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Multi-site calibration of hydrological model and the response of water balance components to land use land cover change in a rift valley Lake Basin in Ethiopia

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ABSTRACT

This study aims to perform multi-site calibration and validation of SWAT model using streamflow data, and investigating the responses of water balance components to land use land cover (LULC) change in the Gidabo river sub-basin of rift valley lake basin in southern part of Ethiopia. SUFI-2 algorithm embedded in the SWAT-CUP was employed for sensitivity analysis, calibration, and validation on a monthly basis. The 17 years (1990–2006) streamflow data for three (Aposto, Bedessa, and Measso) gauging stations were used for calibrating the model while 8 years (2007–2014) streamflow data was used for validating the model. The calibrated and validated SWAT model was then used to investigate the response of water balance components to LULC change for three periods (1990, 2005, and 2019) which were performed using ERDAS Imagine 2014 with a maximum likelihood classifier. The most common statistical model performance evaluation indices namely Coefficient of Determination (R^2), Nash-Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS) were used to evaluate performance of the SWAT model in simulating sub-basin hydrology; in addition to physical inspection of observed and simulated streamflow hydrograph. The findings of the multi-site model performance evaluation indicated that the values of R2 ranged from 0.80 to 0.64 and 0.74 to 0.72 during calibration and validation periods respectively. The values of NSE ranged from 0.74 to 0.61 and 0.71 to 0.65 during calibration and validation periods respectively whereas PBIAS ranged from 19.70 to -3.20 and 18.10 to 0.80 during calibration and validation periods respectively. The calibration and validation results indicated that the SWAT model would simulate fairly well the historical streamflow at three gauging stations. The mean annual streamflow response to LULC change for the periods 1990–2005 and 2005–2019 was observed to increase by 2.13% (1.16m^3/s) and 3.62% (2.04m^3/s), respectively and the mean seasonal streamflow was obtained to increase during wet season (April-September) while decreasing trend was observed during dry season (October-March) in all three gauged stations. Results also revealed that there were significant spatiotemporal variations of surface runoff, groundwater flow, lateral flow, and evapotranspiration in the sub-basin. The multi-site calibration and validation together with uncertainty analysis detects spatial variability and simulates the water balance components under changing LULC, which is paramount importance for planning and formulating appro-

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priate integrated land and water resources management and development strategies in the rift valley lake basin of Gidabo river sub-basin in Ethiopia.

Introduction

Hydrological models are very basic mathematical demonstration of a real-world multifarious system that is used to improve the understanding of complex hydrologic processes [1,2]. The precision of the input data, model structure, and probabilistic character of most hydrological parameters all influence how well hydrologic models can describe the watershed hydrologic process [3]. [4,5]. Physically-based distributed (semi and fully) models are effective in capturing physical properties and spatially heterogeneity of the watershed amongst different hydrological models [6]. Amongst these models, "the SWAT model has been widely used in many countries [7–9] over a long period efficiently for evaluating the impacts of different land management practices on hydrologic processes under complex watersheds with varying land uses, soils, and management conditions with reasonable accuracy [10]".

To perform uncertainty analysis, various approaches are available, including "Generalized Likelihood Uncertainty Estimation (GLUE), Particle Swarm Optimization (PSO), Markov Chain Monte Carlo (MCMC), Sequential Uncertainty Fitting (SUFI-2), and Parameter Solutions (ParaSol)" in the SWAT-Calibration and Uncertainty Programs (SWAT-CUP) auto-calibration tool. These algorithms differ in terms of assessment methodologies and parameter range estimates for a certain target function [11,55]. Several research conducted in various river basins throughout the world (e.g., [11–14]) concluded that SUFI-2 gives better results and optimal parameter ranges with the shortest running time. SUFI-2 is a semi-automatic optimization technique that employs the Latin Hypercube sampling scheme, which is a highly efficient sampling method for obtaining optimal results and performing calibration and validation at multi-site hydrometric stations, and it supports the use of a variety of objective functions [13]."

Calibration and validation of hydrological model is an important stair for attaining a representative and stable model at the river basin and sub-basin scale. The calibration and validation of hydrological models might be performed manually, nevertheless it' subjective and laborious [5,15]. Hence, currently, utilizing auto-calibration method has become common in various water resources management and development studies [16]. Wheater et al. [17] in their research outlined that calibrated and validated hydrological models offer possibility to assess variables that are tough to quantify in the actual field due to their intrinsic nature (spatiotemporal variation) and they can be applied for various water resources management and development activities, particularly for 'what if scenarios'. For example, how hydrological processes are responding under changing environment in general (i.e., under changing land use-land cover, climate variability, population growth, economic development, various watershed management activities; these are just to name a few).

Calibration and validation of hydrological model at a single confluence point in a basin is a commonly accepted approach [18]. Nevertheless, calibration and validation of multifaceted hydrological models using multi-site streamflow data is suggested by many scholars [19–21] to attain the required model performance efficiency and to detect spatial variability within the basins. Besides, multi-site calibration and validation approach affords an incremental stage of parameter freedom, encouragements of the model performance as compared to single-site calibration [22,23].

The application of several hydrological models to simulate catchment hydrological processes considering single-site calibration has been studied in Ethiopia [24–27]. Besides, SWAT hydrologic model has been calibrated and validated fairly using single-site streamflow data, and then investigating hydrological processes under changing landuse land cover and climate in various river basins in Ethiopia (e.g. [28–31]). Amidst single-site calibration and validation is widespread application, only a few studies have concentrated on multi-site calibration of hydrological models in Ethiopia.

Several hydrological models have also been calibrated and validated using single-site streamflow data, and then investigating different hydrological processes under changing landuse land cover and climate in the RVLB in Ethiopia (e.g. [32–36]); but not considered multi-site calibration and validation which is paramount importance for researchers and decision makers to plan and implement appropriate water resources management and development strategies considering spatial variability for a particular sub-basin. Hence, in this study, calibration and validation of SWAT hydrologic model considering multi-site streamflow data was applied for performing SWAT's ability in simulating historical streamflow in the rift valley lakes basin in Ethiopia.

Changes in LULC have a significant influence on natural resources, the most essential of which is water. Because of the LULC modification, there is a rise in storage fluctuation, resulting in frequent high water shortage during high water demand and frequent floods during the rainy season. The effects of land cover changes on water resource systems vary depending on site-specific variables, which are currently ongoing concerns that require further investigation (Bewket and Sterk, 2005). As a result, scientific research on the topic is required.

At present, the Rift Valley Lakes Basin (RVLB) in Ethiopia has fronting many challenges like ever-increasing water demand for various water competing sectors such as domestic, industrial, public institutions, agriculture (irrigation and livestock),

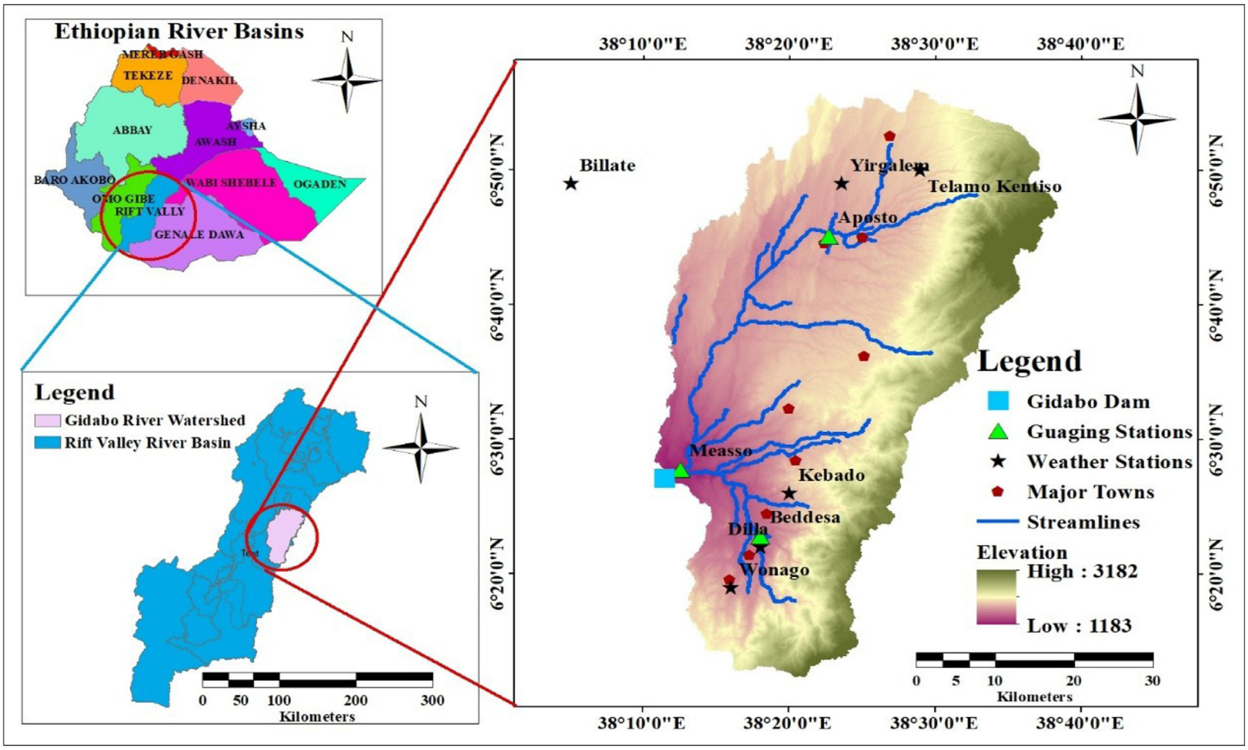

Fig. 1. Location of the study area with dam site, hydrometric stations, major towns, and streamlines.

and environmental flow to maintain ecosystem health [37–40] and as a result, competition has seriously increased in most RVLB including Gidabo river sub-basin [41]. Currently, the population of Gidabo river sub-basin is over 1.5 million and increased by 33.3% in the last decades [42]. This increasing population growth and the socio-economic developments in the watershed exert pressure on LULC changes and consequently result in increasing water [43].

The multi-site calibration and validation with sensitivity analysis to manage uncertainty detects the spatial variability and estimates the water balance components which is very helpful for planning and designing appropriate water resources management and developing strategies in the rift valley lakes basin. Thus, the aim of this study was to calibrate and validate SWAT hydrologic model with SUFI-2 algorithm using multi-site observed streamflow, perform sensitivity analysis to alleviate model uncertainty, and estimate water balance components under changing LULC in the rift valley lake basin of Gidabo river sub-basin in Ethiopia.

Materials and methods

Description of the study area

The Gidabo River is located in the Abaya-Chamo sub-basin of the Rift Valley Lakes basin situated in the southern part of Ethiopia. It originates from the highland area of Aletawendo escarpment, joining numerous large streams and finally passing through Gidabo dam before draining into Lake Abaya. It has been contributing water for Gidabo irrigation project available downstream of Gidabo dam. The Gidabo river sub-basin is found in Borena zone in Oromia Region, Sidama Region, and Gedeo Zone in SNNP Region. The upstream of Gidabo dam sub-basin lies approximately between 38°10′00′′ to 38°40′00′′E longitude and 6°10′00′′ to 6° 60′ 00′′ N latitude (Fig. 1). Its elevation is varying between 1183 and 3182 m above mean sea level (a.m.s.l.).

There are rainy and dry seasons in the Gidabo sub-basin. The main rainy season is from April to October with a peak rainy season from April to May and a second peak rainy season from September to October. These two peak seasons are separated by the relatively small rainy season in June to August while the rest seasons from November to February are dry. The mean annual precipitation of the sub-basin varied from 954.98 to 1843.70 mm while mean monthly variation is between 36.82 mm to 187.93 mm (Fig. 2). The mean monthly maximum and minimum temperatures of the sub-basin vary between 24.2 °C to 33.06 °C and 10.7 °C to 17.43 °C, respectively (Fig. 3).

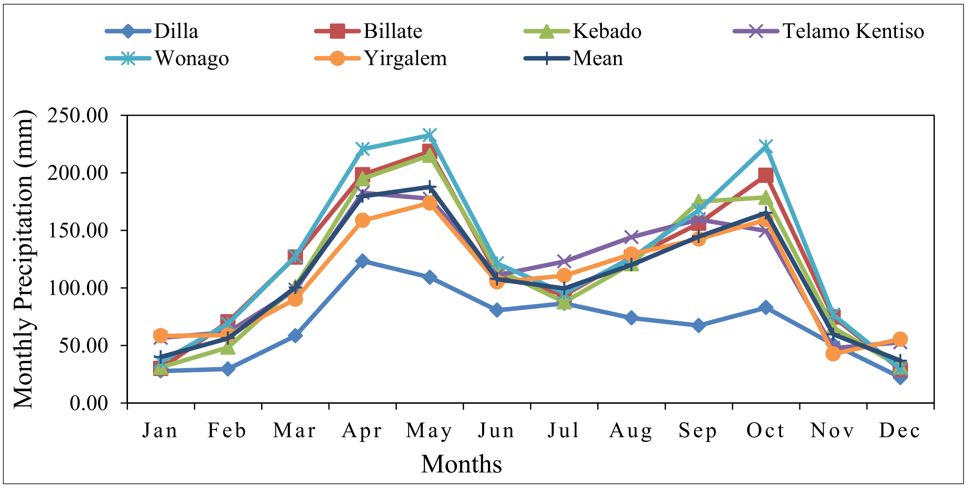

Fig. 2. Spatial variation of mean monthly precipitation in Gidabo river sub-basin.

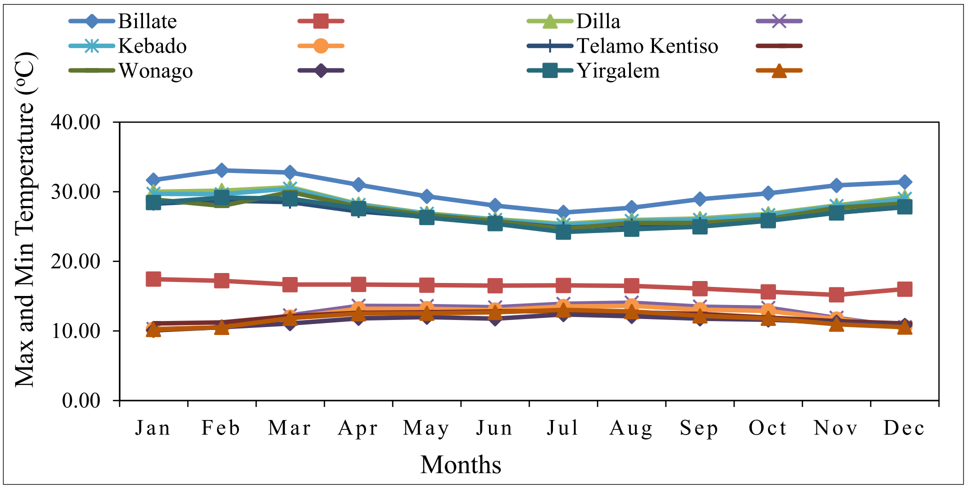

Fig. 3. Spatial variation of mean monthly maximum and minimum temperature in Gidabo river sub-basin.

Input data

The main data required to calibrate SWAT hydrological model in a particular basin are (i) daily weather data (rainfall, maximum and minimum temperature, wind speed, solar radiation, and relative humidity), (ii) hydrologic data (streamflow in this case), and (iii) spatial data (DEM, soil map, and LULC map). The details are given in the subsequent section.

Weather data

For this study, daily weather data listed in Section 2.2 above from six weather stations (Dilla, Kebado, Telamo Kentiso, Wonago, and Yirgalem, and Billate) located within and very nearby Gidabo sub-basin for the period of 1988 to 2014 were collected from Ethiopian National Meteorological Agency (NMA) (Figs. 2 and 3). To estimate missing meteorological data, the inverse distance weighted (IDW) approach was applied, and a double mass curve was used to assess the consistency of rainfall. Furthermore, the homogeneity test was assessed using RAINBOW [44] software and frequency analysis.

Streamflow data

Daily streamflow data recorded at three (Aposto, Bedessa, and Measso) major gauging stations in the Gidabo river sub-basin for the years 1988–2014 were collected from the Ministry of Water, Irrigation and Energy of Ethiopia (MoWIE). Spatial variation of streamflow considering peak and low flow hydrology of Gidabo river sub-basin is shown in Fig.4.

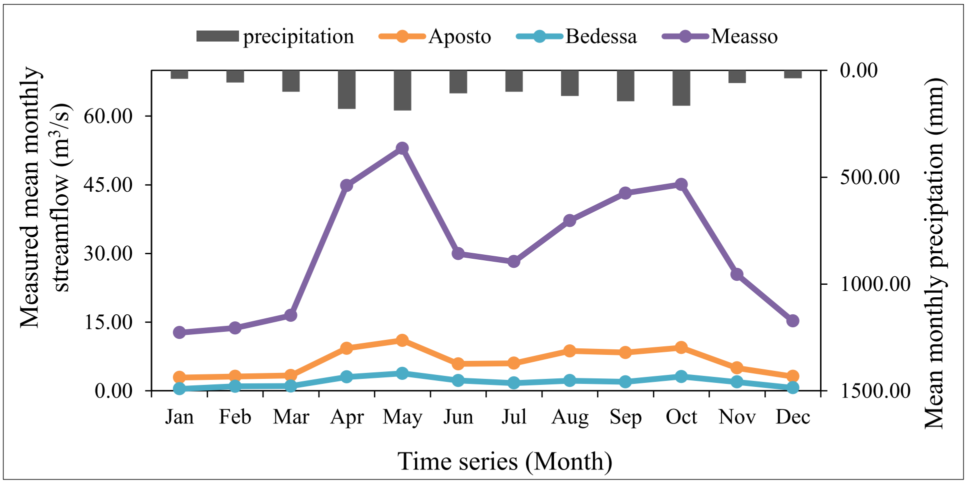

Fig. 4. Spatial variation of mean monthly peak and low flows in Gidabo river sub-basin (from 1988 to 2014).

Table 1
Source and characteristics of satellite imagery used in this study.

Satellite Data	Path/Row	Image Date	Number of Bands	Cloud Cover (%)	Spatial Resolution
L5-	168/55	16/01/1990	7	0	30 m
TM	168/56	16/01/1990	7	0	30 m
L7-	168/55	01/01/2005	8	0	30 m
ETM+	168/56	01/01/2005	8	0	30 m
L8-	168/55	18/12/2019	11	0	30 m
OLI	168/56	18/12/2019	11	0	30 m

Digital elevation model (DEM)

A 30 $m \times 30$ m resolution Shuttle Radar Topography Mission (SRTM) DEM data was used in this study. DEM was extracted using the GIS software by masking the shapefile of the Gidabo sub-basin which was used later to delineate the sub-basin and analyses the stream network in the basin.

Soil data

A soil map as well as major soil physicochemical properties (depth of soil layer, soil texture, hydraulic conductivity, bulk density, and organic carbon content) were found from Ethiopian Ministry of Water, Irrigation, and Energy (MoWIE). Accordingly, eleven different soil types were classified. As a result, 22.98% of Pellic Vertisols, 22.37% of Eutric Cambisols, 19.33% Chromic Vertisols, and 13.81% Orthic Luvisols are the major soil types in the sub-basin. The other soil types such as Calcaric Flubisols, Calcic Fluvisols, Chromic Luvisols, Dystric Gleysols, Dystric Nitisols, Eutric Nitisols, and Orthic Acrisols covers 22.51%. The soil map of the study is presented in Fig. 5.

Land use and land cover data

The land use land cover (LULC) data sets for the three historical periods were derived from multi-temporal series Landsat images. Landsat 5 Thematic Mapper (L5-TM) images of 1990, Landsat 7 Enhanced Thematic Mapper Plus (L7-ETM+) of 2005, and Landsat-8 Operational Land Imager and Thermal Infrared Sensor (L8-OLI/TRS) of 2019 at 30 m resolution (Table 1) were obtained from the United States Geological Survey (USGS) earth explorer website (http://earthexplorer.usgs.gov/). These images were selected as they are cloud-free and acquired in the same season to avoid seasonal variation in vegetation pattern and distribution throughout the year.

Preprocessing satellite imagery before conducting image classification is very vital to minimize instrumental errors and to build a more thorough association between the obtained data and surface features on the ground [45]. In this study, sequential preprocessing steps were performed using ArcGIS 10.4, ERDAS Imagine 2014, and ENVI 5.3 software packages. Furthermore, supervised classification was applied for LULC classification using ERDAS Imagine 2014 software. Consequently, six major LULC classes such as agricultural land, bare land, built-up land, forest land (dense forest), shrubland (open forest), and water bodies as shown in Table 2 were chosen for mapping the entire Gidabo river sub-basin as shown in Fig. 6.

The LULC change detection indicated, there were increasing in agricultural land, built-up area, and bare land whereas decreasing forest land, shrubland, and water body for the two consecutive periods (1990–2005 and 2005–2019). Agricultural land was increased by 5.79% but forest land and shrubland were decreased by 5.43% and 2.72% for the period 1990–2005. For the period 2005–2019 a slight increase in agricultural and a decrease in forest land with the high decrement of shrubland

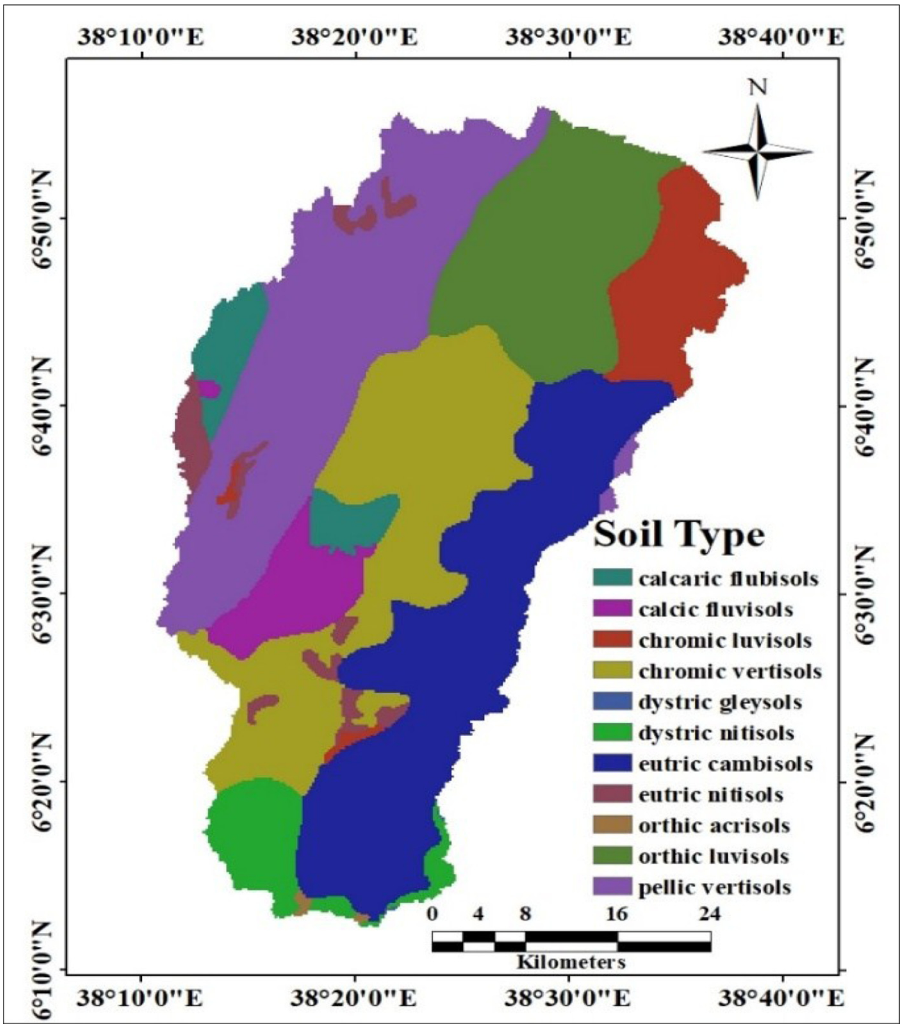

Fig. 5. Soil map of the Gidabo river sub-basin.

Table 2
Land use and land cover categories identified in the Gidabo sub-basin.

LULC Class	SWAT Code	Description
Agricultural Land	AGRL	Land areas used for crop cultivation area currently under crop, fallow, and land under preparation and the scattered rural settlement that is closely associated with the cultivated fields.
Bare Land	BARR	Land areas with low or no vegetation including rocky areas
Built-up Area	URBN	Land areas where most land is covered with structures including urban and rural residential and roads
Forest Land	FRSE	The land area covered with highly dense trees
Shrubland	FRST	Land areas with scattered trees mixed with short bushes, grasses, and areas under agroforestry
Water Body	WATR	Land areas which are waterlogged, swampy throughout the year, reservoir and rivers.

were obtained as compared with the first period. The result revealed that agricultural land was increased by 3.11% and forest land and shrubland were decreased 1.68% and 4.81% respectively as shown in Table 3.

SWAT model set-up

SWAT is a semi-distributed, physically based, watershed scale, continuous model that can run at a daily, monthly or yearly time steps. It is capable of simulating “surface and subsurface flows, pesticide, and nutrient and sediment movement

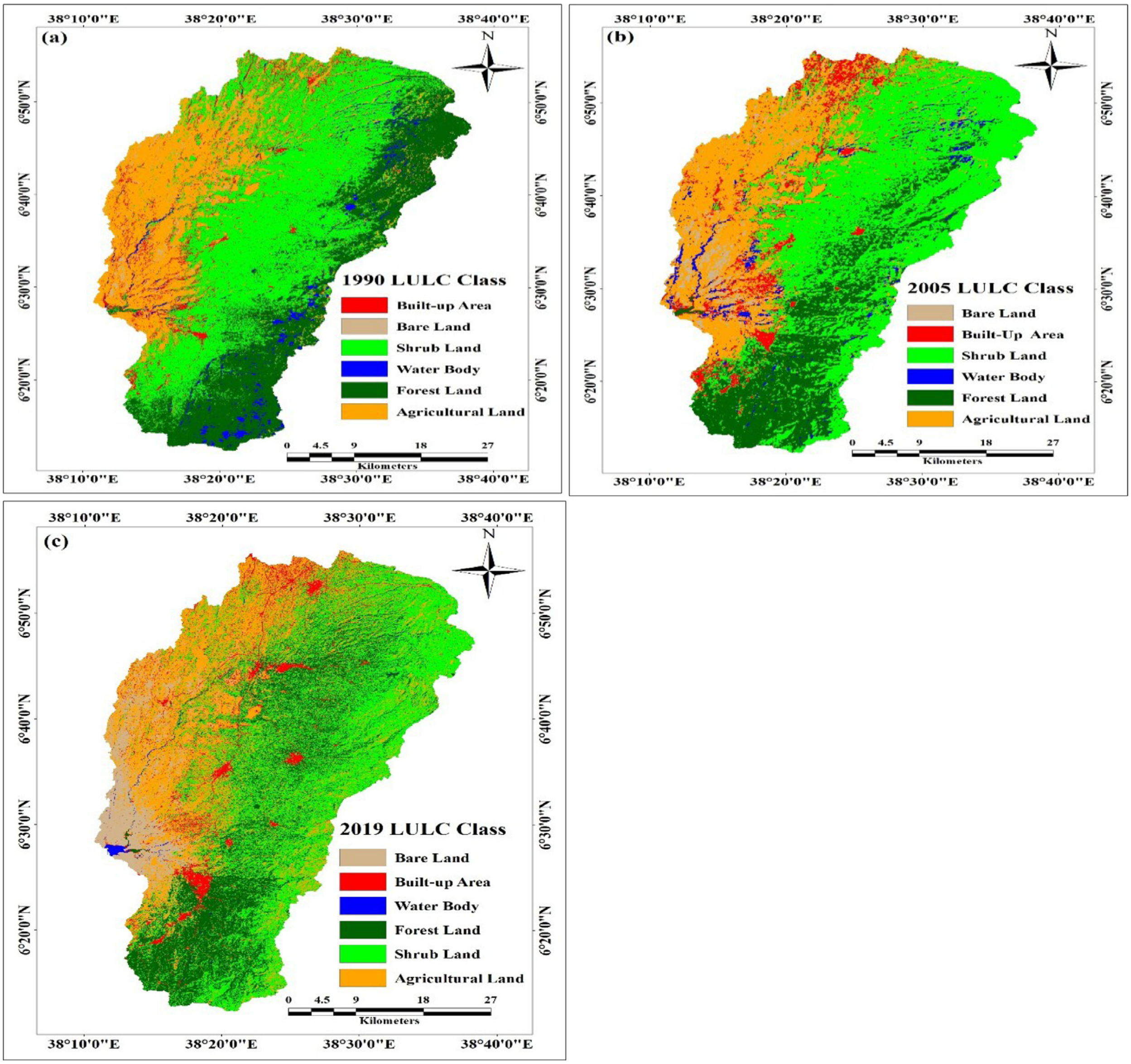

Fig. 6. Land use land cover map of (a) 1990, (b) 2005, and (c) 2019.

in the hydrologic cycle of a watershed. The several hydrological processes employed in the model are evaporation, infiltration, percolation, plant uptake, lateral and groundwater flows, snowfall and snowmelt [46,47]. modelling basin hydrology using SWAT involves the division of watershed into sub-watersheds, and their subsequent segmentation into hydrological response units (HRUs). The HRUs illustrate the basin's physical heterogeneity and are based on the unique combination of land use, soil type, and slope. Soil water balance is estimated on a HRU basis, and flow is routed from HRU to sub-watersheds and then to the watershed outlet. In SWAT, soil water balance in each HRU is represented as [48,49]:"

$$SW_t = SW_0 + \sum_{i=0}^{t} \left(R_{day} - Q_{surf} - E_a - W_{sweep} - Q_{gw} \right) \tag{1}$$

Where SW_t is the final soil water content (mm), SWo 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_{sweep} 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).

In this present study, considering available data in the Gidabo river sub-basin, the SCS curve number method [50] and penman monteith method [51] were employed to estimate surface runoff and potential evapotranspiration during SWAT sim-

Table 3
Land use land cover change detection.

LULC Class	1990–2005 Change		2005–2019 Change		1990–2019 Change	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Agricultural	+137.76	+5.79	+74.09	+3.11	+211.85	+8.90
Bare Land	+34.32	+1.44	+54.01	+2.27	+88.33	+3.71
Built-up	+25.84	+1.09	+54.68	+2.30	+80.52	+3.38
Forest Land	−129.16	−5.43	−39.87	−1.68	−169.04	−7.11
Shrubland	−64.64	−2.72	−114.45	−4.81	−179.09	−7.53
Water Body	−4.08	−0.17	−28.29	−1.19	−32.37	−1.36

ulation process, respectively. In the particular study, ArcSWAT 2012.10_4.21 version which is compatible with ArcGIS 10.4.1 was used.

SWAT-Calibration and uncertainty programs (SWAT-CUP)

It is an “auto-calibration tool developed by Abbaspour et al. [4] as an interface to SWAT model and has capable of carrying out sensitivity analysis, calibration and validation, and uncertainty analysis. There are various approaches of uncertainty analysis such as PSO, MCMC, SUFI-2, GLUE, and Parasol available in the SWAT-CUP. Midst these approaches, SUFI-2 algorithm is computationally effective and has the best prediction uncertainty ranges (P-factor) and the relative coverage of measurements (R-factor) ([13,52]; Paul and Negahban-Azar 2018). The P-factor is described as the percentage of the historical data linked by the 95% prediction uncertainty (95PPU) and is estimated at 2.5% and 97.5% levels of the cumulative distribution of output variable acquired using Latin hypercube sampling [53]. The R-factor is the ratio of the average thickness of the 95PPU band and the standard deviation of the measured data [53]. For streamflow simulation, Abbaspour [53] suggested the ‘P-factor’ value of >0.7 as adequate and the R-factor value of around 1.0 depending on the situation.”

Sensitivity analysis

The first step in the calibration and validation process in SWAT is the estimation of the most sensitive parameters for a given basin and sub-basin [54]. In this study, the global sensitivity analysis method in the SWAT-CUP software package [4] was used for sensitivity analysis. During the analysis, the larger value of the t-stat and the smaller p-value was taken as a more sensitive parameter considering observed and simulated data and the most sensitive parameters to change streamflow in the sub-basin.

Calibration and validation

In this study, the SWAT model was calibrated and validated considering streamflow for each of the three hydrometric gauging stations namely Aposto, Bedessa, and Measso using SWAT-CUP which provides a decision-making framework that incorporates a semi-automated Sequential Uncertainty Fitting version 2 (SUFI-2). For calibration, the most sensitive parameters were used, and their values were changed iteratively within the allowed upper and lower ranges until the acceptable agreement between measured and simulated streamflow was obtained. After successful calibration, model validation was employed by running a model using input parameters estimated during the calibration process. Validation process involves running a model using parameters that were identified during the calibration process and comparing the predictions to observed data which are not used in the calibration. Calibration and validation were carried out by splitting the available observed data into a range of datasets for each of the three hydrometric gauging stations. The selection of observed data periods for calibration and validation was based on the availability of relatively consistent observed streamflow data. First, the model was set to run for 1988–2014 with the initial 2 years (1988–89) as a model warm-up period that allows the model to stabilize for further simulations. Then, the consequent phases were established as calibration (1990–2006) and validation (2007- 2014) periods.

Model performance evaluation measures

In this study, the most widely used three statistical model evaluation indices (R^2, NSE, and PBIAS) were used to assess the performance of the ArcSWAT model in simulating hydrology in the Gidabo river sub-basin, in addition to a physical inspection of the hydrograph developed between measures and observed streamflow values. The selected statistical model performance evaluation indices are based on Moriasi et al. [23] suggestion for streamflow simulation and given by the following Eqs. (2-4);

$$R^2 = \frac{\left(\sum_{i=1}^{n} [X_i - X_{av}][Y_i - Y_{av}]\right)^2}{\sum_{i=1}^{n} [X_i - X_{av}]^2 [Y_i - Y_{av}]^2} \tag{2}$$

$$NS = 1 - \frac{\sum_{i=1}^{n} (X_i - Y_i)^2}{\sum_{i=1}^{n} (X_i - X_{av})^2} \tag{3}$$

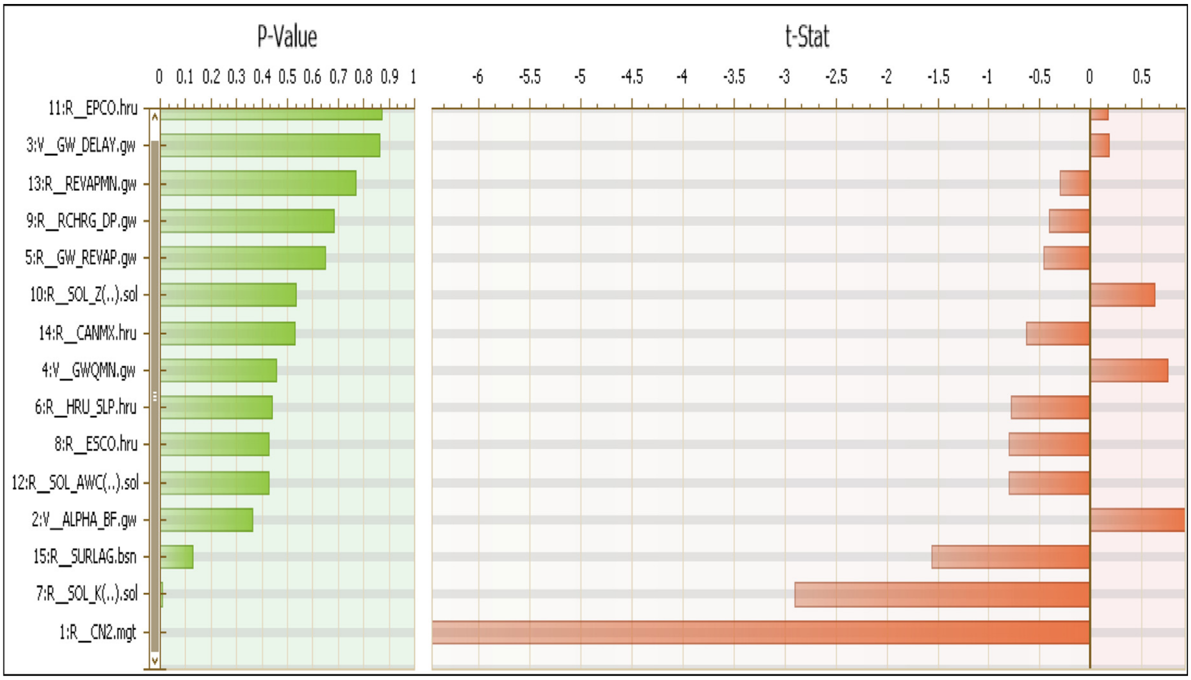

Fig. 7. Streamflow sensitive parameters.

$$\mathrm{PBIAS} = 100\left(\frac{\sum_{i=1}^{n} X_i - \sum_{i=1}^{n} Y_i}{\sum_{i=1}^{n} X_i}\right) \tag{4}$$

Where X_i is the measured value, X_{av} is the average measured value, Y_i is the simulated value and Y_{av} is the average simulated value.

The response of water balance components to land use land cover change

The calibrated and validated SWAT model was used to evaluate the impacts of LULC change on the water balance components based on 1990, 2005, and 2019 LULC inputs. Three independent simulation runs were performed on monthly basis for the period 1988–2014 keeping other input parameters unchanged. The streamflow variability and water balance component responses to LULC change at different spatiotemporal scales were evaluated.

Results and discussion

Sensitivity analysis

The global sensitivity analysis was performed using mean monthly observed data in the SUFI-2 algorithm that is linked with SWAT-CUP. Accordingly, twenty parameters were selected for sensitivity based on manual training in ArcSWAT and after in-depth review of literature (e.g. [28–33, 35–41]). After conducting a series of simulations, SWAT-CUP provides the sensitivity of parameters in rank order based on its t-stat and p-value. The highest value of t-stat indicates the ratio of the high parameter coefficient to standard error and lower the p-value related to the rejection of the hypothesis that an addition in the value of the parameter provides a significant increase in the variable response (Abbaspour et al., 2017). The fifteen sensitive hydrologic flow parameters during calibration and validation in the sub-basin is given in Fig. 7.

As shown in Fig. 7, the surface runoff response parameters SCS CN II value (CN2) was found to be the most sensitive flow parameter in the entire Gidabo sub-basin followed by saturated hydraulic conductivity of the soil layer (SOL_K), surface runoff lag time in the HRU (SURLUG), base flow alpha-factor (ALPHA_BF) and available water capacity of the soil layer (SOL_AWC). Soil evaporation compensation factor (ESCO), average slope steepness (HRU_SLP), threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN), maximum canopy storage (CANMX), and depth from the soil surface to bottom of the layer (SOL_Z) also have influence in controlling the streamflow.

In the calibration, the parameters with p-value <0.06 are considered as sensitive as it is possibly a significant addition to model and variations in predicted value are linked to variability in the response variable [53]. Table 4 shows the best optimized ten parameters value considered during calibration process.

Table 4
Streamflow parameters sensitivity ranking.

Parameter Name	Min Value	Max Value	Fitted Value	Rank
R_CN2	−25%	25%	−16.87	1
R_SOL_K	87.84	1117.84	459.74	2
R_SURLAG	6.36	21.28	17.47	3
V_ALPHA_BF	0.41	0.56	0.51	4
R_SOL_AWC	0.12	0.73	0.32	5
R_ESCO	0.19	0.64	0.36	6
R_HRU_SLP	0.14	0.59	0.44	7
V_GWQMN	2192.61	7057.39	4454.73	8
R_CANMX	11.26	73.74	39.06	9
R_SOL_Z	0.42	1.33	0.57	10

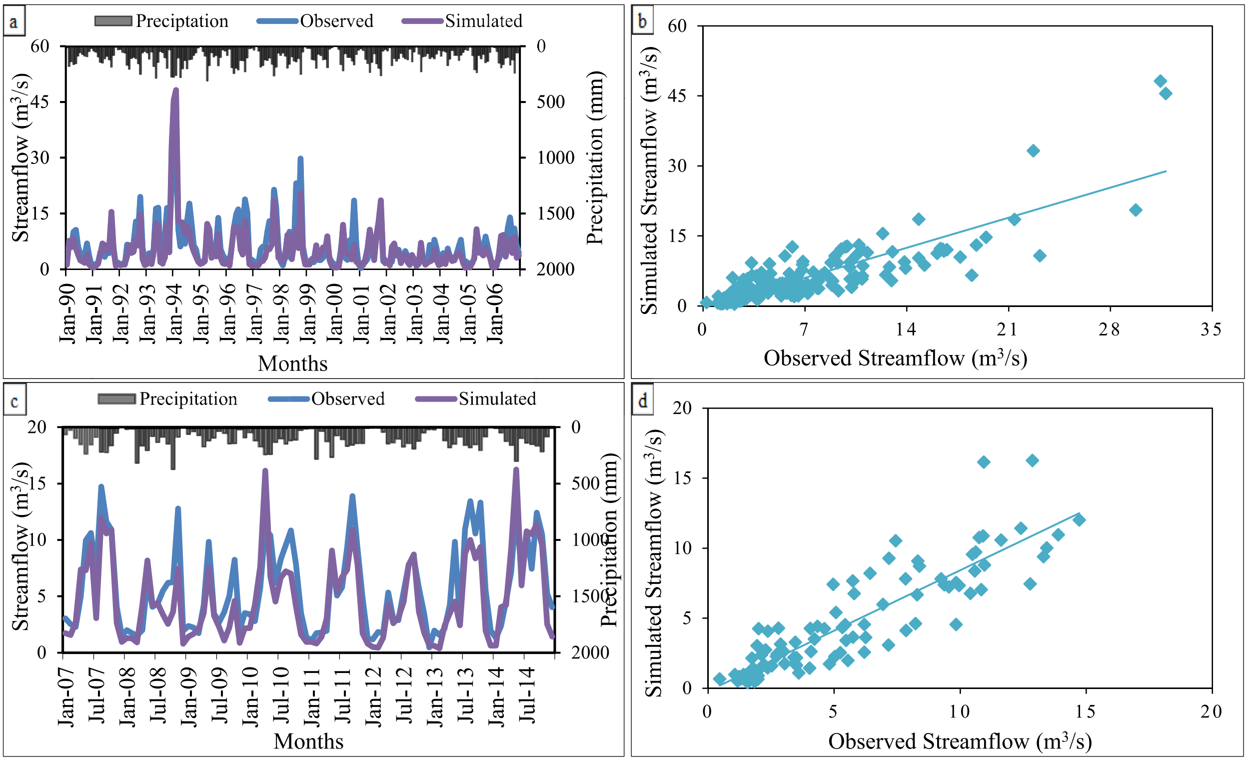

Fig. 8. Observed and simulated streamflow hydrograph and scatter plot at Aposto gauging station: (a) hydrograph during calibration period, (b) scatter plot during calibration period, (c) hydrograph during validation, (d) scatter plot during validation period.

Model calibration and validation

Multi-site streamflow calibration and validation was done in three gauging stations (Aposto, Bedessa, and Measso) using SUFI-2 algorithm in monthly time setup. The model was calibrated for 1990–2006 at each gauging station and the two years from 1988 to 1989 were used as a warm-up period while the model was validated from the year 2007–2014 without further adjustment of best fitted calibrated parameters value for each gauging stations. The performance of the model at each gauging station was tested at every stage of the model simulation with the parameters printed out at the respective stage. The parameter values were changed repeatedly within the allowed ranges until acceptable agreements between observed and simulated streamflow were obtained for each gauged stations. The SWAT model performance was evaluated using R^2, NSE, and PBIAS statistical indices, in addition to physical inspection between observed and simulated streamflow hydrograph at three gauging stations.

The observed and simulated streamflow at Aposto, Bedessa, and Measso gauging stations were compared and shown that the model captured the monthly flows very good during calibration and validation periods as shown in Figs. 8-10 and Table 4. The model performance at Aposto gauging station was very good with R^2, NSE, and PBIAS values of 0.74, 0.66, and 14.9, respectively during calibration and was performed very good in terms of R^2 (0.72), good in terms of NSE (0.65), and satisfactory in terms of PBIAS (18.1) (Fig. 8 and Table 4) during validation period.

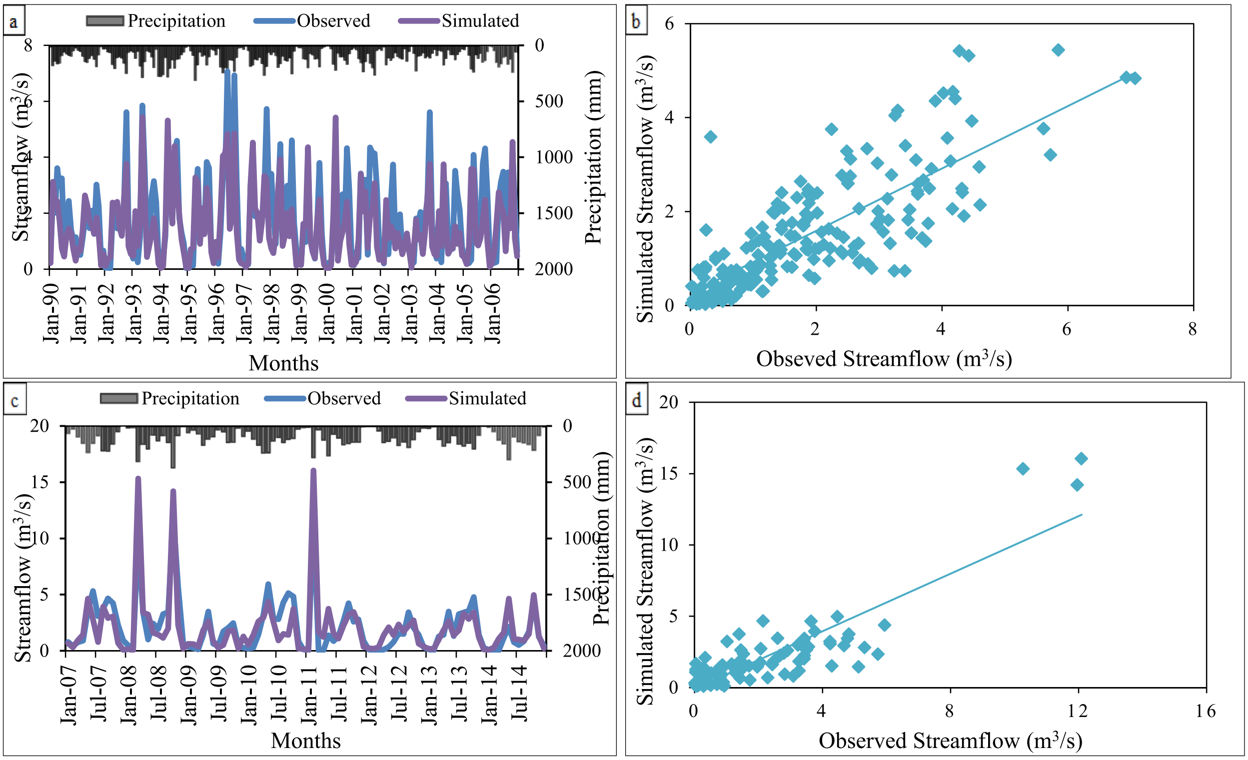

Fig. 9. Observed and simulated streamflow hydrograph and scatter plot at Bedessa gauging station: (a) hydrograph during calibration period, (b) scatter plot during calibration period, (c) hydrograph during validation period, (d) scatter plot during validation period.

Table 5
Calibration and validation statistics for monthly streamflow at three gauging stations.

Statistical Indices	Gauging Stations					
	Aposto		Bedessa		Measso	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
R^2	0.74	0.72	0.64	0.74	0.80	0.74
NSE	0.66	0.65	0.61	0.65	0.74	0.71
PBIAS	14.9	18.1	19.7	1.2	−3.2	8.0

At Bedessa gauged station, the model performed good in terms of R^2 (0.64) and performed satisfactory in terms NSE (0.61) and PBIAS (19.7) during calibration. But, the model performed very well in terms of R^2 (0.74) and PBIAS (1.2) while performed good in terms of NSE (0.65) during validation. In this gauging station, the model performed better during validation than calibration period and this might be due to good measured quality streamflow data during validation than calibration period (Fig. 9 and Table 4).

At Measso gauging station (near at dam outlet), the model performed very good with R^2 value of 0.80 and PBIAS value of −3.2, but performed good in terms of NSE (0.74) during calibration period. During validation at this gauging station, the model performed very good with R^2 value of 0.74 and PBIAS value of 0.80, but performed good in terms of NSE (0.71) (Fig. 10 and Table 4). In all the gauging station, SWAT model performance is rated based on Moriasi et al. [23] evaluation rating for streamflow simulation. Observed and simulated streamflow hydrograph and scatter plot with 1:1 fitting line at three gauging stations during calibration and validation periods are presented in Figs. 8, 9, and 10.

The probable reason for the model simulation uncertainty would be due to spatiotemporal variability of rainfall in the basin. In addition to this, the lack of consistent hydro-metrological and spatial data including soil and LULC data could also be the result in a slight discrepancy in the model simulation. But, the graphical interpretation between observed and simulated streamflow hydrograph together with the statistical model performance measures using most commonly used statistical indices given in Table 5 which meets the criteria suggested by Moriasi et al. [23].

Generally, the multi-site calibration and validation of the ArcSWAT model showed very good to satisfactory model performance in simulating water resources on a monthly time basis in the rift valley lake basin of Gidaba river sub-basin in Ethiopia.

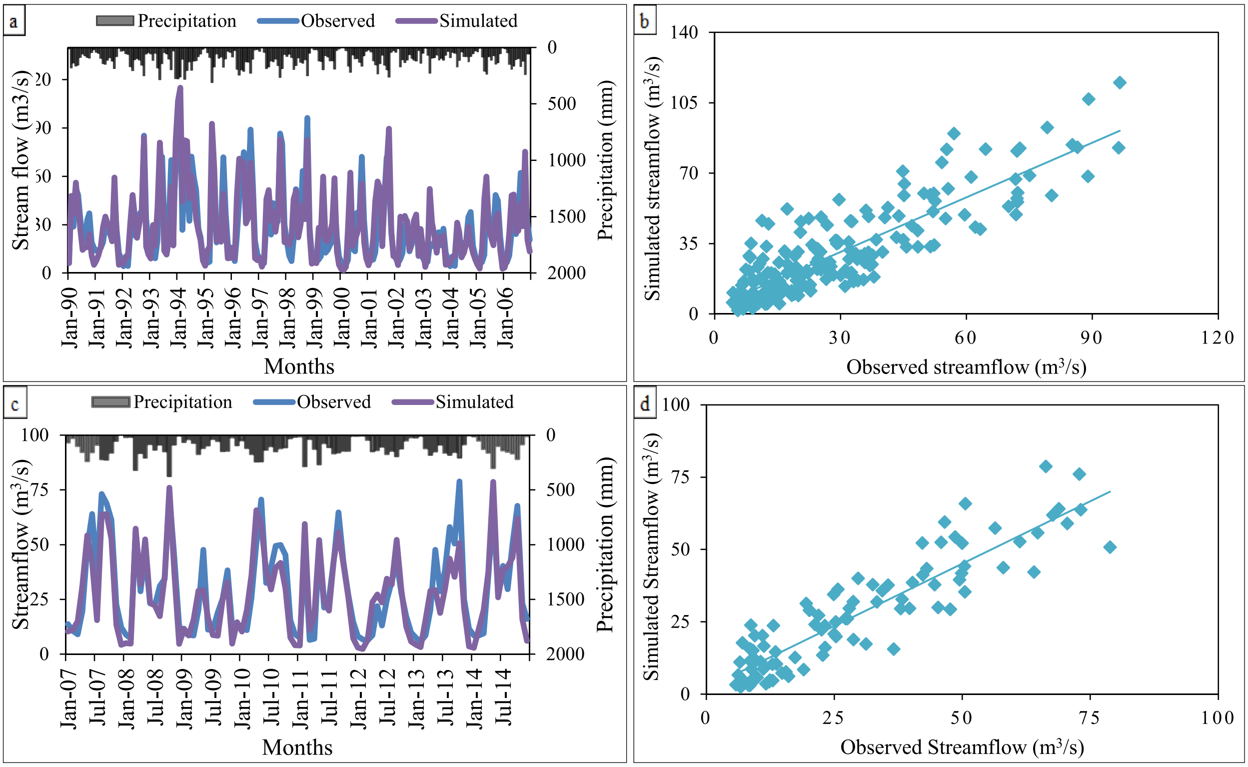

Fig. 10. Observed and simulated streamflow hydrograph and scatter plot at Measso gauging station: (a) hydrograph during calibration period, (b) scatter plot during calibration period, (c) hydrograph during validation, (d) scatter plot during validation period.

Table 6
Multi-site seasonal streamflow variation during 1990, 2005, and 2019 LULC at three gauging stations.

Season	Aposto			Bedessa			Measso		
	1990	2005	2019	1990	2005	2019	1990	2005	2019
Wet (m^3/s)	13.23	14.02	14.69	2.24	2.52	2.85	62.45	66.20	69.15
Dry (m^3/s)	8.65	7.99	7.53	1.53	1.28	1.20	36.32	33.23	31.56

The response of water balance components to land use land cover change

The calibrated and validated SWAT model was used to evaluate the impact of the LULC change on water balance components considering historical LULC data for the year 1990, 2005, and 2019 on annual, seasonal and monthly basis. The long-term hydrologic simulation from the year 1988–2014 was performed to analyse the impact of LULC change on water balance components in the Gidabo river sub-basin.

The response of streamflow to LULC change indicated that mean annual streamflow was increased by 2.13% (1.16m^3/s) and 3.62% (2.04m^3/s) during the periods 1990–2005 and 2005–2019, respectively due to the LULC change. But, the mean monthly streamflow was increased in wet season (April-September) while decreased in dry season (October-March) in all three gauged stations as shown in Table 6. At Aposto gauging station (sub-basin) where a conversion of shrubland to agricultural land was observed, the mean monthly streamflow was increased up to 5.96% and 4.96% during wet season while decreased up to 7.59% and 5.78% during dry season from the period 1990–2005 and 2005–2019, respectively. In Bedessa sub-basins where forest land was converted to shrubland and agricultural land, the mean monthly streamflow was increased by 9.94% and 12.46% in wet season and decreased by 16.85% and 5.97% in dry season from 1990 to 2005 and 2005 to 2019, respectively.

The result of streamflow change at Measso near the dam outlet from the period 1990–2005 and 2005–2019 indicated that the streamflow was increased up to 6% and 4.45% in wet season and decreased by 8.51% and 5.04% in dry season, respectively. The conversion of shrubland to agricultural and built-up land and the decline of forest land to shrubland in the study were highly responsible for the increment of streamflow during wet season and decrement during dry season. The expansion of agricultural land and built-up area over forest land shrubland results in the reduction of lateral flow (downward

Table 7
Mean annual sub-basin water balance value.

LULC	RF (mm)	SURQ(mm)	LAT Q(mm)	GWQ(mm)	ET(mm)	WY(mm)
1990	1366.20	124.40	107.14	498.65	643.90	703.35
2005	1366.20	135.40	104.00	494.21	637.80	718.71
2019	1366.20	158.55	101.37	484.21	619.80	745.77

infiltration) that flows into the shallow aquifer. Hence, the streamflow during dry season that mostly comes from baseflow decreases whereas streamflow during the wet season increases. Because of this reason, streamflow responses to LULC are more sensitive in dry seasons in comparison with wet seasons. The streamflow change was high during the period 1990-2005 as compared with the period 2005–2019 due to LULC change. This is because of less expansion of agricultural land and less reduction of forest land in the second period (2005–2019) than the first period (1990–2005).

The main annual water balance components such as surface runoff (SURQ), groundwater flow (GWQ), lateral flow (LATQ), and evapotranspiration (ET) based on three independent LULC indicated significant temporal variability in the Gidabo sub-basin (Table 7). SURQ indicated increasing up to 8.12% and 14.60% for the period 1990–2005 and 2005–2019 LULC, respectively while GWQ, LATQ, and ET indicated decreasing trends. In other words, GWQ, LATQ, and ET contribution to streamflow was decreased by 0.90%, 2.15%, and 0.95% for the year 1990–2005 and decreased by 2.00%, 3.17%, and 2.90% respectively during 2005–2019 LULC. The increasing of SURQ and decreasing trend of GWQ, LATQ, and ET is directly attributed to the intensification of agricultural land, bare land, and built-up area over forest land and shrubland. This expansion causes the increase of SURQ following rainfall and variation in lateral flow and groundwater storage.

The result of previous studies in Ethiopia on the impact of LULC on watershed hydrological response has shown a decreasing trend in mean monthly streamflow during dry season, GWQ, LATQ, and ET while the increasing trend in mean monthly streamflow, SURQ, and WY during wet season due to expansion of agricultural land over shrubland and forest land. Choto and Fetene (2019), Shawul et al. (2019), Gashaw et al. (2018), and Kassa (2009) in their studies reported that the expansion of agricultural land, bare land, and built-up area over forest and shrubland results in increasing SURQ and wet season streamflow while decreasing dry season streamflow, LATQ, and GWQ. Therefore, the results of this particular study revealed that LULC has a significant impact on streamflow as well as water balance components.

Conclusions

This study investigated the responses of water balance components to LULC change in the Gidabo river sub-basin considering multi-site calibration and validation using SWAT model. The investigation of areal LULC change in the last decades from 1990 to 2019 was evident and happened as either an expansion or a decrease between successive research periods. The LULC change detection demonstrated a continual expansion in the spatial extent of agricultural land, built-up area, and bare land, whereas shrubland, forest land, and water body revealed a continuous decrease between successive research periods.

SWAT-CUP was used to simulate historical streamflow on a monthly basis for multi-site calibration and validation of the SWAT model. SUFI-2 algorithm embedded in the SWAT-CUP was applied for sensitivity and uncertainty analysis, and calibration and validation of SWAT model. Sensitivity analysis result showed that CN2, SOL_K, SURLAG, ALPHA_BF, SOL_AWC, ESCO, HRU_SLP, GWQMN, CANMX, and SOL_Z were the most sensitive parameters for the basin. The performance of the SWAT hydrologic model in simulating Gidabo sub-basin hydrology was measured using R^2, NSE, and PBIAS statistical model performance evaluation indices, in addition to physical inspection of observed and simulated streamflow hydrograph at three gauging stations during calibration and validation periods. The results revealed that the SWAT model would simulate monthly streamflows very well at three spatially dispersed gauging stations in the Gidabo river sub-basin. The model performed comparatively better improved during calibration period than the validation period.

The calibrated and validated SWAT model was used to investigate the impact of the LULC change on water balance components considering historical LULC of 1990, 2005, and 2019 on annual, seasonal and monthly basis. The remotely sensed LULC data for the year 1990, 2005, and 2019 were classified using ERDAS Imagine 2014 integrated with GIS data to analyse response of water balance components to LULC change in the Gidabo river sub-basin. The response of water balance components to LULC change revealed that mean annual streamflow was shown an increasing trend at both LULC periods (1990 to 2005 and 2005 to 2019). But, seasonal analysis shows that streamflow was increased during wet season while decreasing trend was observed during dry season in all three gauged stations. The main annual water balance components such as SURQ, GWQ, LATQ, and ET have shown significant spatiotemporal variations to LULC change in the Gidabo sub-basin. SURQ showed an increasing trend while GWQ, LATQ, and ET revealed a decreasing trend for both LULC periods (1990–2005 and 2005–2019). Therefore, the results of this particular study revealed that LULC has a significant impact on streamflow as well as water balance components.

In this regard, quantifying and addressing challenges on the availability and sustainability of water resources significantly demanded by planners and decision makers for water resources management and development. Hence, appropriate land and water resources management and development strategies sought to implement in the Gidabo river sub-basin. Eqn (1)

Based on the findings and challenges encountered throughout the study execution period, two major limits and future research directions are proposed. **1.** This study solely evaluated historic land use land cover change on hydrological responses, which provides policy and decision makers with information for proper water resource management. However, LULC change is likely in the future unless effective land management practices are implemented, and we firmly suggest more research to investigate the influence of future LULC and climate change on hydrological responses in the Gidabo river sub-basin. **2**. Data quality and availability are very important while applying distributed hydrological models. In this study, finding quality hydro-metrological data in the basin was the biggest challenges. Without proper data, model implementation is impossible and very difficult to reach reliable output. Therefore, the respective local, regional, and federal authorities should be involved in integrated and coordinated data compilation.

Declaration of Competing Interest

The authors declare that they have no competing financial interest or personal relationships that could have appeared to influence the work reported in this paper.

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