ORIGINAL ARTICLE

Hydrological modeling in the Upper Blue Nile basin using soil and water analysis tool (SWAT)

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Abstract

Hydrological models are essential to understand the hydrological response of the basin. It is one of the most significant aspects of water resources management and development programs at the small catchment or basin level. A semi-distributed, physical-based hydrologic modeling system, SWAT, was used to model the hydrological responses of the Upper Blue Nile basin. The model was calibrated and validated using the sequential uncertainty fitting (SUFI-2) algorithm in SWAT-CUP. The coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), and percent of bias (PBIAS) were used to measure the performance of the model. The value of R^2, NSE, PBIAS was range from 0.81–0.85, 0.68–0.83 and − 10.8 to (− 4.7%) during calibration and 0.89–0.93, 0.88–0.89 and 8.3–9.7% during validation period, respectively. The results indicated a strong correlation between the observed and simulated streamflow during the calibration and validation periods. The overall hydrological water balance analysis showed that 49.5% of precipitation is lost by evapotranspiration, while 22.43% of precipitation is contributed to streamflow as surface flow. Furthermore, the hydrological water balance components of the basin showed a good spatial correlation. Since the water resource planning and management need the temporal and spatial water resource information, the results of this study will be used as a guide for the proposed water resource development projects of the basin.

Keywords Upper Blue Nile basin · Hydrological modeling · SWAT model · Water balance

Introduction

Hydrology is the science that studies the water cycle and its movement in terms of the topographic features of an area (Zhihua et al. 2020). A river basin or watershed is an area over which various hydrologic processes such as precipitation, snowmelt, interception, evapotranspiration, infiltration, surface runoff, and sub-surface flow are integrated (Islam 2011). Understanding the amount of water produced in the river basin in many ways is essential for managing water resources (Zhihua et al. 2020). However, the estimation of the hydrological parameters by the conventional method is not reliable and time-consuming (Gull and Shah 2020).

Besides, the spatial and temporal occurrences of both surface water resource and groundwater resources within most watersheds are not properly known (Tufa and Sime 2020).

Consequently, numerous hydrological models have been developed across the world to know and understand the hydrology and water resources of basins (Devia and Ganasri 2015). The development of hydrologic models that consider physical characteristics of the watershed helps in accurate prediction of hydrological processes of a watershed (Devia and Ganasri 2015; Salih and Hamid 2017; Sime et al. 2020; Tufa and Sime 2020). Therefore, the hydrologic model has become an increasingly important tool to understand the hydrological cycle and can assist in the management of water resources in a watershed (Saifullah et al. 2016; Shiferaw et al. 2018; Serrão et al. 2019). They are used for hydrological simulation to water resource assessment, water allocation, climate change impact assessment, satellite data performance evaluation, and many other purposes (Setegn et al. 2008; Gebre and Ludwig 2015; Asitatikie and Gebeyehu. 2020; Lakew et al. 2020; Aawar and Khare 2020).

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The common approach in hydrologic modeling is that the model is used to calculate streamflow based on meteorological data and catchment characteristics (Vidyarthi et al. 2020). Accordingly, two important inputs required for all models are rainfall data and drainage area (Ashenafi and Hailu 2014). Along with these, hydrological models consider watershed characteristics like soil properties, vegetation cover, watershed topography, and soil moisture content; characteristics of groundwater aquifer are also considered (Devia and Ganasri 2015; Roth et al. 2016). Moreover, hydrological modeling uses the conceptual representation of the hydrological cycle to describe the physical process in a watershed and regulate the processes of rainfall to runoff. Subsequently, the spatial and temporal variation and the interaction of hydrological processes are understood (Khayyun et al. 2019). The physical models represent different hydrological processes through mass, momentum, and energy conservation equations and define and analyze the various hydrological parameters like runoff and sediment yield (Jaiswal et al. 2020; Gull and Shah 2020). Thus, they are capable to deal with hydrological processes and predict different components of the hydrological cycle of the watershed by considering the spatial variability of land use, slope, and climate (Jaiswal et al. 2020).

Several studies have been conducted in the Upper Blue Nile basin to simulate and evaluate the water resources of the basin using hydrological models (Tekleab et al. 2011; Mengistu and Sorteberg 2012; Ashenafi and Hailu 2014; Dile and Srinivasan 2014; Abera et al. 2017; Polanco et al. 2017; Liersch et al. 2018; Roth et al. 2018; Woldesenbet et al. 2017; Walelgn 2018; Chimdessa et al. 2019; Dibaba et al. 2020; Tufa and Sime 2020). Some researchers reported successful application of the hydrological model for streamflow and water balance assessment at the basin and sub-basin scale (Tekleab et al. 2011; Abera et al. 2017). Some also model the entire basin to assess the impact of climate change on annual streamflow and hydrological regime of the basin through hydrological simulations (Mengistu and Sorteberg 2012; Liersch et al. 2018; Roth et al. 2018).

However, most of the studies do not provide detailed assessment for each of the hydrological processes and water balance components of the basin in the temporal and spatial extent. Hence, this research applies the physical-based, semi-distributed soil and water assessment tool (SWAT) hydrological model to simulate and examine the hydrological processes of the Upper Blue Nile basin. Furthermore, this study explores the spatial distribution of the hydrological components of the basin. Hence, the results obtained in this research are expected to improve water resource management of the basin and partly overcome problems due to data scarcity of the basin.

Materials and methods

Description of the study area

The Upper Blue Nile river basin is made from multiple tributaries that drain from the northwestern and western parts of Ethiopia. Geographically, the basin covers 7°44′32″–12°45′19″ N latitude in the south–north direction and 34°29′20″–39°48′17″ E longitude in the west–east direction (Fig. 1). The basin surface area is about 174,166 km^2. The topography of the Upper Blue Nile is composed of highlands, hills, valleys, and occasional rock peaks (Conway 2000). Most of the streams feeding the Upper Blue Nile are perennial. The basin has an uneven spatial distribution of rainfall and the average annual rainfall varies between 1200 and 1800 mm/year (Fig. 2). The Upper Blue Nile consists of three seasons; from October to the end of February is the dry season, from March to May is a short rainy season, and June to September is the long rainy season (Tesemma et al. 2010).

Data collection and sources

A range of multiple and spatially distributed datasets such as topographic features, soil types, land use/land cove, climate, and hydrological data are needed for the SWAT model (Neitsch et al. 2011). In the present study, the topographic, land use, soil, climate, and hydrological data of the Upper Blue Nile basin were collected from different sources (Table 1).

Data preparation

Spatial data preparation

The DEM data acquired from Alaska Satellite Facility (ASF) were preprocessed in ArcGIS software using a geospatial toolbox. Subsequently, the watershed and drainage patterns of the study area were delineated from the digital elevation model. Besides, the sub-basin parameters such as slope gradient, slope length of the terrain, and the stream network characteristics such as channel slope, length, and width were derived from the digital elevation model. The elevation band of the preprocessed image is range from 478 to 4258 m (Fig. 3).

The second physiological data highly required for the SWAT model setup is the land use map, which is one of the main factors affecting water resources in a watershed (Koycegiz and Buyukyildiz 2019). The land use map extracted from Copernicus Global Land Service (CGLS) was classified based on the CGLS guide into10 main classes: agricultural land, bare land, closed forest, grassland, mixed forest, open forest, shrubs, urban, water,
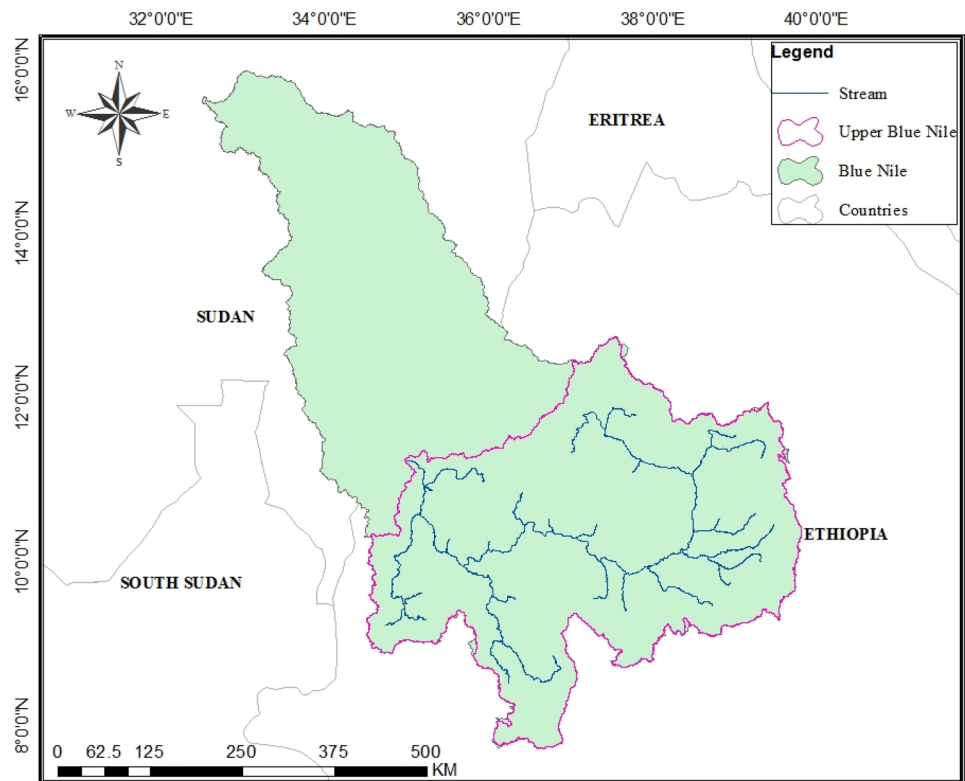
Fig.1 Map overview of Upper Blue Nile basin

Fig. 2 Spatial variation of average annual rainfall of the Upper Blue Nile basin
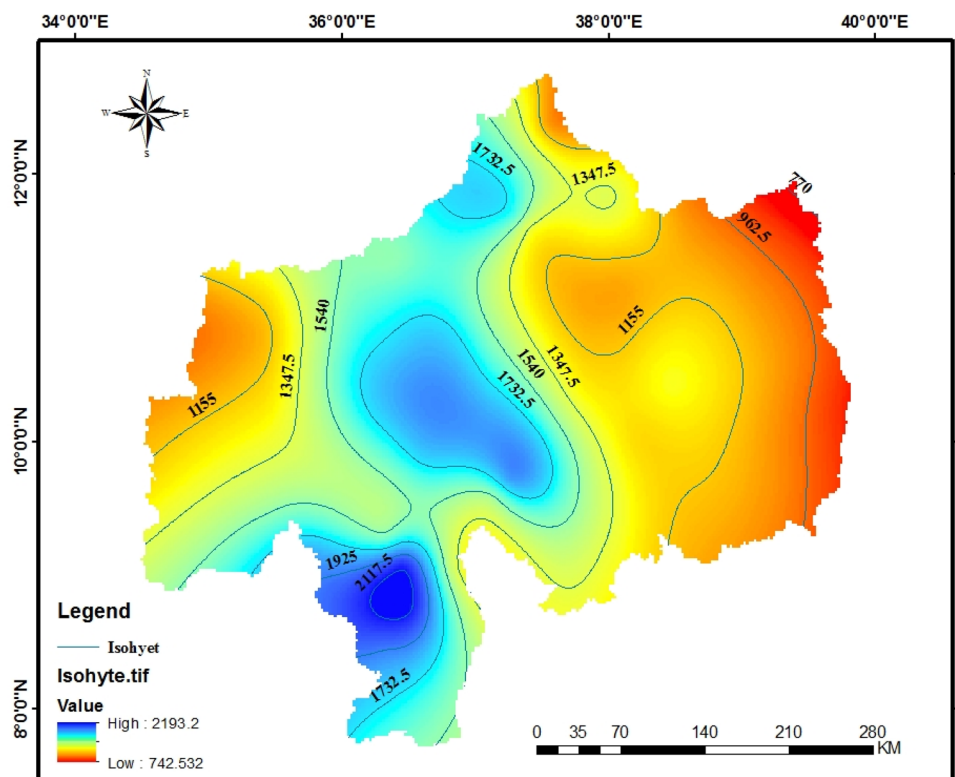
Table 1 Data type, source and resolution

S.N	Data type	Source	Resolution
1	Digital elevation model (DEM)	Alaska satellite facility (ASF)	12.5 m
2	Land use/land cover	Copernicus Global Land Service	100 m
3	Soil map	World Food and Agriculture Organization (FAO)	5 km
4	Meteorological data	National Meteorological Service Agency (NMSA) of Ethiopia	Point
5	Hydrological data	Ethiopian Ministry of Water, Irrigation and Energy	Point

Fig. 3 Elevation map of the Upper Blue Nile basin
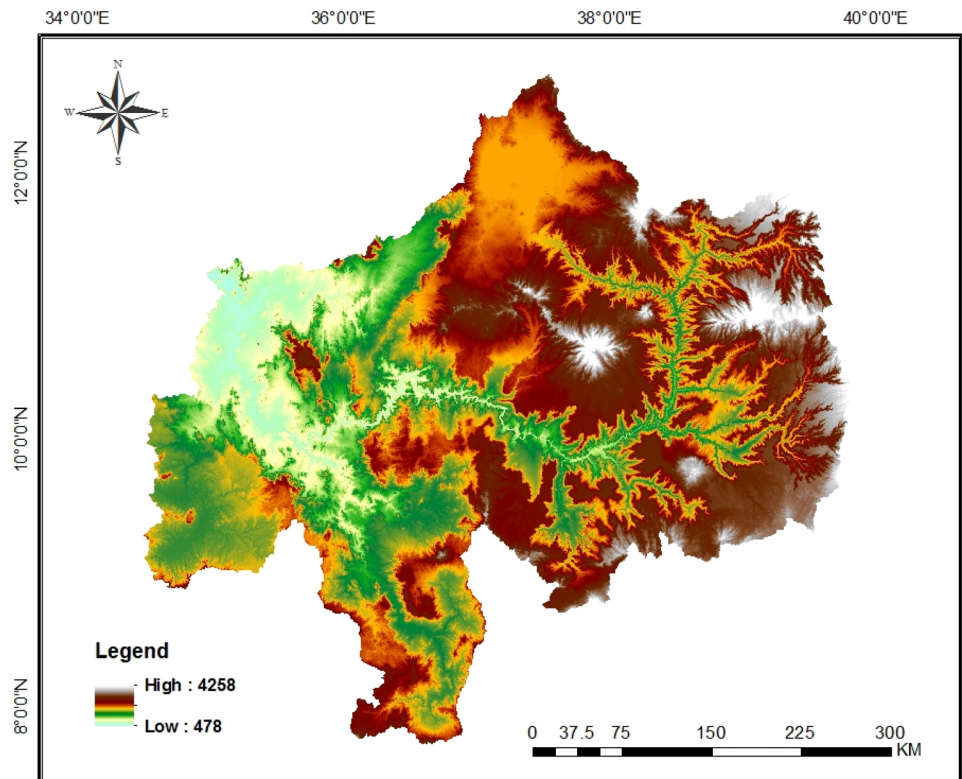
and wetland. Accordingly, about 55.94% of the Upper Blue Nile basin is covered by agricultural land, 18.04% by closed forest, 14.5% by mixed forest, 6.12% by shrubs, and the rest 5.4% by other land use classes (Fig. 4). The land-use types of the study basin were coded into SWAT by using the master database as a lookup table.

Different types of soil texture and physical–chemical properties of soils are required for SWAT simulations (Neitsch et al. 2011). The soil map of the study area (Fig. 5) was obtained from the World Food and Agriculture Organization of the United States (FAO) database. The physical and chemical properties of each soil type of the study area were extracted from the SWAT database.

Meteorological data preparation and quality assurance

Hydrological modeling and water resource studies have required the evaluation of the consistency and quality of the observed weather data (Talaee et al. 2014). The meteorological data of the study area were collected from the National Meteorological Service Agency (NMSA) of Ethiopia for 18 years (1999–2016). About 150 meteorological stations were found in the Upper Blue Nile basin, from which 55 stations were selected based on the length of the recording period and their completeness. Among these, 32 stations (Table 2; Fig. 6) were selected as a target station, and the remaining 23 stations were used to fill the missing data to

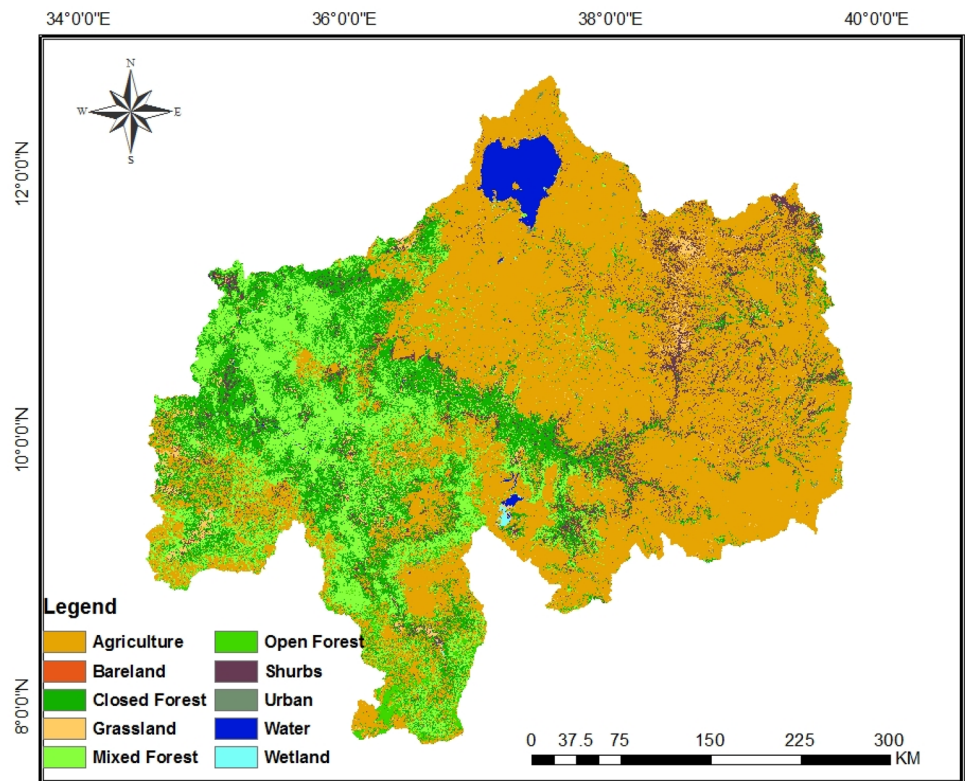**Fig. 4** Land use map of the
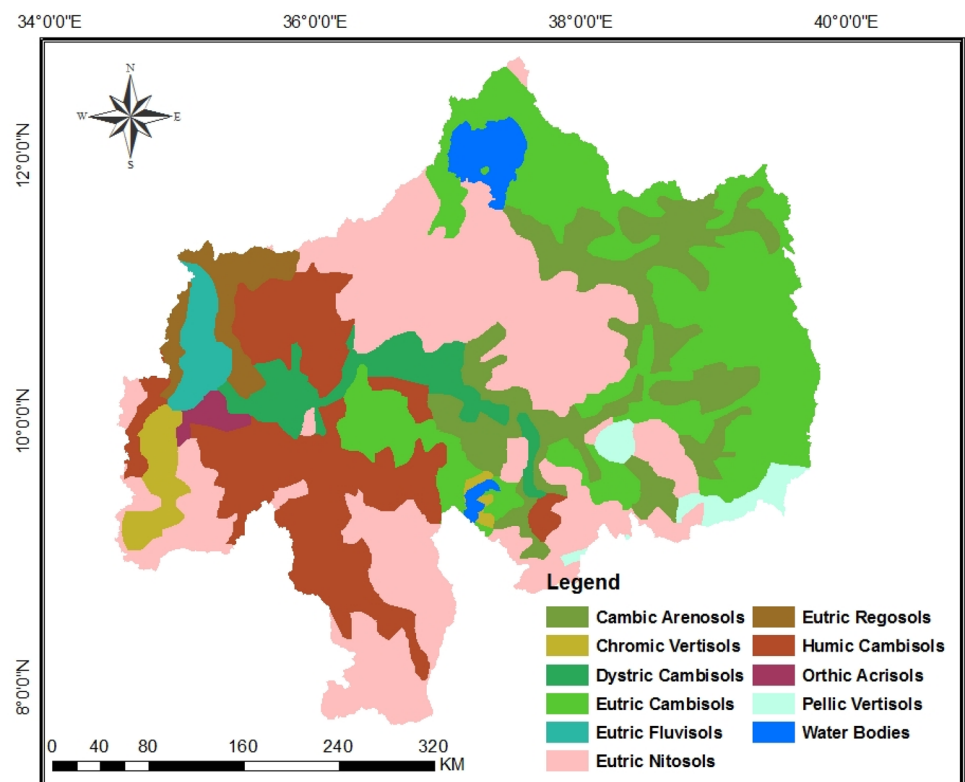Upper Blue Nile basin

Fig. 5 FAO soil map of the
Upper Blue Nile basin

Table 2 Selected meteorological stations and their description

Id	Name	Lat	Long	Elevation	Record period	Annual rainfall (mm)
1	Addis zemen	12.07	37.52	1975	1999–2016	1399
2	Adet	11.27	37.49	2179	1999–2016	1172
3	Alem ketema	10.03	39.03	2616	1999–2016	1118
4	Anger	9.27	36.33	1350	1999–2016	1600
5	Arjo	8.75	36.5	2565	1999–2016	2135
6	Asosa	10	34.52	1600	1999–2016	1116
7	Bahir dar	11.6	37.39	1800	1999–2016	1358
8	Bedele	8.45	36.33	2011	1999–2016	1932
9	Chagni	10.97	36.5	1614	1999–2016	1711
10	Debre birhan	9.63	39.5	2750	1999–2016	954
11	Debre markos	10.33	37.74	2446	1999–2016	1310
12	Debre tabor	11.87	38	2612	1999–2016	1360
13	Fiche	9.77	38.73	2738	1999–2016	1160
14	Fincha	9.57	37.37	2248	1999–2016	1723
15	Gidayana	9.87	36.62	1850	1999–2016	1764
16	Gimbi	9.17	35.78	1970	1999–2016	1835
17	Gohatsion	10.02	38.25	2495	1999–2016	1187
18	Gondar	12.52	37.43	1987	1999–2016	1218
19	Jimma	7.66	36.81	1718	1999–2016	1518
20	Lemi	10.4	38.49	2673	1999–2016	1279
21	Maksegnit	12.39	37.56	1923	1999–2016	1054
22	Mehalmeda	10.31	39.66	3084	1999–2016	891
23	Mendida	9.67	39.33	2683	1999–2016	1017
24	Nedjo	9.5	35.45	1800	1999–2016	1519
25	Nefasmewucha	11.73	38.47	3150	1999–2016	1098
26	Nekemte	9.08	36.46	2080	1999–2016	2068
27	Neshi	9.72	37.27	2060	1999–2016	1865
28	Pawi	11.31	36.41	1119	1999–2016	1566
29	Shambu	9.57	37.12	2460	1999–2016	1498
30	Sibusire	9.04	36.87	1826	1999–2016	1349
31	Wereilu	10.6	39.43	1870	1999–2016	1010
32	Zege	11.69	37.31	1801	1999–2016	1620

the neighboring stations. The consistency of the meteorological data of the selected stations was checked using a double mass curve method. Finally, the missed data were filled and homogeneity analysis was executed using CLIMATOL v3.3 package of the R programming.

Filling missing data and homogeneity analysis The main objective of doing the quality control and homogeneity analysis of the meteorological data for this study was detecting data values that are obviously in error. Apart from affecting the value of a dataset in its own right, this is necessary because large outliers can influence subsequent climate analysis. Therefore, before applying raw meteorological data to subsequent analysis, quality control and homogeneity analysis are required. For the present study, due to the spatial heterogeneity of the Upper Blue Nile basin CLI-

MATOL package was selected to fill the missing data and homogeneity analysis.

CLIMATOL applies a spatial interpolation and rates of the normals to fill daily rainfall data; an algorithm developed by Paulhus and Kohler (1952) and standardized values method to fill temperature data. This implies knowing the averages and standard deviations of all series for a common and long period of observation, and incompatible constraints within a fragmented dataset. Therefore, averages and standard deviations are computed first with the available data, and missing data are filled with the unstandardized reference series computed for each station (Guijarro 2018).

The program uses the Standard Normal Homogeneity Test (SNHT) method to test the homogeneity of neighboring stations. The SNHT for the rainfall and/or temperature is based upon the assumption that the ratio q for rainfall and

Fig. 6 Spatial locations of the selected meteorological and streamflow gauge stations
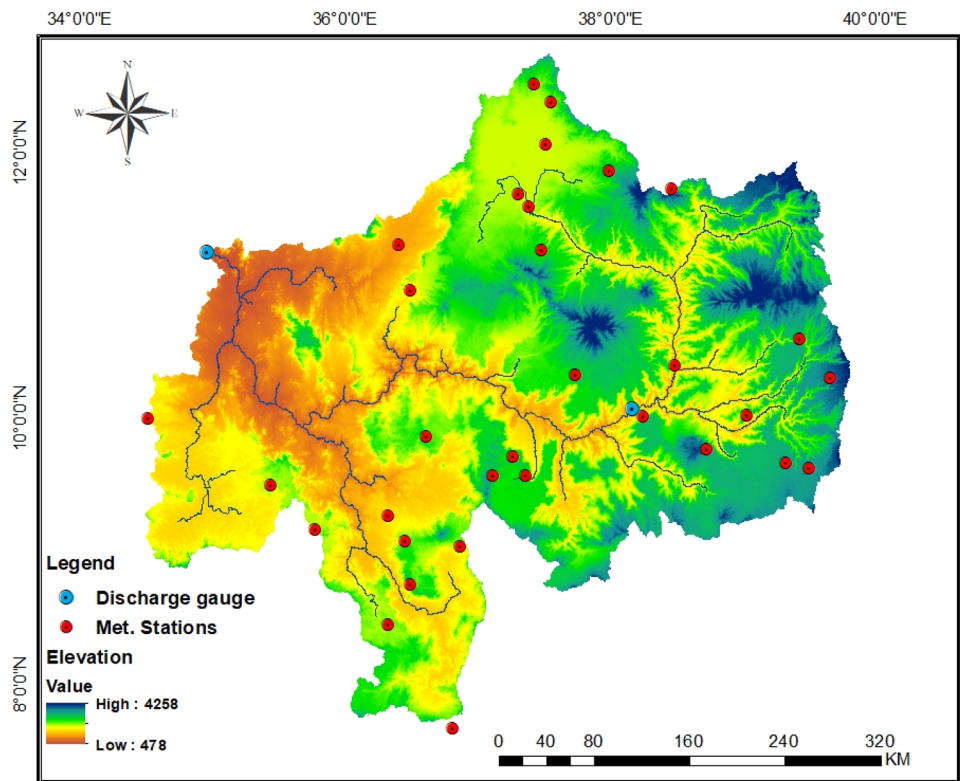

Table 3 Selected streamflow gauge stations and their spatial location

ID	Name	Lat	Log	Record year	Average annual discharge (m³/s)
1	Kessie	10.14	38.16	1999–2014	652
2	Border	11.30	34.88	1999–2014	1871

temperature at the station being tested (target station) and a neighboring station (reference station) is fairly constant in time. An inhomogeneity is one of the series that will then be revealed by a systematic change in this ratio. Consequently, the time series of this ratio q_i (index i denoted to time step-i.e., year) is a suitable variable for testing the significance of a suspected homogeneity.

A standardized series of the ratio, z_i, is defined as

$$z_i = (q_i - \hat{q})/s_q \tag{1}$$

where q is the sample mean and s_q is the sample standard deviation of the q_i's the sample mean value of z_i then 0, while the sample standard deviation is 1 (Tuomenyirta 2002).

After the meteorological data quality was controlled, the observed data were used to generate additional weather data. PcpSTAT (precipitation index) and Dew point programs were employed to generate the required weather data.

Accordingly, the generated weather data were exported into the SWAT database.

Hydrological data

Streamflow data of 14 years (2001–2014) recorded at Kessie and Border gauging stations (Table 3; Fig. 6), which are situated at the mainstream of the basin were used for calibration and validation purposes. These two-gauge stations were selected because they have adequate streamflow information needed for this study. The data were obtained from the Ethiopian Ministry of Water, Irrigation and Energy.

SWAT model description

Soil and water assessment tool (SWAT) model is a continuous-time, semi-distributed, process-based river basin scale model (Arnold et al. 2012). The model is designed to test and forecast the impact of water management on water, sediment, and agricultural chemical yields in ungagged watersheds on a daily time step (Gassman et al. 2007; Devia and Ganasri 2015). The main components of the model are weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management (Neitsch et al. 2005).

SWAT model operates on a daily time step for each hydrologic unit based on the water balance equation (Eq. 2)

(Gassman et al. 2007). The simulation of the model is separated into two phases: Land phases control the loading of the amount of water, sediment, and nutrients to the main channel in each subbasin (watershed), and the second phase defines the movement of water, sediments, and nutrients through the channel of the HRUs or watershed outlets. The water balance in SWAT is calculated at the watershed level using the following equation (Neitsch et al. 2011; Arnold et al. 2012).

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day,i} - Q_{surf,i} - E_{a,i} - Q_{lat,i} - Q_{gw,i} \right) \tag{2}$$

where SW_t stands final soil water content, SW_o stands initial water content on day i, t is the time in day, R_{day} stands the amount of rainfall on day i, Q_{surf} stands the amount of surface runoff on day i, E_a is amount of evapotranspiration on day i, Q_{lat} stands amount of water entering vadose zone from the soil profile on day i, and Q_{gw} stands amount of return flow on day i (Neitsch et al. 2011).

The USDA Soil Conservation Service runoff curve number (CN) method (USDA 1972) is used to compute runoff as follows:

$$Q_{surf} = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)} \tag{3}$$

where Q_{surf} is the accumulated runoff or rainfall excess, R_{day} is the rainfall depth for the day, I_a is the initial abstraction, which includes infiltration, interception and surface storage before runoff. S (Eq. 4) is the retention parameter calculated from the curve number.

$$S = 25.4 \left(\frac{1000}{CN} - 10 \right) \tag{4}$$

Curve number is important during the model calibration process and determines the surface runoff of the watershed (Arnold et al. 2012). Another important parameter, especially for densely vegetated watersheds, is evapotranspiration. In the SWAT model, three evapotranspiration estimation methods are employed; Penman–Monteith, Priestley-Taylor, and Hargreaves (Neitsch et al. 2011). Due to data availability and the modest nature of the method, the Hargreaves method was employed for estimating potential evapotranspiration.

Model setup

The Upper Blue Nile basin modeling framework was developed to understand the spatial and temporal variation of water resources in the basin include precipitation, streamflow, runoff (surface and groundwater), and evapotranspiration.

Watershed delineation

Watershed delineation is the initial stage of the SWAT model building (Luo et al. 2011). Since SWAT is a physical-based model, the subbasin and reaches of the watershed are derived from a digital elevation model. The watersheds of the Upper Blue Nile basin were delineated from the digital elevation model using ArcSWAT 2012 automatic delineation toolbox. The delineation was done based on the spatial distribution of the selected meteorological stations and the numbers of tributaries of the basin. Accordingly, 45 sub-basins were delineated with the minimum threshold value of 100,000 ha.

Hydrological response unit (HRU) definition

After watershed and their parameters were created, the hydrological response units (HRUs) were defined. Subsequently, the SWAT model requires the physiographical data (land use, soil type, and slope) to define the HRUs (Her et al. 2015; Devia and Ganasri 2015; Nasiri et al. 2020). Here, the slope map of the study basin was derived from the digital elevation model. Before the numbers of HRUs were defined, the land use, soil, and slope maps were reclassified and overlaid. As a result, 1138 HRUs were created using a 5% threshold value for land use, soil, and slope maps.

Writing climate dataset

The station-level climate data (temperature and precipitation) were encoded into the SWAT model database. Essentially the model requires humidity, solar radiation, and wind dataset. Due to lack of data, the generated weather data by the SWAT weather generator were encoded into the model database.

Model simulation

The encoded hydro-climatic parameters into the model were used to simulate hydrological processes of the Upper Blue Nile basin. The simulated years of the model are ranged from 1999 to 2016. The first 2 years (1999 and 2000) were used for model warm-up, to alleviate the effects of unknown initial conditions, and subsequently, this time period was excluded from the analysis.

Sensitivity analysis, model calibration and validation

Sensitivity analysis is the process of determining the rate of change in model output concerning changes in model inputs (parameters) (Arnold et al. 2012). The sensitivity analysis provided an understanding of the parameters and helps to identify the most dominant parameters that should be used for calibration (Worqlula et al. 2018). The responsive

parameters are calculating using a multiple regression system with Latin hypercube samples by means of the objective function (*t* stat and *P* value) (Narsimlu et al. 2015). The *t* test provides the measures of the degree of sensitivity and the *p* value provides the significance of the sensitivity (Narsimlu et al. 2015). A larger absolute *t* stat means greater sensitivity and a *p* value close to zero represents higher significance (Abbaspour et al. 2007). Based on their *t* stat and *p* value the most sensitive parameters were selected and used for model calibration and validation.

Model calibration is performed by selecting the fitting values for the model input parameters by comparing the model simulated value for given local conditions with observed data for the same conditions (Arnold et al. 2012). Validation is performed by running a model using parameters with their fitting value that were determined during the calibration period and comparing the simulations to observed data not used in the calibration period (Abbaspour et al. 2015).

In this study, the sensitivity analysis, model calibration, and validation activities were performed by using SUFI-2 (Sequential Uncertainty Fitting ver. 2) under SWAT-CUP ver-2012 (the SWAT Calibration and Uncertainty Programs) specialized computer program. SUFI-2 is one of the optimization algorithms in SWAT-CUP developed by Abbaspour et al. (2004) that was used in this study. 14-year streamflow data of Border and Kessie stations at the mainstream of the Upper Blue Nile basin (Fig. 6) were used for model calibration and validation. The data from 2001 to 2009 were used for model calibration and 2010–2014 used for model validation.

Model performance evaluation

Statistical performance measures for hydrological model are computed to determine how the simulated values by the model match with those of observed. In this study, three statistical measures have been used for model performance evaluation, namely Nash–Sutcliffe efficiency (NSE), coefficient of determination (R^2), and percent of bias (PBIAS), which were described in detail (Nash and Sutcliffe 1970; Krause et al. 2005; Gupta et al. 1999) as well as an appropriate range of values for these measures are listed in Table 4 (Moriasi et al. 2007; Ayele et al. 2017).

Nash–Sutcliffe efficiency (NSE) is a standardized statistic that describes differences between the simulated and observed values normalized by the variance of the observed values during the study period. The value ranges from $-\infty$ to 1. An NSE = 1 indicates simulated data are equal to that of the observed data and NSE = 0 indicates that the simulated data are as accurate as the mean of the observed data (Nash and Sutcliffe 1970).

$$NSE = 1 - \frac{\sum_{i}^{n}(Q_m - Q_s)_i^2}{\sum_{i}^{n}(Q_{m,i} - \overline{Q}_s)^2} \tag{5}$$

where Q represents the discharge values, "m" and "s" stand for the measured and simulated data, respectively, and the bar stands for the average values of measured and simulated data.

The coefficient of determination (R^2) is the square of the correlation (r) and measure the goodness of fit between the simulated and observed values; it ranges from 0 to 1. An R^2 of 1 means the simulated data are equal to that of the observed data and R^2 of 0 means no correlation between the simulated and observed data (Krause et al. 2005).

$$R^2 = \frac{\left[\sum_i^n(Q_{m,i} - \overline{Q}_m)(Q_{s,i} - \overline{Q}_s)\right]^2}{\sum_i^n(Q_{m,i} - \overline{Q}_m)^2 \sum_i^n(Q_{s,i} - \overline{Q}_s)^2} \tag{6}$$

where Q is representing discharge, and m and s stand for measured and simulated data, i is the ith measured or simulated data.

The percent of bias (PBIAS) measures the average propensity between the simulated and observed data, indicating how much the simulated data to be larger or smaller than the observed data. The optimal value of PBIAS is zero, where low magnitude values indicate better model simulations. The positive PBIAS value indicates model underestimation, and the negative PBIAS value indicates model overestimation (Gupta et al. 1999).

$$PBIAS = \frac{\sum_i^n(Q_m - Q_s)_i}{\sum_i^n Q_{m,i}} \times 100 \tag{7}$$

where Q is denoting for discharge, and m and s stand for measured and simulated value, respectively.

Table 4 General performance ratings for simulated streamflow (Moriasi et al. 2007; Ayele et al. 2017)	Performance rating	R^2	NS	PBIAS
	Very good	$0.7 < R^2 \leq 1$	$0.75 < NS \leq 1$	PBIAS $< \pm 10$
	good	$0.6 < R^2 \leq 0.7$	$0.65 < NS \leq 0.75$	$\pm 10 \leq$ PBIAS $< \pm 15$
	Satisfactory	$0.5 < R^2 \leq 0.6$	$0.5 < NS \leq 0.65$	$\pm 15 \leq$ PBIAS $< \pm 25$
	Unsatisfactory	$R^2 \leq 0.5$	$NS \leq 0.5$	PBIAS $\geq \pm 25$

Results and discussion

Sensitivity analysis

Sensitivity analysis has to be performed to prior model calibration and to determine parameters most affect the variable of interest in the watershed, which helps to decrease the number of parameters in the calibration procedure by eliminating the parameters identified as not sensitive (Nazari-Sharabian et al. 2020). Accordingly, the analysis has been executed using the SUFI-2 module of the SWAT-CUP program over the simulated period (2001–2014).

In the sensitivity analysis, the whole discharge parameters were considered, from which thirteen parameters were found to be relatively most sensitive ranging from very high to medium. Among the sensitive parameters, the groundwater flow parameters were found to be more sensitive to streamflow. The sensitivity rank of the selected parameters was selected based on their t stat, and p value is shown in Table 5. SCS runoff curve number, deep aquifer percolation fraction, threshold depth of water in the shallow aquifer for "revap" to occur, available water capacity of the soil layer, groundwater delay, effective hydraulic conductivity in main channel alluvium, baseflow alpha-factor, groundwater "revap" coefficient, saturated hydraulic conductivity, threshold depth of water in the shallow aquifer required for return flow to occur, soil evaporation compensation factor, maximum canopy storage and manning's "n" value for the main channel were identified. These parameters were considered for model calibration.

Model calibration and validation

By considering the most sensitive parameters (Table 5), the SWAT model has been calibrated and validated on the observed streamflow at Kessie and Border stations. To improve the efficiency of the model during calibration, the selected parameters were used to account for over and under prediction responses of the model as suggested by Neitsch et al. (2011). Until a satisfactory agreement between observed and simulated streamflow is attained, several calibration runs have been executed. Eventually, the calibration process using the SUFI-2 algorithm gave the final fitted parameters (Table 6). The available streamflow data of 14 years (2001–2014) were used for model calibration and validation. The streamflow data from 2001 to 2009 were used for calibration and 2010–2014 used for the validation period. The graphical comparison of monthly observed streamflow with simulated data streamflow for the calibration and validation periods is shown in Figs. 7 and 8.

Table 5 Description of the most sensitive parameters in the SWAT model for the Upper Blue Nile basin

Parameter name	Ranking	t Stat	p value
CN2.mgt	1	− 11.13	0.00
RCHRG_DP.gw	2	− 2.73	0.01
REVAPMN.gw	3	− 2.5	0.02
SOL_AWC.sol	4	− 2.05	0.05
GW_DELAY.gw	5	− 1.46	0.15
CH_K2.rte	6	− 1.26	0.21
ALPHA_BF.gw	7	1.17	0.25
GW_REVAP.gw	8	1.11	0.27
SOL_K.sol	9	− 1.07	0.29
GWQMN.gw	10	0.49	0.62
ESCO.hru	11	0.2	0.84
CANMX.hru	12	− 0.07	0.94
CH_N2.rte	13	− 0.01	0.99

Table 6 Final calibration parameters and their fitted value

| Rank	Parameter name	Range used in calibration		Fitted	Process
		Minimum value	Maximum value		
1	CN2.mgt	− 8	10	− 2.78	Runoff
2	RCHRG_DP.gw	0	0.3	0.003	GW
3	REVAPMN.gw	1	350	227.85	GW
4	SOL_AWC.sol	0.1	0.7	0.35	Soil
5	GW_DELAY.gw	0	60	2.77	GW
6	CH_K2.rte	0	200	130	Channel
7	ALPHA_BF.gw	0.1	0.8	0.345	GW
8	GW_REVAP.gw	0.03	0.19	0.14	GW
9	SOL_K.sol	0	0.2	0.15	Soil
10	GWQMN.gw	100	4000	2401	GW
11	ESCO.hru	0	0.2	0.014	Evaporation
12	CANMX.hru	0	10	4.9	Runoff
13	CH_N2.rte	0.03	0.15	0.084	Channel
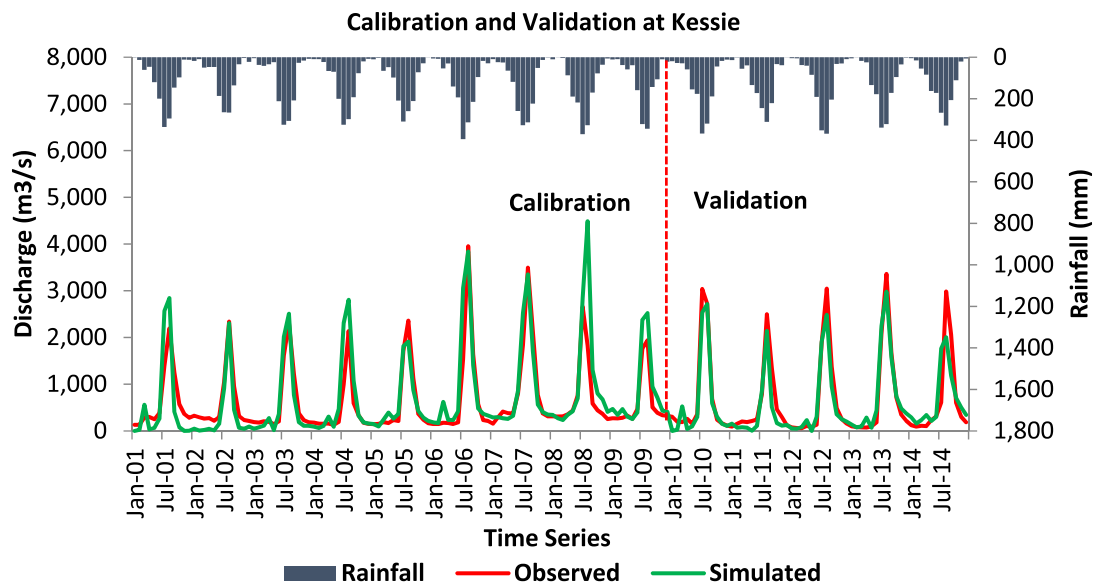
Fig. 7 Observed and simulated flow hydrograph for the calibration and validation period at Kessie
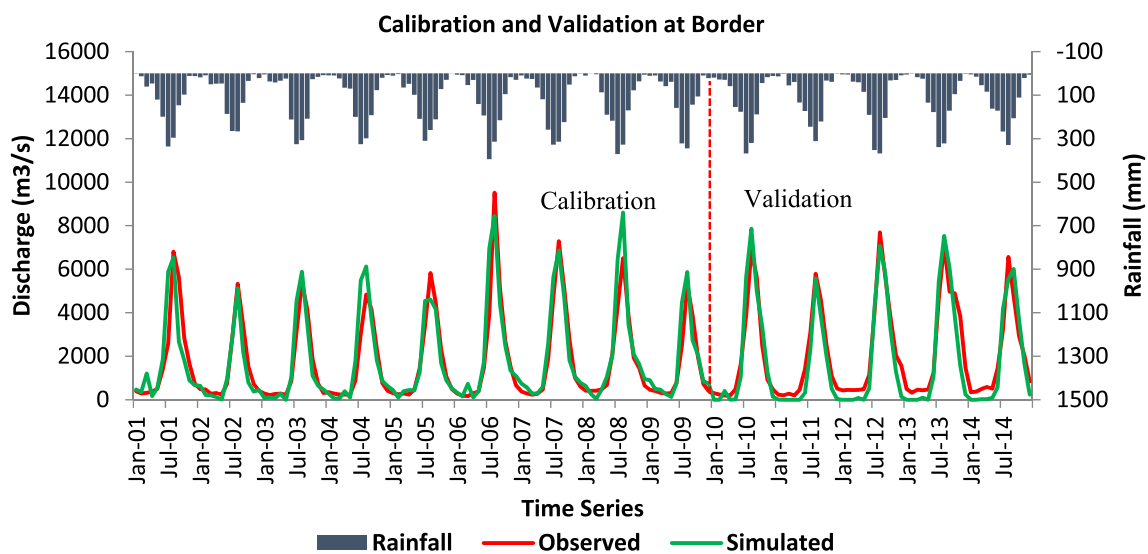

Fig. 8 Observed and simulated flow hydrograph for the calibration and validation period at Border

Table 7 R^2, NSE and PBIAS value for the calibration and validation period at Kessie and Border stations

Station	Calibration			Validation		
	R^2	NSE	PBIAS	R^2	NSE	PBIAS
Kessie	0.81	0.68	− 10.8	0.89	0.88	8.3
Border	0.85	0.83	− 4.7	0.93	0.89	9.7

Performance evaluation

The performance of the SWAT model is analyzed based on a graphical representation of observed and simulated stream-flow and the basis of various statistical parameters. The

statistical results that the SWAT model performed (Table 7) were acceptable at the Kessie station with Nash–Sutcliffe efficiency (NSE) 0.68 and 0.88 for calibration and validation periods, respectively. The values of coefficient of determination (R^2) for the calibration and validation period are 0.81
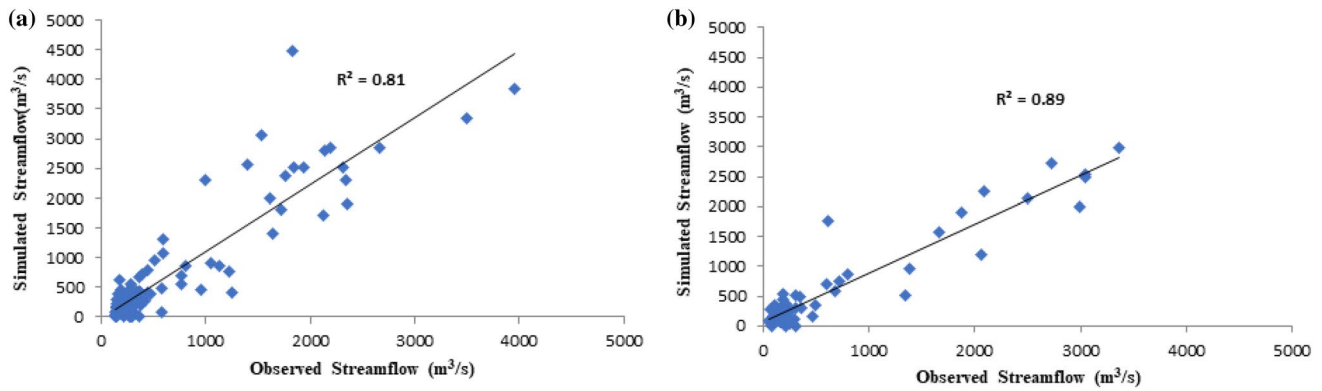
Fig. 9 Scatter plot of observed and simulated streamflow for calibration period (**a**) and validation period (**b**) at Kessie

and 0.89, respectively, which indicated that the agreements between observed and simulated streamflow for both periods were strong (Fig. 9). The PBIAS values were − 10.8% and 8.3% for the calibration and validation periods, respectively, which showed that the model slightly overestimated the flow during calibration and underestimated the flow during validation with reference to the observed data.

Based on the PBIAS value, the streamflow rate at the Kessie station was overestimated by 9.75% during the calibration period and underestimated by 8.31% during the validation period. The hydrograph of simulated and observed monthly streamflow at the Kessie station for calibration and validation is also presented in Fig. 7. It can be seen that the SWAT model overestimated for most years in the calibration period and underestimated for all years in the validation period.

At the Border gauging station, SWAT model performed very well (Table 7) with Nash–Sutcliffe efficiency (NSE) 0.83 and 0.89 for calibration and validation periods, respectively. The values of coefficient of determination (R^2) for the calibration and validation periods were found to be 0.85 and 0.93, respectively, which reflected that the agreements between observed and simulated streamflow for both periods

were strong (Fig. 10). The PBIAS values were found − 4.7% and 9.7% for the calibration and validation periods, respectively, which indicated that the model slightly overestimated the flow during calibration and underestimated the flow during validation.

Regarding to the PBIAS results, the streamflow rate at Border station overestimated by 4% during the calibration period and underestimated by 15% during validation period. The hydrograph of simulated and observed monthly streamflow at the Border station for model calibration and validation is presented in Fig. 8. It can be seen that the SWAT model overestimated for some years in the calibration period and underestimated for most years in the validation period.

Overall, the SWAT model results showed that there was a good agreement between observed and simulated monthly streamflow at the Upper Blue Nile basin. Previously several authors calibrated and validated the SWAT model in the Blue Nile river basin, and their report showed that the statistical parameters such as R^2 and NSE varied between 0.59–0.96 and 0.43–0.92 respectively (Gebremicael et al. 2013; Roth et al. 2016; Polanco et al. 2017; Tegegne et al. 2017; Lemann et al. 2019; Nigussie et al. 2019). Hence, the SWAT hydrological model is applicable in the Upper Blue
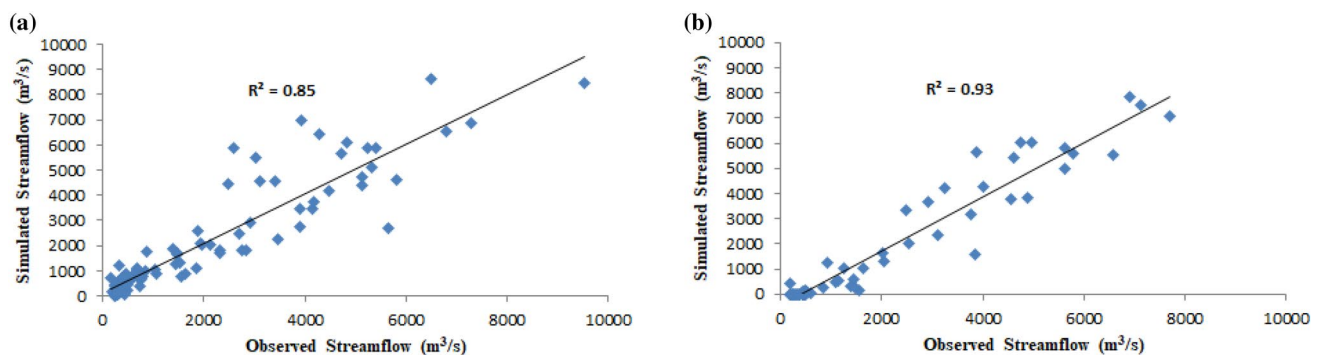

Fig. 10 Scatter plot of observed and simulated streamflow for calibration period (**a**) and validation period (**b**) at Border

Nile basin. Accordingly, the simulated values of this study can be acceptable.

Hydrological water balance

Water balance in watersheds is one of the most important factors used to determine if a model is good enough for any particular application (Polanco et al., 2017). Based on the simulated precipitation, evapotranspiration, total discharge, and water yield of the SWAT model, the water balance of the Upper Blue Nile basin was analyzed. Table 8 lists the simulated water balance components on an annual average basis for the Upper Blue Nile basin over the whole simulation, calibration, and validation periods.

The results indicated that in the simulation period, 22.43% of the precipitation of the basin contributed to streamflow, whereas 49.5% of the precipitation is lost by evapotranspiration. Moreover, in the simulation period, the contribution of surface runoff (SUR_Q), lateral flow (Lat_Q), and groundwater flow (GW_Q) for the annual water yield (WYLD) was 43.7% and 13.48%, 40.44%, respectively. This shows as the contribution of surface runoff is higher than other water balance components of the basin.

For the calibration period, 22.05% of the precipitation of the basin contributed to streamflow; 50.17% of the precipitation is returned to the atmosphere through evapotranspiration. Besides, the contribution of the surface runoff (SUR_Q), later flow (Lat_Q), and groundwater flow (GW_Q) for water yield (WYLD) was 44.95%, 12.41%, and 40.15%, respectively. For the calibration period, 22.88% of the precipitation of the basin contributed to streamflow; 48.58% of the precipitation is returned to the atmosphere through evapotranspiration. Also, the contribution of the surface runoff (SUR_Q, later flow, (Lat_Q) and groundwater flow (GW_Q) for water yield (WYLD) was 45.26%, 12.22%, and 40.28%, respectively. The water yield (Table 8) during the validation period was higher than the calibration period. This could be because the rainfall amount during the validation period was relatively higher.

The spatial distribution of the water balance components shows a better understanding of the basin (Fig. 11). At the basin scale, the annual precipitation in the Upper Blue Nile basin varied from 734 to 2118 mm. The amount of precipitation falling on the south tip and southwest of the basin was more than that of the eastern and western tip of the basin. The annual evapotranspiration of the basin varied from 475 to 1159 mm, and likewise precipitation, the value of evapotranspiration was high on the south tip and southwest part of the basin. The water yield at the basin scale of the Upper Blue Nile basin varied from 115 to 1201 mm. Alike to precipitation, higher water yield was found on the south tip and southwest part of the basin. Hence, the SWAT output of the study area indicates a good spatial correlation among precipitation, evapotranspiration, potential evapotranspiration, and water yield.

Conclusion

Spatially semi-distributed hydrological model, SWAT was applied to model the hydrological processes and water balance components of the Upper Blue Nile basin. The model was calibrated and validated using monthly streamflow data by applying the SUFI-2 algorithm in SWAT-CUP2012. Sensitivity analysis was done to identify flow-sensitive parameters, and groundwater flow parameters were found to be more sensitive to streamflow.

Nash–Sutcliffe efficiency (NSE), coefficient of determination (R^2), and percent of bias (PBIAS) statistical measures are considered to evaluate the performance of the model. In the calibration period, the value of NSE, R^2, and PBIAS was 0.68, 0.81, and − 10.8%, respectively, for Kessie station and 0.83, 0.85, and − 4.7%, respectively, for the Border station. In the calibration period, NSE, R^2, and PBIAS were 0.89, 0.88, and 8.3% for Kessie station and 0.93, 0.89, and 9.7%, respectively, for the Border station. Therefore, the result indicates that the SWAT model gave good simulation results and performed well in the Upper Blue Nile basin, and the results were acceptable.

Table 8 Upper Blue Nile basin simulated annual water balance components for total simulated, calibration and validation periods

| Hydrological parameters	Total time (2001–2014) (mm)	Calibration period (2001–2009) (mm)	Validation period (2010–2014) (mm)
Precipitation	1393	1376	1424
Surface runoff	311.44	303.42	325.88
Ground water flow	278	271	290
Lateral flow	85.27	83.78	87.96
Shallow aquifer recharge	325	318	338
Potential evapotranspiration	1591	1587	1598
Evapotranspiration	690.87	690.38	691.76
Total water yield	691	675	720
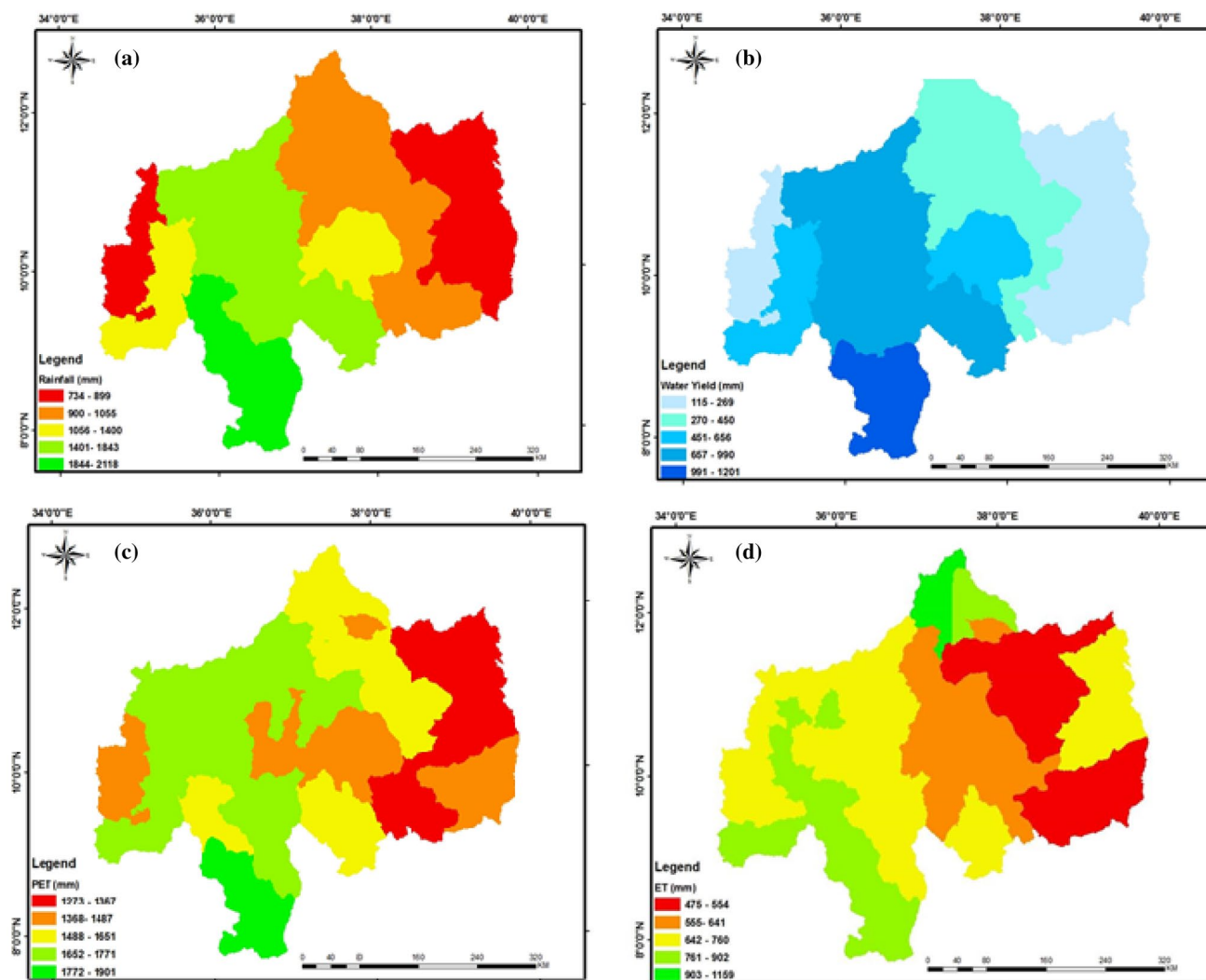
Fig. 11 Simulated rainfall (**a**), water yield (**b**), PET (**c**) and ET (**d**) across the Upper Blue Nile basin

The hydrological water balance analysiss showed that 22.43% of the precipitation of the basin contributed to streamflow as surface flow, whereas 49.5% of the precipitation is lost by evapotranspiration. Hence, the runoff of the basin is affected by evapotranspiration. Surface runoff, lateral flow, and baseflow contributed 44.95%, 12.41%, and 40.15%, respectively, for the annual water yield of the basin. The water yield during the validation period was higher than the calibration period. This could be because the rainfall amount during the validation period was relatively higher. For the spatial distribution of the water balance components, the result indicated a good correction among the hydrological components.

Overall, the finding of this research demonstrated the high potential applicability of the SWAT model for the assessment of hydrological processes at a large river basin. Perhaps, the findings of the study are useful for basin-wide water resources planning and management in the Upper Blue Nile basin, as they not only provide a proportion of water resource of the basin but also give a better understanding of the capacity of the available water resource for future water-based development projects.

Compliance with ethical standards

Conflict of interest The authors declare that they have no competing interest.

References

Aawar T, Khare D (2020) Assessment of climate change impacts on streamflow through hydrological model using SWAT model: a case study of Afghanistan. Model Earth Syst Environ 6:1427–1437

Abbaspour K, Johnson C, van Genuchten MT (2004) Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure. Vadose Zone J 3:1340–1352

Abbaspour K, Yang J, Maximov I, Bogner K, Mieleitner J, Zobri J, Srinivasan R (2007) Modelling hydrology and water quality in the pre-alpine/alpine Thur Watershed using SWAT. J Hydrol 333:413–430. https://doi.org/10.1016/j.jhydrol.2006.09.014

Abbaspour K, Rouholahnejad E, Vaghefi S, Srinivasan R, Yang H, Kløve B (2015) A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. J Hydrol 524:733–752. https://doi.org/10.1016/j.jhydrol.2015.03.027

Abera W, Formetta G, Brocca L, Rigon R (2017) Modeling the water budget of the Upper Blue Nile basin using the JGrass-New age model system and satellite data. Hydrol Earth Syst Sci 21:3145–3165

Arnold G, Moriasi D, Gassman P, Abbaspour K, White M, Srinivasan R, Santhi C, Harmel R, Van Griensven A, Van Liew MW (2012) SWAT: model use, calibration, and validation. Am Soc Agric Biol Eng 55(4):1491–1508

Ashenafi Y, Hailu D (2014) Assessment of the use of remotely sensed rainfall products for runoff simulation in the Upper Blue Nile of Ethiopia. J EEA 31:1–9

Asitatikie A, Gebeyehu W (2020) Assessment of hydrology and optimal water allocation under changing climate conditions: the case of Megech river sub basin reservoir, Upper Blue Nile basin, Ethiopia. Model Earth Syst Environ. https://doi.org/10.1007/s40808-020-01024-0

Ayele G, Teshale E, Yu B, Rutherfurd I, Jeong J (2017) Streamflow and sediment yield prediction for watershed prioritization in the Upper Blue Nile river basin. Ethiopia Water 9(782):1–29

Chimdessa K, Quraishi S, Kebede A, Alamirew T (2019) Effect of land use land cover and climate change on river flow and soil loss in Didessa river basin, South West Blue Nile. Ethiopia Hydrol 6(2):1–20

Conway D (2000) The climate and hydrology of the Upper Blue Nile river. Geogr J 166(1):49–62

Devia G, Ganasri B, Dwarakish G (2015) International conference on water resources, coastal and ocean engineering (icwrcoe 2015): a review on hydrological models. Aquat Proc 5:1001–1007. https://doi.org/10.1016/j.aqpro.2015.02.126

Dibaba W, Demissi T, Miegel K (2020) Drivers and implications of land use/land cover dynamics in Finchaa Catchment, Northwestern Ethiopia. Land 9(113):1–20

Dile Y, Srinivasan R (2014) Evaluation of CFSR climate data for hydrologic prediction in data scarce Watersheds: an application in the Blue Nile River basin. J Am Water Resour Assoc (JAWRA) 50(5):1226–1241

Gassman PW, Reyes MR, Green CH, Arn JG (2007) The soil and water assessment tool: historical development, applications, and future research directions. Am Soc Agric Biol Eng 50(4):1211–1250

Gebre S, Ludwig F (2015) Hydrological response to climate change of the Upper Blue Nile river basin: based on IPCC fifth assessment report (AR5). Climatol Weather Forecast 3(1):1–5

Gebremicael T, Mohamed Y, van der Zaag P, Teferi E (2013) Trend analysis of runoff and sediment fluxes in the Upper Blue Nile basin: a combined analysis of statistical tests, physically-based models and landuse maps. J Hydrol 482:57–68

Guijarro A (2018) Homogenization of climatic series with Climatol. State Meteorological Agency (AEMET), Balearic Islands office, Spain, 1–23

Gull S, Shah R (2020) Watershed models for assessment of hydrological behavior of the catchments: a comparative study. Water Pract Technol 15(2):261–281

Gupta HV, Sorooshian S, Yapo PO (1999) Status of autoautomatic calibration for hydrologic models: comparison with multilevel expert calibration. J Hydrol Eng 4(2):135–143

Her Y, Frankenberger J, Chaubey I, Srinivasan R (2015) Threshold effects in HRU definition of the soil and water assessment tool. Am Soc Agric Biol Eng 58(2):367–378

Islam Z (2011) A review on physically based hydrologic modeling. https://www.researchgate.net/publication/272169378

Jaiswal R, Ali S, Bharti B (2020) Comparative evaluation of conceptual and physical rainfall–runoff models. Appl Water Sci 10(48):1–14

Khayyun S, Alwan A, Hayder M (2019) Hydrological model for Hemren dam reservoir catchment area at the middle river Diyala reach in Iraq using ArcSWAT model. Appl Water Sci 9(133):1–15

Koycegiz C, Buyukyildiz M (2019) Calibration of SWAT and two data-driven models for a data-scarce mountainous headwater in semi-arid Konya closed basin. Water. https://doi.org/10.3390/w11010147

Krause P, Boyle D, Ase F (2005) Comparison of different efficiency criteria for hydrological model assessment. Adv Geosci 5:89–97

Lakew H, Moges S, Asfaw D (2020) Hydrological performance evaluation of multiple satellite precipitation products in the Upper Blue Nile basin, Ethiopia. J Hydrol Reg Stud. https://doi.org/10.1016/j.ejrh.2020.100664

Lemann T, Roth V, Zeleke G, Subhatu A, Kassawmar T, Hurni H (2019) Spatial and temporal variability in hydrological responses of the Upper Blue Nile basin, Ethiopia. Water. https://doi.org/10.3390/w11010021

Liersch S, Tecklenburg J, Rust H, Dobler A, Fischer M, Kruschke T, Koch H, Hattermann FF (2018) Are we using the right fuel to drive hydrological models? A climate impact study in the Upper Blue Nile. Hydrol Earth Syst Sci 22(4):2163–2185

Luo Y, Su B, Yuan J, Li H, Zhang Q (2011) GIS techniques for watershed delineation of SWAT model in plain polders. Proc Environ Sci 10:2050–2057

Mengistu T, Sorteberg A (2012) Sensitivity of SWAT simulated streamflow to climatic changes within the Eastern Nile River basin. Hydrol Earth Syst Sci 16(2):391–407

Moriasi D, Arnold J, Van Liew M, Bingner R, Harmel R, Veith T (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Am Soc Agric Biol Eng 50(3):885–900

Narsimlu B, Gosain A, Chahar B, Singh S, Srivastava P (2015) SWAT model calibration and uncertainty analysis for streamflow prediction in the Kunwari River Basin, India, using sequential uncertainty fitting. Environ Process 2:79–95. https://doi.org/10.1007/s40710-015-0064-8

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual model. Part 1—a discussion of principles. J Hydrol 10:282–290

Nasiri S, Ansari H, Ziaei N (2020) Simulation of water balance equation components using SWAT model in Samalqan watershed (Iran). Arab J Geosci 13:421

Nazari-Sharabian M, Taheriyoun M, Karakouzian M (2020) Sensitivity analysis of the DEM resolution and effective parameters of runoff

yield in the SWAT model: a case study. J Water Supply Res Technol Aqua 69(1):39–54. https://doi.org/10.2166/aqua.2019.044

Neitsch SL, Arnold JG, Kiniry JR, Williams JR (2005) Soil and water assessment tool-theoretical documentation,Version2005. Texas, USA

Neitsch S, Arnold J, Kiniry J, Williams J (2011) Soil and water assessment tool theoretical documentation Version 2009, Texas Water resources Institute. Texas AgriLife Research and USDA Agricultural Research Service, Temple, Texas, USA

Nigussie G, Moges M, Moges M, Steenhuis T (2019) Assessment of suitable land for surface irrigation in ungauged catchments: Blue Nile basin, Ethiopia. Water. https://doi.org/10.3390/w11071465

Paulhus JL, Kohler M (1952) Interpolation of missing precipitation records. Monthly Water Rev 80(8):129–133

Polanco E, Fleifle A, Ludwig R, Disse M (2017) Improving SWAT model performance in the Upper Blue Nile basin using meteorological data integration and subcatchment discretization. Hydrol Earth Syst Sci 21:4907–4926

Roth V, Tibebu K, Lemann T (2016) Model parameter transfer for streamflow and sediment loss prediction with SWAT in a tropical watershed. Environ Earth Sci 75(1321):1–13

Roth V, Lemann T, Gete Z, Alemtsehay T, Tibebu K, Hurni H (2018) Effects of climate change on water resources in the Upper Blue Nile Basin of Ethiopia. Heliyon 4(4):1–28

Saifullah M, Li Z, Li Q, Zaman M, Hashim S (2016) Quantitative estimation of the impact of precipitation and land surface change on hydrological processes through statistical modeling. Adv Meteorol. https://doi.org/10.1155/2016/6130179

Salih A, Hamid A (2017) Hydrological studies in the White Nile state in Sudan. Egyptian J Remote Sens Space Sci 20:S31–S38. https://doi.org/10.1016/j.ejrs.2016.12.004

Serrão E, Silva M, Soua F, Lima A, Santos C, Ataide L, Silva V (2019) Four decades of hydrological process simulation of the Itacaiúnas River watershed, Southeast Amazon. Bull Geod Sci 25(3)

Setegn S, Srinivasan R, Dargahi B (2008) Hydrological modelling in the Lake Tana basin, Ethiopia using SWAT model. Open Hydrol J 2:49–62

Shiferaw H, Gebremedhin A, Gebretsadkan T, Zenebe A (2018) Modelling hydrological response under climate change scenarios using SWAT model: the case of Ilala watershed, Northern Ethiopia. Model Earth Syst Environ 4:437–449. https://doi.org/10.1007/s40808-018-0439-8

Sime CH, Demissie TA, Tufa FG (2020) Surface runoff modeling in Ketar watershed, Ethiopia. J Sediment Environ 5:151–162. https://doi.org/10.1007/s43217-020-00009-4

Talaee H, Kouchakzadeh M, Some's S (2014) Homogeneity analysis of precipitation series in Iran. Theor Appl Climatol 118:297–305

Tegegne G, Park D, Kim Y (2017) Comparison of hydrological models for the assessment of water resource in a data scarce region, the Upper Blue Nile basin. J Hydrol Reg Stud 14:49–66

Tekleab S, Uhlenbrook S, Mohamed Y, Savenije H, Temesgen M, Wenninger J (2011) Water balance modeling of Upper Blue Nile catchments using a top-down approach. Hydrol Earth Syst Sci 15:2179–2193

Tesemma ZK, Mohamed YA, Steenhuis TA (2010) Trends in rainfall and runoff in the Blue Nile Basin:1964–2003. Hydrol Process 24:3747–3758

Tufa F, Sime C (2020) Stream flow modeling using SWAT model and the model performance evaluation in Toba sub-watershed, Ethiopia. Model Earth Syst Environ. https://doi.org/10.1007/s40808-020-01039-7

Tuomenyirta H (2002) Homogeneity testing and adjustment of climatic time series in Finland. Geophysica 38:15–41

USDA (1972) National engineering handbook, section 4, Hydrology. Washington, DC, pp 15-7–15-11

Vidyarthi V, Jain A, Chourasiya S (2020) Modeling rainfall-runoff process using artificial neural network with emphasis on parameter sensitivity. Model Earth Syst Environ. https://doi.org/10.1007/s40808-020-00833-7

Walelgn D (2018) Assessing the impacts of land use/cover change on the hydrological response of Temcha watershed, Upper Blue Nile basin, Ethiopia. Int J Sci Res Civ Eng 2(5):10–19

Woldesenbet T, Elagib N, Ribbe L, Heinrich J (2017) Hydrological responses to land use/cover changes in the source region of the Upper Blue Nile basin, Ethiopia. Sci Total Environ 575:424–741

Worqlula A, Ayanab E, Yena H, Jeonga J, MacAlisterc C, Taylor R, Greik TJ, Steenhuis TS (2018) Evaluating hydrologic responses to soil characteristics using SWAT model in a paired-watersheds in the Upper Blue Nile basin. CATENA 163:332–341. https://doi.org/10.1016/j.catena.2017.12.040

Zhihua LV, Zuob J, Rodriguez D (2020) Predicting of runoff using an optimized SWAT-ANN: a case study. J Hydrol Reg Stud. https://doi.org/10.1016/j.ejrh.2020.100688

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