and Jimma Rare. The area of the watershed is about 2,619 km^2. The elevation in the watershed varies from 902 to 3,171 m asl. The Blue Nile River (aka the Abbay River in Ethiopia) borders the watershed on the north, the Guder River Basin on the east, the Awash River Basin on the south, and the Dhidhessa River Basin on the west. With an average annual rainfall of 1763.6 mm, the Finca'aa watershed has a tropical highland Monsoon climate. During the rainy season, the watershed experiences regular torrential showers and flash floods due to its location in a high rainfall area.

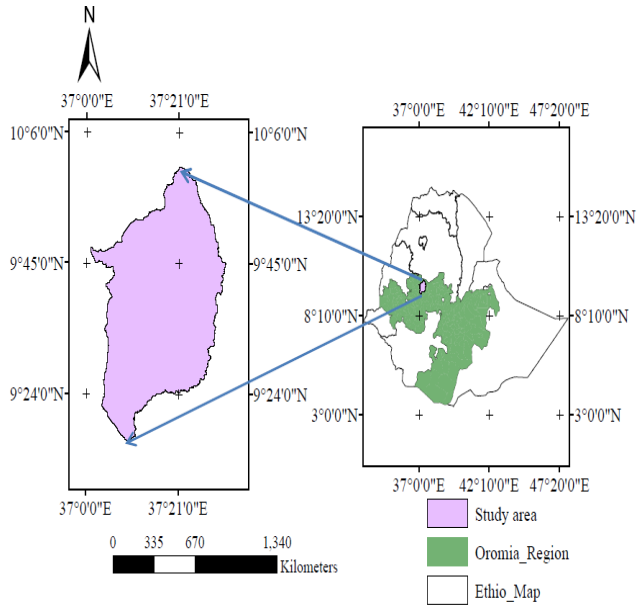

Figure 1: Map of the study area.

2.2 Materials

ArcVIEW GIS version 10.4.1, ArcSWAT 2012, SWAT-CUP 2012, different maps, map window, pcpSTAT, dew02.exe, angstrom, and Microsoft excel were the main tools utilized in this study for data collection, preparation, and analysis.

2.3 The SWAT model

The Soil and Water Assessment Tool, SWAT, model is a river basin, or watershed scale model developed to predict the effects of land management practices on water, sediment, and agricultural chemical yields over long periods of time in large complex watersheds with varying soils, land use, and management conditions (Neitsch., et al., 2005). SWAT is a versatile model that integrates numerous environmental processes, which supports more effective watershed management and the creation of better-informed policy. It is one of the most promising and computationally efficient models. In the land phase of the hydrologic cycle, SWAT uses the water balance equation (Eq. (1)). to simulate the hydrological cycle.

$$S_{wt} = S_{wo} + \sum\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \quad (1)$$

Where, S_{wt} was the final soil water content (mm), S_{wo} is the initial soil water content for a day (mm); t is the time (days), R_{day} is the day precipitation (mm), Q_{surf} is the surface runoff (mm), E_a is the evapotranspiration (mm), W_{seep} is the seepage from the bottom soil layer (mm) and Q_{gw} is the groundwater flow in day I (mm). For predicting surface runoff using daily rainfall, the SCS (Soil Conservation Service) curve number process (USDA-SCS, 1972) method was employed. SWAT simulates surface runoff volumes and peak runoff rates for each HRU. The SCS curve number approach was utilized to estimate surface runoff in this investigation using Eq. (3). The mathematical equation (Eq. (2)) was used to compute the retention parameter, which varies regionally due to changes in soils, land use, management, slope, and soil water content.

$$S = 25.4\left(\frac{100}{CN} - 10\right) \quad (2)$$

$$Q_{surf} = \frac{\left(R_{day} - 0.25\right)^2}{R_{day} + 0.8S} \quad (3)$$

Where, CN is the curve number for the day; Q_{surf} is the accumulated runoff or rainfall excess (mmH_2O); R_{day} is the rainfall depth for the day (mmH_2O); and S is the retention parameter (mmH_2O)

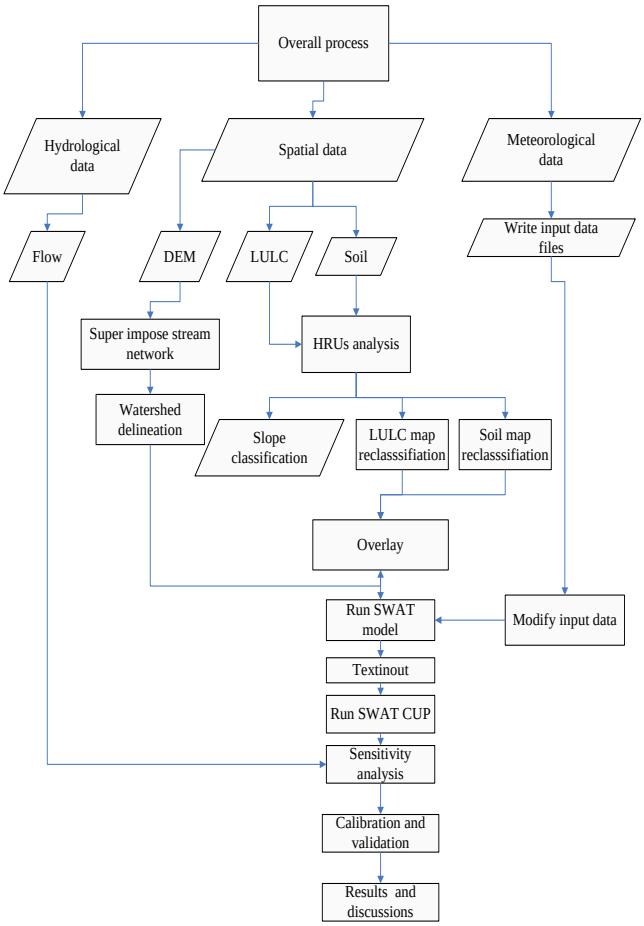

Figure 2: General framework of the methods.

2.4 Data sources and collection

Secondary data and field research were utilized. Digital elevation model (DEM), land use land cover (LULC), soil, meteorological, and hydrological data are examples of secondary data. The Ministry of Water, Irrigation, and Electricity, the Ethiopian Mapping Agency, the National Meteorological Agency, and the International Water Management Institute provided the information (Table 1).

Table 1: Data type, format, their description and sources of Finca'aa watershed

Data type	Data format	Descriptions	Source
DEM	Grid	30 m x 30 m grid DEM for Finca'aa watershed delineations	MoWIEoE
Land use and land cover	Grid/ Shape file	The land use data contains crop, specific digital layers, suitable in GIS and SWAT model	MoWIEoE
Soils data	Grid/ Shape file	Soil types and physical properties of Finca'aa watershed for the model	MoWIEoE
Weather data	text	Daily (precipitation , max and min temp erature, solar radiations, wind speed and relative humidity) from four stations (Kom bolcha, Finca'aa, Hareto and Shambu)	ENMA for the period from (1996-2020)
Hydrologic al data	text	Observed daily stream flow of the watershed for calib rations, validations and sensitivity analysis	MoWIEoE

2.5 Model inputs and data preparation

2.5.1 Digital elevation model

The DEM was used to demarcate watersheds, assess drainage patterns on the land surface, and establish sub-watersheds. It was also employed to generate the terrain characteristics for this study (Figure 3). The DEM was used to calculate terrain factors, including slope gradient and slope length, and stream network properties like channel slope, length, and breadth.

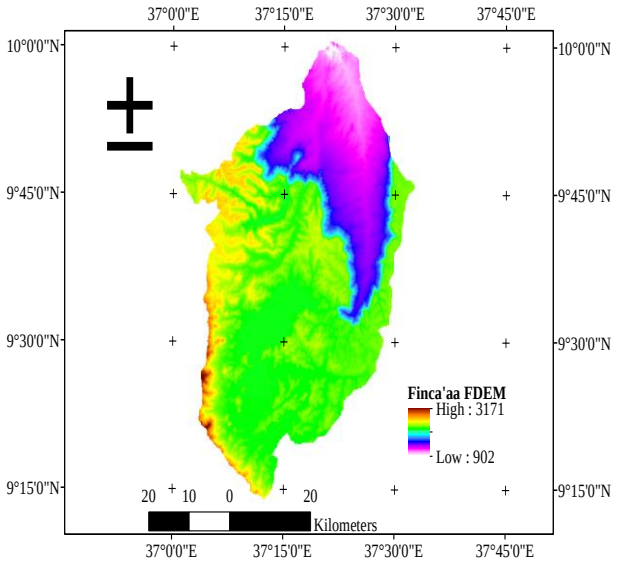

Figure 3: DEM of Finca'aa watershed.

2.5.2 Land use land cover

The Ethiopian LULC map and the Finca'aa basin was overlaid, and the LULCs of study area, were clipped and projected to UTM Zone 37. Nine LULC classes (Figure 4) were recognized, coded by four letters compatible for ArcSWAT, linked to SWAT land use databases (Table 2), and finally loaded into the ArcSWAT model via a lookup table.

Table 2: LULC, SWAT code and area covered of Finca'aa watershed.

LULC category	SWAT code	Area	
		km²	%
Bush land	RNGB	55.79	2.13
Dominantly cultivated	AGRR	958.52	36.60
Moderately cultivated	AGRL	763.12	29.14
Irrigated land	CORN	50.72	1.94
Grass land	RNGE	278.67	10.64
Water bodies	WATR	298.99	11.42
Swamp area	WETN	66.34	2.53
Urban	URBN	40.33	1.54
Woodland open	FRST	106.33	4.06

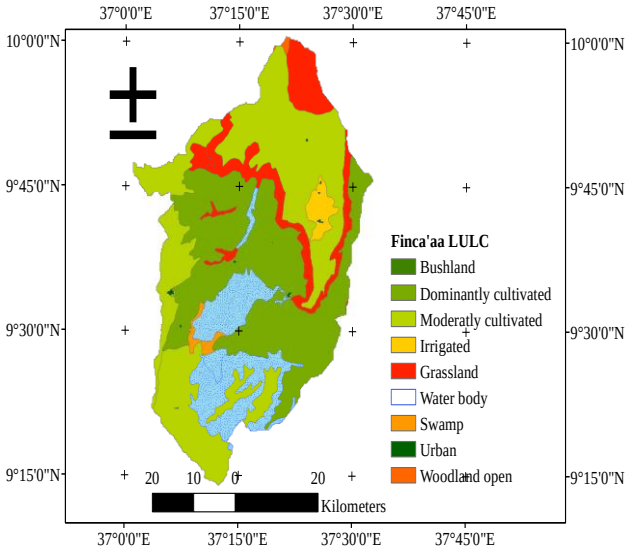

Figure 4: Major LULC classes in Finca'aa watershed.

2.5.3 Soil data

The watershed for the SWAT model was extracted from the Ethiopian Soil Map shapefile, projected to UTM Zone 37, and categorized (Table 3, Figure 5). Because these soil data were not included in the existing SWAT soil database, they were compiled as a map in text format and then linked to a SWAT soil database created by the user.

Table 3: Soil and area covered in Finca'aa watershed.

Soil category	Soil name from Map window	Area	
		km²	%
Chromic Luvisols	Lc13-1a-127	2.60	0.10
Chromic Vertisols	Vc23-3a-262	528.36	20.17
Dystric Cambisols	Bd31-2c-11	620.64	23.70
Eutric Cambisols	Be8-3c-24	426.27	16.28
Eutric Nitosols	Ne20-3b-160	21.82	0.83
Eutric Regosols	Re59-2c-246	545.18	20.82
Haplic Phaeozems	Hh23-3a-6524	34.84	1.33
Humic Cambisols	Bh12-3c-31	132.97	5.08
Water	WATER-6997	306.38	11.70

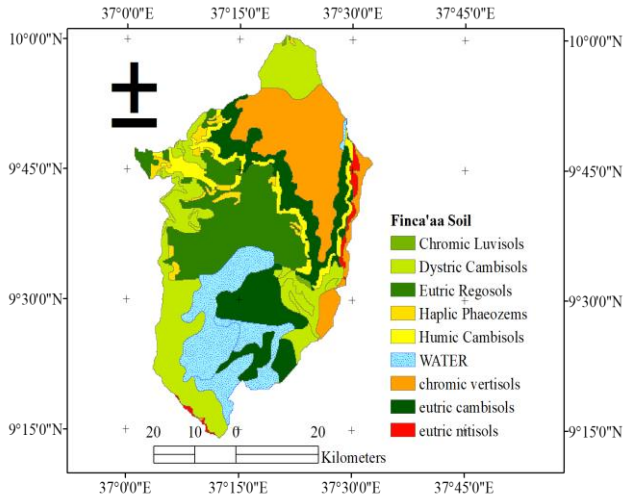

Figure 5: Major soil classes of Finca'aa watershed.

2.5.4 *Meteorological data*

Precipitation, maximum and minimum air temperature, solar radiation, wind speed, and relative humidity are all required by the SWAT model. The model was built utilizing measured or generated data from a weather generator, depending on their availability. Kombolcha, Finca'aa, Hareto, and Shambu Metrological Stations provided 25-year data from 1996 to 2020 (Table 4, Figure 6). Missed data were created from the main station (Shambu) by the weather generator components in this investigation. PcpSTAT (for precipitation), dew02.exe (for the maximum and minimum average temperature with average relative humidity), and pivot tables for the rest of the data were used to provide monthly statistical numbers for the weather generator. The consistency of the filled data was examined, and the correlation coefficient for precipitation and temperature were closer to one, indicating satisfactory agreement. Finally, meteorological data were generated in a text format according to the model's compatibility and imported into the SWAT database.

Table 4: Locations of the weather stations

Station	Easting (m)	Northing (m)
Kombolcha Station	332344.2	1050758
Finca'aa Station	321142.7	1058294
Hareto Station	293528.8	1034098
Shambu Station	293789.3	1058566

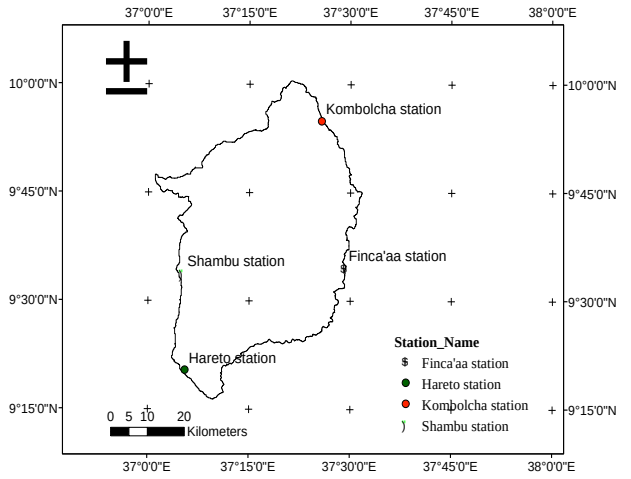

Figure 6: Climate station in Finca'aa watershed.

2.5.5 *Hydrological data*

Daily observed stream flow was the most essential hydrological data for this study, as it was used for sensitivity analysis, calibration, and validation processes at the outlet of the watershed using the SWAT CUP 2012 model (Eckhardt and Arnold, 2001; Mehan et al., 2015; Mendoza et al., 2021). The Hydrology Department of the MoWIE provided data for twenty-five years (1996 to 2020). An automated base flow and surface runoff separation technique from total daily stream flow was used to establish a realistic water balance of the watershed using the SWAT model (Aboelnour et al., 2020; Hughes et al., 2003).

2.6 Model setup

2.6.1 *Watershed delineation*

Model setup and parameterization are required for the ArcSWAT. The watershed of the study area was automatically delineated using a 30 m resolution DEM. Based on the threshold area; the watershed was divided into many hydrologically related sub watersheds (Figure 7). DEM setup, stream definition, outlet and inlet definition, watershed outlet selection, and computation of sub-basin parameters were the five phases of the process.

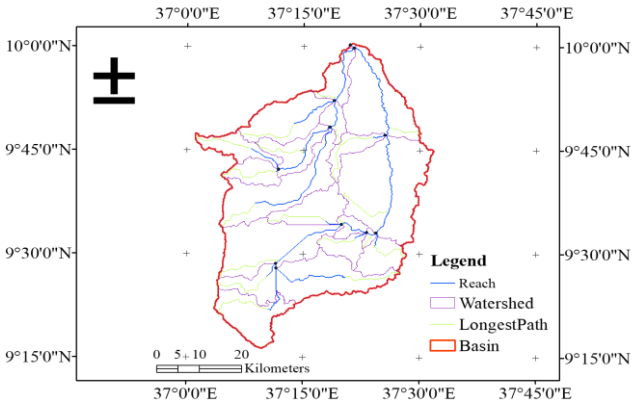

Figure 7: Finca'aa watershed.

2.6.2 *HRU analysis*

The HRUs allow the model to account for variations in evapotranspiration and other hydrologic conditions for various land coverings and soils. Multiple slope classes were applied after the land use, land cover, and soil type in the shapefile format were input into the ArcSWAT and classed. Finally, the land use, soil layers, and numerous slopes were all overlaid. In this study area, the threshold value for land use, land cover, soil layers, and various slopes was 10% for each. Multiple HRU distributions were chosen for each sub-watershed in this study from various HRU definition possibilities. Finally, stream flow was forecasted independently from each HRU and routed to obtain the overall value from the entire watershed, which provided a far better physical description of the water balance than forecasting from the entire catchment at once.

2.7 Sensitivity analysis

Using SWAT-CUP, which uses the SUFI-2 algorithm, sensitivity analysis was performed to reduce the number of optimized parameters to establish a good fit between the simulated and measured data (Mendoza et al., 2021; Moreira et al., 2018). For sensitivity analysis and model calibration, ten-year data, from 1999 to 2008, were used, with one-year data used for the warm-up period. The t-stat and p-value were used to rank the sensitivity parameters. The most sensitive and significant parameters were the absolute values of t-stat (the larger absolute value) and p-value (the smaller values) values, respectively.

2.8 Calibration

Both automatic and manual calibration procedures were used in this investigation. From 2000 to 2008, manual calibrations of the stream flow parameter values were used to ensure that the model satisfied the criteria. To acquire optimal fit values, automatic calibration was performed based on the results of manual calibration. The SWAT model calibration operations continued until the conditions of $R^2 = 0.6$ and $E_{NS} = 0.5$ are met (Eckhardt and Arnold, 2001; Mendoza et al., 2021).

2.9 Validation

The model was run with input parameters defined during the calibration phase, and data from a six-year stream flow recording from 2009 to 2014 were used, based on monthly readings and a one-year warm-up time. The model validation was evaluated based on the coefficient of determination, R^2, and the Nash-Sutcliffe simulation efficiency, E_{NS}, performance evaluation standards (Eckhardt and Arnold, 2001; Mendoza et al., 2021).

2.10 Evaluation of model performance

The model prediction capacity was assessed evaluating the obtained R^2 and E_{NS}. The approach to a unit of the values of R^2 and E_{NS} indicates the best fit between the observed and simulated stream flow data. When the values are closer to 0, it is the worst fit; and values between 0 to 1 show deviation between observed and simulated data. The equations of E_{NS} and R^2 are expressed in Eqs. (4) and (5), respectively.

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (4)$$

$$R^2 = \frac{\left(\sum_{i=1}^{n}(O_i - \bar{O})\left(P_i - \overline{P}\right)\right)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2 \sum_{i=1}^{n}\left(P_i - \overline{P}\right)^2} \quad (5)$$

Where E_{NS}, R^2, Oi, Pi, $\bar{O}$, $\overline{P}$ and n are the Nash-Sutcliffe efficiency of the model, coefficient of determination, observed, predicted, the average observed, average predicted values and number of observations during the simulation period, respectively.

3. Results and Discussion

3.1 Sensitivity analysis

The most sensitive parameters were identified using the SUFI2 uncertainty software and the SWAT CUP 2012 package approach. Only seventeen of the twenty-seven factors were effective for monthly stream flow analysis. These factors were ranked using global sensitivity analysis technique based on the t-stat and p-value that ranges from 3.278 to -0.049; and 0.003 to 0.961, respectively (Table 5). The most sensitive stream flow parameters were SCS runoff curve number for moisture condition II (CN2), RCHRG_DP.gw, the base flow alpha factor (ALPHA BF), ground water delay time (GW DELAY), shallow-water threshold depth (GWQMN), plant uptake compensation factor (ESCO), effective hydraulic conductivity in main channel alluvium (CH_N2), effective hydraulic conductivity (CH_K2), base flow alpha factor for bank storage (ALPHA_BNK), soil hydraulic conductivity (SOL_K), surface runoff lag time (SURLAG), threshold depth of water in a shallow aquifer to occur (REVAPMN), Maximum canopy index (CANMX).

Table 5: Sensitive parameters for calibration of the process

S.No	SWAT input parameter	Global sensitivity		
		t-stat	p-value	Rank
1	r_CN2.mgt	3.278	0.003	1
2	v_ALPHA_BF.gw	-2.699	0.011	2
3	v_GW_DELAY.gw	2.516	0.017	3
4	v_GWQMN.gw	-2.344	0.026	4
5	v_ESCO.hru	2.280	0.030	5
6	v_CH_K2.rte	1.382	0.177	6
7	v_ALPHA_BNK.rte	1.005	0.323	7
8	r_SOL_K.sol (1).sol	0.923	0.364	8
9	r__SURLAG.bsn	0.838	0.409	9
10	v_REVAPMN.gw	-0.763	0.451	10
11	v_CANMX.hru	0.704	0.487	11
12	v_ESCO.hru	-0.528	0.601	12
13	v_EPCO.bsn	0.513	0.612	13
14	v_SLSUBBSN.hru	0.413	0.682	14
15	r_SOL_AWC (1).sol	-0.200	0.843	15
16	v_GW_REVAP.gw	0.089	0.930	16
17	v_REVAPMN.gw	-0.049	0.961	17

3.2 Calibration

The thirteen most sensitive stream flow parameters were utilized for calibration and optimized values were obtained with 1000 iterations. The calculated values of R^2 and E_{NS} from monthly observed and simulated stream flows were 0.81 and 0.76, respectively, indicating that the observed and simulated stream flow values were in good agreement. The subsurface water source supplied 65% of the overall water production, which was higher than surface runoff involvement at the outlet of the watershed, according to the base flow separation technique. The SWAT model offers strong predictive capacity for modeling of stream flow for the Finca'aa watershed at monthly time steps, based on the calibration results (Table 6, Figure 8).

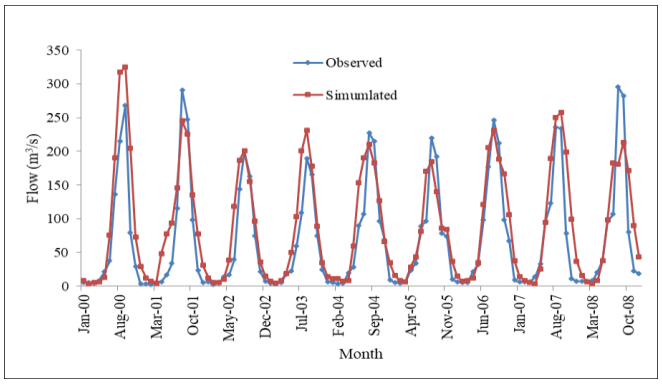

Figure 8: Monthly observed and simulated flow for calibration period.

3.3 Validation

The model was run with the same input parameters as during the calibration procedure, and the results were compared to the remaining observational data to assess the model's prediction capacity. During the validation period, the R^2 and E_{NS} values were 0.79 and 0.74, respectively, exceeding the criterion ($R^2 > 0.6$ and $E_{NS} > 0.5$). These values revealed that the actual and simulated stream flow data fitted well and the model can predict stream flow in the Finca'aa watershed for the feature (Table 6, Figure 9).

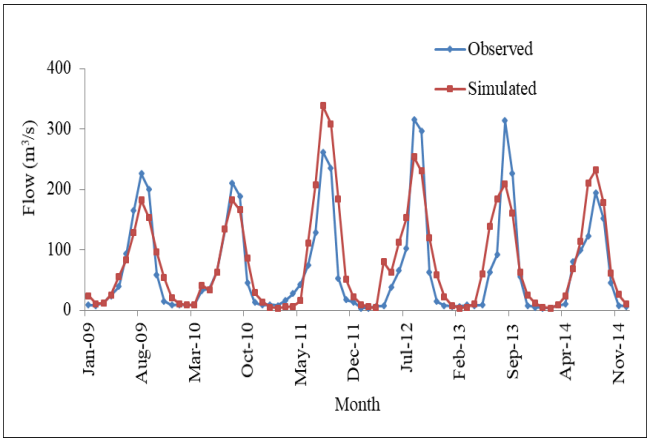

Figure 9: Monthly observed and simulated flow for validation period.

Table 6: Calibration and validation performance criteria for stream flow the watershed				
Performance criteria	**Calibration**	**Validation**	**Standard values (Neitsch., et al., 2005)**	**Remark**
R^2	0.81	0.78	≥ 0.6	Best fit
E_{NS}	0.76	0.74	≥ 0.5	Best fit

3.4 Monthly and seasonal water yield simulation

The simulated monthly water yield at the outlet of Finca'aa watershed seasonally varied. The wet season in this study lasted from June to September, with maxima in July and August, an intermediate period from October to January, and a nearly dry period from February to May. The simulated average monthly and annual water yields for the period of 25 years were 107.70 and 1292.34 mm, respectively. During the wet, intermediate, and dry seasons, the values were 328.25, 77.53 and 39.31 mm, respectively. The northeastern part of the watershed contributed more to the total water yield of the watershed. The reason for the variation of water yield could be the effect of topography, variability of climatic conditions, LULC, soil properties, location of groundwater table, water conservation techniques, and landscape managements. Previous studies conducted in the upper Tekeze Basin, Big-Akaki watershed, upper Awash Basin, Holatta River and Awash subbasin in Ethiopia observed similar seasonal variations in the water yield (Abebe, 2019; Wondimu, 2019; Tibebe et al., 2017).

3.5 Average annual water balance

The SWAT model also forecasted average annual basin values for various water balance components based on gains and losses when soil water storage changed. The simulated values of average annual water balance of the watershed include precipitation, percolation, ET and transpiration, evaporation from shallow aquifer, recharge to deep aquifer, lateral flow, return flow, surface runoff were 1763.20, 670.02, 417.30, 11, 33.13, 4128.42, 617.97 and12.85 mm, respectively. The results showed that the rainfall is comparatively higher than runoff, which contributes the water yield from the Finca'aa watershed. Percolation is the second largest water balance component. The soils of the watershed had high soil permeability coefficients. Runoff is the least component and contributes less water yield from the watershed. Overall, water losses from Finca'aa watershed is significant. Therefore, effective and efficient water conservation and management practice should be implemented.

3.6 Rainfall and surface runoff relationship

The maximum rainfall and peak surface runoff occurred in July, with nearly null in January, February and December (Figure10). This could be because of the rainy season of the watershed occurred in June, July and August. During rainy season, soil moisture became saturated, duration and amount of rain fall increased and surface runoff increased. Drainage area of the watershed is the major effect of that alters the rainfall-runoff. The f per unit area decreases with watershed size for a specified rainfall depth. This is because of the rainfall intensity existence less for storms of extensive size, and the extended time required for the total watershed area to subsidize to the peak runoff. Studies showed that the factors that affect rainfall of a specific watershed are the area of the catchment, climatic conditions, LULC and it permeability coefficients, infiltration rate (Tibebe et al., 2017; Dessu and Melesse, 2012; Peel and McMahon, 2020; Muke and Prof, 2016). Furthermore, in this study these factors were the influencing parameters for rainfall runoff interaction. However, four meteorological stations for model simulation and a nine-year hydrological data were used to check the model efficiency for the capability of modeling rainfall-runoff which makes it different from the previous analysis.

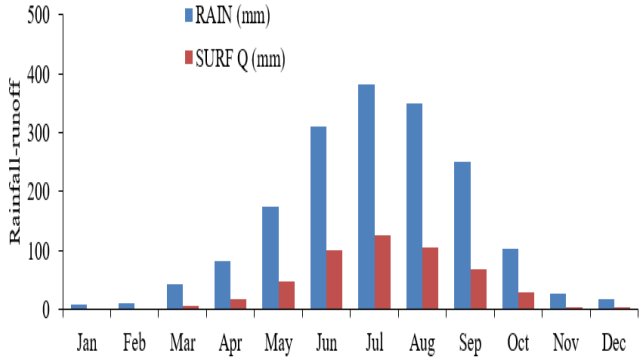

Figure 10: Average monthly rainfall and surface runoff

3.7 Sub basin level surface runoff

Sub basins 4 and 5 produced the largest runoff (567.4 mm), while sub basins 8 and 11 produced the least (0 mm) (Figure 11). The runoff values were divided into four categories (Figure 12). The I classes were sub basins 2, 4, 5, 13, 14 and 16 that covered about 35.06% of the total area. The II were sub basins 1, 3, 6, 9, 15 and 17 that accounted for 24.70% of the total area. The III were sub basins 7, 10, 12 and 20 were covered 22.79% of the whole watershed. The IV classes were from sub basins 8, 11, 18, 19 and 21 with 17.46% area covered. The values of runoff from I, II and III classes were ranging from 347 to 567.4, 16.9 to 347 and 161.40 to 216.90 and 0 to 161.4 mm respectively (Figure 12). As the result showed, runoff from each sub basin is not similar because of different factors like duration of rainfall, rainfall intensity, infiltration, drainage area, shape of the basin, slope of the basin, land use cover, geological conditions.

From the developed spatial distribution map of the study area (Figure 12), n and e parts of the watershed were experienced high runoff, especially due to agricultural activities and topography (Figure 4); whereas in the s part runoff was comparatively samller. Uncontrolled agricultural practice is one of the main driving force of runoff formation, and the steepest slope is resulted with peak runoff from the watershed. High infiltration rate reduces runoff formation since premeability coefficient of the soil increased with high transmissivities. The study agreed with the reviuos studies idea since discussing of surface runoff at the sub-basin level is a hydrological cycle phenomenon and is fundamental for an effective watershed management program for conservation and development of natural resources (Degefie and Bewket, 2011; Desta and Lemma, 2017; Lv et al., 2020; Mapes and Pricope, 2020).

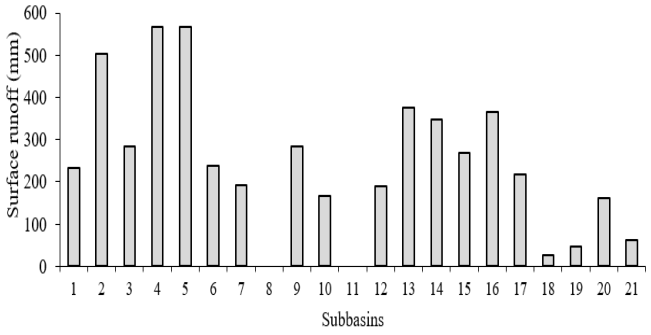

Figure 11: Average surface runoff at sub-watershed level.

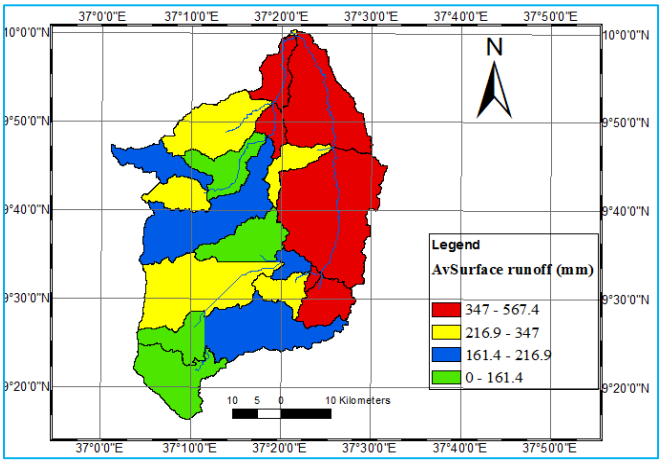

Figure 12: Spatial distributions of average surface runoff.

4. Conclusions

The SWAT model was run for 25 years, from 1996 to 2020, and produced 21 sub-watersheds, 205 HRUs, and a 2,619 km² catchment. Nine LULCs and nine key soil types were identified from the HRUs studied. The stream flow sensitivity analysis, calibration, and validation of the model were all

done using SUFI-2, uncertainty analysis in SWAT CUP. The most sensitive parameter for stream flow was the base flow alpha factor (ALPHA BF). The computed values of R^2 and E_{NS} show that there is a good agreement between observed and simulated stream flow data, indicating that the SWAT model has the capacity to predict the hydrological processes in the Finca'aa watershed. The water yield of the watershed varies monthly and seasonally, and the overall water losses are significant as per water balance simulation. The simulated total annual surface runoff from the watershed was 449.81 mm. Sub-basins 4 and 5 are runoff prone areas in the watershed. Agricultural activities in the watershed promote runoff. The results of the study point out the need for implementation appropriate watershed management techniques to conserve the soil and water sources of the watershed.

Authors' Contributions

Data acquiring and analysis, conceptualization, methodology, results and discussions, manuscript preparation, review and editing were done by Seifu Kebede (BSc, MSc, lecturer and researcher) and Fekadu Fufa (PhD, Associated Professor and researcher). All authors have read and agreed to the published version of the manuscript.

Acknowledgments

Authors thank the Ethiopian National Meteorological Agency and Ethiopian Ministry of Water, Irrigation and Electricity (MoWIE) for providing rainfall, land use land cover and soil data respectively.

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