

Modeling the impact of agricultural crops on the spatial and seasonal variability of water balance components in the Lake Tana basin, Ethiopia

Tibebe B. Tigabu, Paul D. Wagner, Georg Hörmann and Nicola Fohrer

ABSTRACT

The Lake Tana basin hosts more than three million people and it is well known for its water resource potential by the Ethiopian government. The major economic activity in the region is agriculture, but the effect of agricultural crops on water resources is poorly understood. Understanding the crop water interaction is important to design proper water management plans. Therefore, the primary objective of this research is to investigate the effect of different agricultural crops on the spatial and seasonal variability of water balance components of Gilgelabay, Gumara, and Ribb catchment areas of Lake Tana basin, Ethiopia. To this end, the hydrologic model SWAT (Soil and Water Assessment Tool) was used to simulate the water fluxes between 1980 and 2014. The water balance components, which were mapped for each hydrologic response unit, indicated the spatial variations of water fluxes in the study. Cereal crops like teff and millet had significant effect in enhancing groundwater recharge, whereas leguminous crops like peas had significant impact in increasing runoff generation. Moreover, the model outputs showed that the total streamflow is dominated by baseflow and about 13%, 9%, and 7% of the annual rainfall goes to the deep aquifer system of Gilgelabay, Gumara, and Ribb catchment areas, respectively.

Key words | groundwater recharge, Lake Tana, land use land cover, SWAT

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INTRODUCTION

Agriculture, food production, and water are inseparably linked (Watts *et al.* 2015). Water use in agriculture accounts for 70% of the global total water use (Hatfield 2014). Consequently, it has a significant impact on the water balance components. Agricultural land use affects the hydrologic cycle in terms of the partitioning of rainfall between evapotranspiration (ET), runoff, and groundwater recharge (Watts *et al.* 2015). The quality of surface water and groundwater has generally declined in recent decades mainly due to an increase in agricultural and industrial activities (Parris 2011). The complete drying up of Haramaya Lake in Eastern Ethiopia since 2005 is an example of the consequences of decreasing groundwater levels due to over-pumping for

agriculture and household use (Abebe *et al.* 2014). To prepare for the future and avoid past mistakes, modeling the effect of agricultural crops on the spatial and seasonal variation of water balance components is required. Although several water balance studies have been performed globally, only a few of them focused on the effect of agricultural crops on water balance components. For example, Zhao *et al.* (2010) studied the effect of vegetation change and climate variability on streamflow of seven paired catchments in Australia, New Zealand, and South Africa. Li *et al.* (2019) also studied the spatio-temporal impacts of land use and land cover changes on the hydrology of the Wei River basin, China.

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The agriculture sector plays a central role in the Ethiopian economy, where about 85% of all employment relies on it (FAO 2014). This economic sector is dominated by small-scale farmers who depend on rain-fed mixed farming. Crop production accounts for about 60% of the agricultural outputs (Gebre-Selasie & Bekele 2012). The crop productivity varies with the availability of water and water use in agriculture. Although Ethiopia is perceived as the water tower of Eastern Africa, temporal variability (seasonality) and uneven spatial distribution of water resources remain the primary challenge. Availability of water is highly dependent on the seasonality and inter-annual variability of rainfall and streamflow. The temporal variabilities of rainfall and streamflow extremes are linked to low frequency climate processes centred over the mid-latitudes of the Pacific basin (Taye *et al.* 2015). These temporal variabilities are manifested in widespread, devastating droughts and floods (World Bank 2006). Thus, agricultural crop yields are frequently affected by the quantity and timing of rainfall. To overcome this widespread problem, understanding the effect of agricultural crops on the hydrologic cycle is important.

Due to the complex physical processes of the hydrologic cycle, direct measurement of the water balance components such as groundwater recharge, evapotranspiration, and surface runoff on a spatial basis is difficult. Therefore, process-based distributed parameter models are needed to simulate the spatial and temporal patterns of hydrologic response (Jiang *et al.* 2007). Among others, the semi-distributed Soil and Water Assessment Tool (SWAT) hydrologic model (Arnold *et al.* 1998) is suitable to determine recharge rate, ET, and runoff on various spatial and temporal scales (Gemtzi *et al.* 2017).

Because of its national and international importance, the Lake Tana basin has become a focus area of many scientific studies under different perspectives. These include water balance analyses of different sub-catchments including the lake (Derib 2013; Tegegne *et al.* 2013; Dessie *et al.* 2015), hydrological modeling with emphasis on surface water (e.g., Dessie *et al.* 2014; Worqlul *et al.* 2015; Polanco *et al.* 2017), hydrometeorological trend analyses (e.g., Gebrehiwot *et al.* 2014; Mengistu & Lal 2014; Tigabu *et al.* 2018), climate change impact studies (e.g., Koch & Cherie 2013; Teshome 2016), land use/cover change impact on hydrologic responses (e.g., Gumindoga *et al.* 2014; Woldesenbet *et al.* 2017),

implications of water harvesting intensification on upstream–downstream ecosystem services and water availability (e.g., Dile *et al.* 2016), and groundwater and hydrogeology (e.g., Yitbarek *et al.* 2012; Awange *et al.* 2014).

Most of the hydrological studies in the Lake Tana basin focus on water balance evaluations at catchment outlets and lack detailed mapping of water balance components on a spatial basis. Another important research gap is that the hydrologic studies do not investigate the hydrologic mass balance in relation to vegetation types (van Griensven *et al.* 2012). Although the SWAT model was used to investigate the effect of land use change on the hydrology of the basin, none of the papers explicitly addressed the crop-related effects on the water fluxes. Hence, the overarching goal of this research is to analyze how the hydrologic mass balances are affected by agricultural crops and soil types. In particular, we focus on the spatial and seasonal distribution of groundwater recharge, surface runoff, and actual ET in the Gilgelabay, Gumara, and Ribb catchments, Lake Tana basin, Ethiopia. To the best of our knowledge, this is the first attempt to (i) analyze the impact of agricultural crops on the hydrologic cycle and (ii) map major water balance components in the Lake Tana basin in detail.

MATERIALS AND METHODS

Study area

The Lake Tana basin is located in the north-western highlands of Ethiopia. It is the second largest sub-basin of the Blue Nile River. Lake Tana is the largest freshwater lake in Ethiopia and the third largest in the Nile basin (Figure 1). The catchment area of the lake at its outlet is 15,321 km². About 20% of the catchment area is covered by Lake Tana (Alemayehu *et al.* 2010). The catchment is approximately 84 km long and 66 km wide. The lake has a surface area of 3,156 km². Lake Tana is the source of the Blue Nile River. It contains about 50% of the country's fresh water (Costa *et al.* 2014). More than 40 rivers and streams flow into Lake Tana with a mean annual inflow of 158 m³/s (Alemayehu *et al.* 2010), but 86% of the water originates from three major rivers: Gilgelabay, Gumara, and Ribb (Setegn *et al.* 2008; Alemayehu *et al.* 2010). The only surface

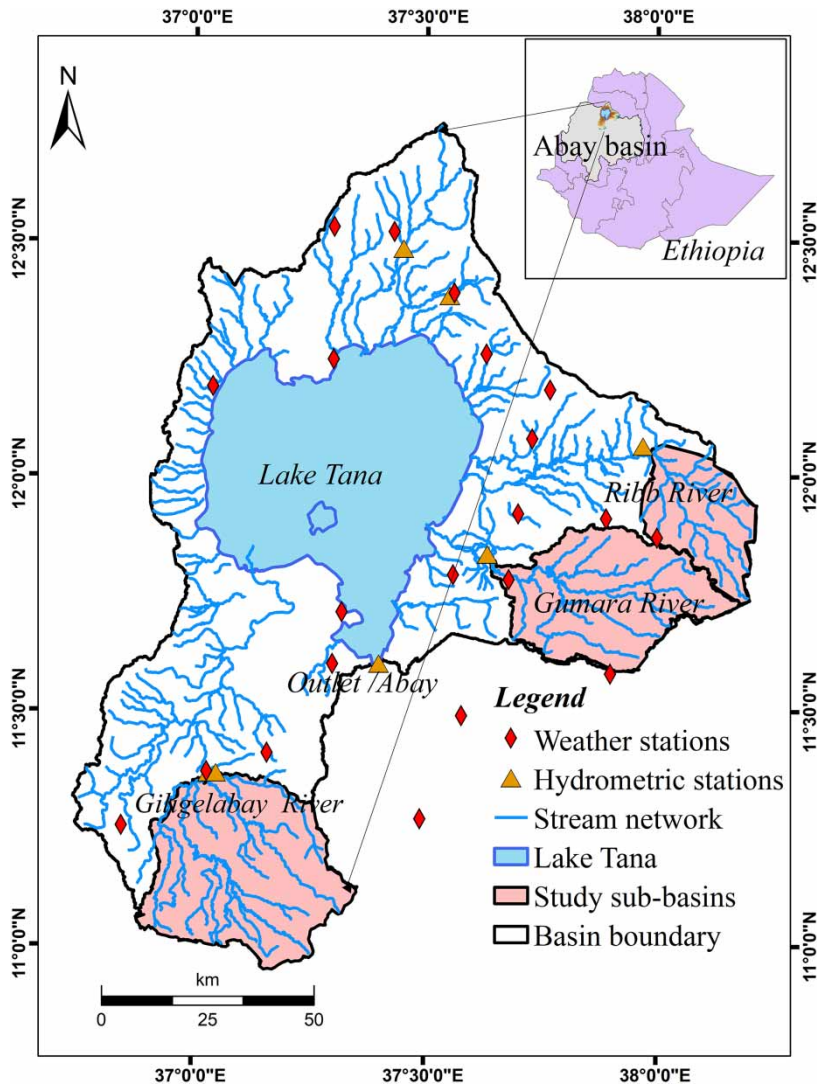


Figure 1 | Location map and major tributaries of Lake Tana including river gauging and weather stations.

outflow from the lake is the Blue Nile (locally referred to as Abay) River with an annual flow volume of 4 billion m^3 ($127 \text{ m}^3/\text{s}$) measured at the lake outlet (Setegn *et al.* 2008).

The spatial and temporal variation of rainfall in the basin is determined by elevation and the movement of the inter-tropical convergence zone (ITCZ). The position of the ITCZ is the most dominant factor that controls the amount of summer rainfall in the basin. In the Lake Tana basin, rainfall has a high seasonal variability: July, August, and September are wet months with the highest amounts of rainfall when the ITCZ position is in the northern hemisphere. June and October are transition months between wet and dry seasons, November through March belong to

the dry season, and April and May are months with small rainfall amounts. There is also high spatial variability of annual, seasonal, and monthly rainfall amounts in the study area because of small changes in the location of the ITCZ (Woldesenbet *et al.* 2017). Additionally, topography has a pronounced impact on rainfall amounts in the region. The topography varies significantly from lowland flood plain (1,700 m) to high mountain ranges (4,400 m). This variation leads to annual rainfall variability and occurrence of different climatic zones within the basin (Melesse *et al.* 2011). The amount of annual rainfall is directly related to elevation above mean sea level: high rainfall is observed in the highlands, whereas low rainfall is measured in

the lowlands (Tigabu *et al.* 2018). Moreover, large (global) atmospheric circulation and sea surface temperatures such as large-scale forcing through El Niño Southern Oscillation (ENSO), Quasi-Biennial Oscillation (QBO), as well as west-east sea surface temperature gradients over the equatorial Indian Ocean significantly influence rainfall variability (Awange *et al.* 2014).

Data base

Daily rainfall and minimum and maximum temperature values from five meteorological stations for the years 1980 to 2014 were used, which were provided by the National Meteorological Service Agency (NMA 2016). Daily streamflow data of Gilgelabay near Merawi, Gumara near Bahirdar, and Ribb near Addis Zemen gauging stations for the years 1980 to 2014 were obtained from the Department of Hydrology, Ministry of Water,

Irrigation and Electricity of the Ethiopian Government (MoWIE 2016).

Land use and land cover as well as soil data at a scale of 1:50,000 were provided by the Amhara Design & Supervision Works Enterprise (ADSWE 2017). About 60.2% of the basin is covered by agricultural land. This area is further classified as intensively cultivated (37.3%), moderately cultivated (16.0%), and farm villages (6.9%) (Figure 2). The soils in the study area are highly heterogeneous. Eutric Leptosols cover around 50% of the total area followed by Eutric Nitisols (13%). The soil textural classes vary from sandy-loam to clay (Eutric Regosols are grouped to sandy-loam, Eutric Fluvisols and Eutric Leptosol to loam, Chromic Luvisols and Haplic Nitisols to clay-loam, and Haplic Alisols to clay). Infiltration rates vary from moderate (hydrologic soil group B: Eutric-Leptosols and Regosols), to slow (hydrologic soil group C: Chromic Luvisols, Eutric Fluvisols), to very slow (hydrologic soil group D: Eutric Vertisol, Haplic

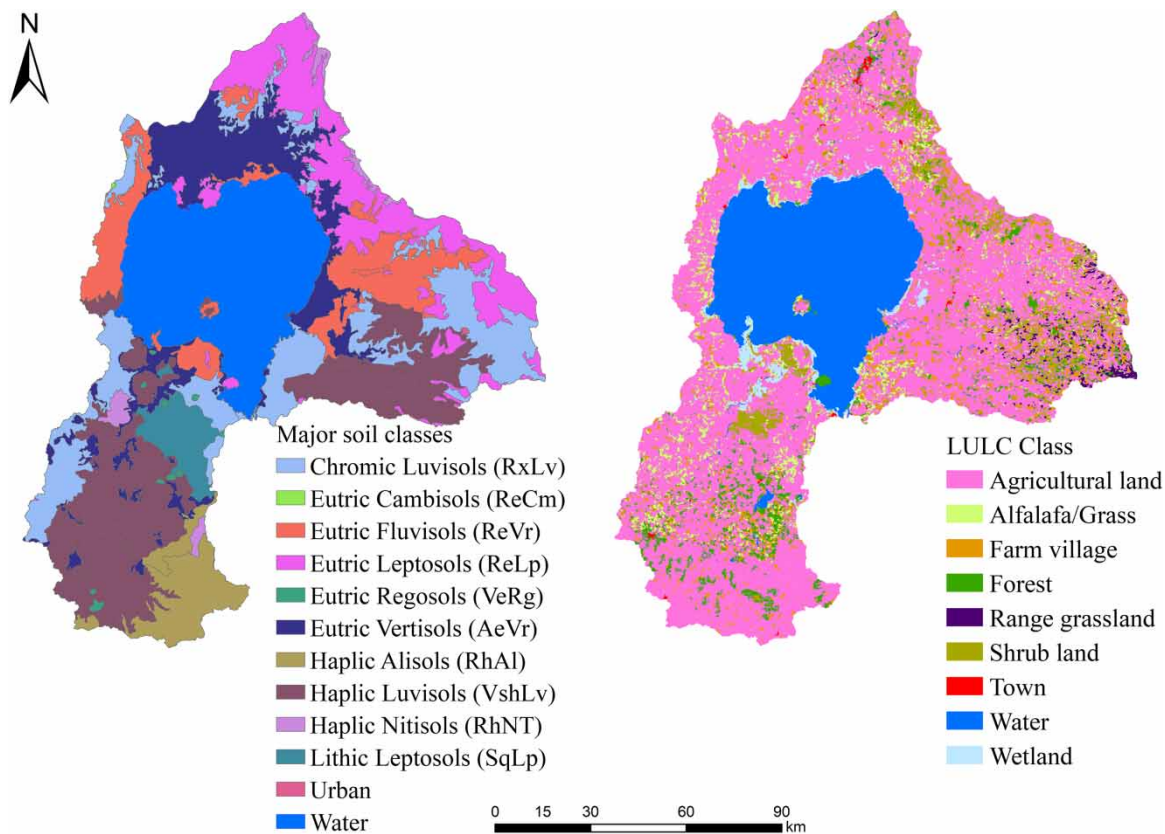


Figure 2 | Spatial distribution of major soil units (left) and land use land cover (LULC) (agricultural land, alfalfa, shrub land, forest, grassland, water body, and wetland) of the Lake Tana basin.

Alisols, Haplic Nitisols). The Shuttle Radar Topography Mission (SRTM) global digital elevation model (DEM) data with a 30 m by 30 m resolution were used as topography input data (USGS 2016).

Hydrologic modeling

To achieve the research goal of the current study, the semi-distributed, continuous eco-hydrologic model SWAT (Arnold *et al.* 1998; Arnold & Fohrer 2005) was used. The model is capable of simulating spatially distributed water balance components based on hydrological response units (HRUs). Four main steps comprise the modeling approach, as follows.

Hydrological model setup

Three independent SWAT models were set up for the three catchments Gilgelabay, Gumara, and Ribb based on available climate, land use, soil, and DEM data. No water withdrawal was considered in the model setup as this information was not available. The three independent model setups were used to better represent each catchment, e.g., by a more precise representation of the stream network. In this study, the SWAT model was not set up for the entire Lake Tana basin. Although there are measured streamflow data at the lake outlet, they could not be used to calibrate and validate the SWAT model as there is water abstraction from Lake Tana for different purposes and there is no information about the amount of water withdrawn for such purposes (Setegn *et al.* 2008).

ArcSWAT 12.102.19 was used to compile the SWAT input files and SWAT2012 revision 664 was used to run the simulations. Each catchment was divided into sub-basins. Nine land use land cover (LULC) units were used as input for the hydrologic models (Figure 2). Agricultural land is the dominant land use class in the study area (ADSWE 2017). We further split the agricultural land use class into different crop units based on their aggregate areal coverage proportions. Splitting of the agricultural land at this step allows for a detailed consideration of the spatial distribution of the crop units in each HRU (Guse *et al.* 2015). Cereal crops, vegetables, root crops, and fruit crops are the common agricultural products in Ethiopia. Cereal crops including teff, corn, sorghum, and wheat are

the dominant cereal crops both with regard to yields and area coverage. About 24%, 17%, 15%, and 13% of the national agricultural land is covered by teff, corn, sorghum, and wheat, respectively (CSA 2017). To account for the spatial variation of these crops, we calculated their coverage for each catchment based on the respective administrative zone of the Amhara Regional State Government (Awi, West Gojam, and South Gondar). The crop distributions of Awi and West Gojam zones were used to estimate the percentage distribution of agricultural crops in the Gilgelabay catchment. As the Gumara and the Ribb catchment are entirely located in the South Gondar zone, the percentage distribution of this zone was used to estimate the areal coverage of crop units in these catchments. We applied a random distribution to produce the spatial maps of the catchments based on the percentage distributions of agricultural crop units. Table 1 shows the final land use/land cover percentage distribution in the study catchments.

A static land use map was used in our model setup due to the lack of a time series of land use maps. Wubie *et al.* (2016) and Central Statistical Agency (CSA 2017) reported

Table 1 | Areal coverage of LULC types (% of total catchment area)

Crop type	Percentage of different LULC classes (areal coverage calculated from total catchment area)			SWAT code
	Gilgelabay	Gumara	Ribb	
Teff	18.50	12.11	16.50	TEFF
Barley	2.74	2.78	3.47	WBAR
Wheat	4.28	0.89	9.10	WWHT
Rice	0.00	18.70	0.00	RICE
Pulses	0.00	8.15	4.26	FPEA
Corn	26.11	4.46	9.40	CORN
Mixed crop land	14.94	14.59	15.37	AGRL
Millet	8.86	0.00	0.00	PMIL
Plantation and natural forest	11.31	6.71	2.10	FRSE
Alfalfa/Grass	2.84	2.84	9.19	ALFA
Water	0.64	0.06	0.09	WATR
Wetland	0.08	3.46	0.00	WETL
Town	0.02	0.04	0.20	URMD
Range grassland	0.38	12.78	19.50	RNGE
Farm village	9.32	12.43	10.82	URLD

that expansion rates of the agricultural land in the study area are 0.45% and 0.43% per annum, respectively. Thus, a static land use map is a reasonable approximation. For all LULC classes the respective parameter values from the SWAT model database were used, which have similarly been adapted by other studies in the region (e.g., [Setegn *et al.* 2008](#); [Dile & Srinivasan 2014](#); [Woldesenbet *et al.* 2017](#)). Planting and harvesting dates as well as potential heat units to reach maturity were adjusted for each LULC class to ensure an appropriate phenological development. Potential heat units to reach maturity were calculated based on average temperature data from the simulation period.

Physical and chemical properties of the soil parameters used for this study were converted into a parameterization for the SWAT model using pedo-transfer functions (PTFs) developed by [Saxton & Rawls \(2006\)](#). Additional information about soil characteristics were collected from different reports ([Fisseha & Gebrekidan 2007](#); [Dile & Srinivasan 2014](#); [Ayalew *et al.* 2015](#); [IUSS Working Group WRB 2015](#)). Each catchment was classified into five slope classes using the DEM. The slope classification was based on the Food and Agricultural Organization (FAO) guideline as follows: 0–2% (foot slope), 2–5% (gentle sloping), 5–8% (sloping), 8–15% (strongly sloping), and >15% (moderately steep to very steep) ([Jahn *et al.* 2006](#)). To construct a model with high spatial precision, all possible combinations of land use, soil, and slope layers were used to define the HRUs without applying commonly used thresholds ([Her *et al.* 2015](#)) resulting in 1,636, 3,623, and 795 HRUs for the Gilgelabay, Gumara, and Ribb, respectively.

While daily precipitation and minimum and maximum temperatures data were available for the period from 1980 to 2015, the continuity and consistency of relative humidity, sunshine duration, and wind speed data were not reliable. Accordingly, Hargreave's method was chosen for potential ET computation ([Hargreaves & Samani 1985](#)). Moreover, the SCS curve number method was used to estimate surface runoff. Further detailed information on the SWAT model including all processes and equations is provided by [Neitsch *et al.* \(2011\)](#).

Model calibration and validation

The most sensitive parameters that have an impact on streamflow were selected using the Sequential Uncertainty

Fitting ver. 2 (SUFI-2) in SWAT-CUP ([Abbaspour *et al.* 2007](#)). The ranges for each parameter were based on the literature ([Setegn *et al.* 2008](#); [Derib 2013](#); [Koch & Cherie 2013](#); [Woldesenbet *et al.* 2017](#)). Calibration and validation were carried out using measured streamflow at the catchment outlets (Gilgelabay near Merawi, Gumara near Bahirdar, and Ribb near Addis Zemen). The streamflow data were divided into two periods for each of the streams for calibration and validation. Five years (from 1980 to 1984) were used as a warm-up period to define appropriate initial conditions and to reach equilibrium conditions in the model. Calibration and validation periods in SWAT are selected based on availability of continuous model input data (in our case rainfall) and measured data of the output variables (streamflow in this case) that need to be calibrated/validated. In Gilgelabay catchment, there were considerable missing values in the streamflow and rainfall data between 1985 and 1987. Therefore, we excluded this period ([Table 2](#)). A multiple flow segment calibration approach using performance metrics and signature metrics was applied ([Pfannerstill *et al.* 2014a, 2014b](#); [Haas *et al.* 2016](#)). This calibration procedure was conducted using different packages of R including FME ([Soetaert & Petzoldt 2010](#)) to calculate parameter settings based on the Latin hypercube algorithm and hydroGOF ([Zambrano-Bigiarini 2014](#)) to evaluate model performance. Ten sensitive parameters were used in the calibration process, and methods applied to change values for the calibrated parameters are listed in [Table 3](#). Six thousand model runs per catchment were conducted with different parameter sets. The best parameter combination was selected based on the Nash–Sutcliffe efficiency (NSE) of observed and simulated streamflow. Furthermore, the values of Kling–Gupta efficiency (KGE), percent bias (PBIAS), and standardized root mean square error (RSR) were considered. The best performing parameter sets found during the calibration period were validated by analyzing model output for the

Table 2 | Warm-up, calibration, and validation periods for the three study catchments

Catchment	Warm up	Calibration	Validation
Gilgelabay	1980–1984	1988–1996	1997–2011
Gumara	1980–1984	1985–1995	1996–2014
Ribb	1980–1984	1985–1997	1998–2014

Table 3 | List of sensitive parameters used for calibration of the models

Name of parameter	Minimum value	Maximum value	Method	Fitted values		
				Gilgelabay	Gumara	Ribb
SCS runoff curve number (CN2)	-15	15	Add	-6.13	-7.27	-7.362
Surface runoff lag time (SURLAG)	0.05	24	Replace	18.9968	2.8383	11.271
Water capacity of the soil layer (SOL_AWC)	0	1	Add	0.1633	0.1547	0.1695
Saturated hydraulic conductivity (SOL_K)	0	1	Add	0.6357	0.811	0.8369
Soil evaporation compensation factor (ESCO)	0	1	Replace	0.951	0.884	0.7352
Plant uptake compensation factor (EPCO)	0	1	Replace	0.044	0.730	0.6285
Groundwater delay (GW_DELAY)	1	100	Replace	7.9005	4.0970	4.2153
Deep aquifer percolation fraction (RCHRG_DP)	0	1	Replace	0.2806	0.2244	0.2066
Baseflow alpha factor (ALPHA_BF)	0	1	Replace	0.2510	0.0902	0.1803
Groundwater revap coefficient (GW_REVAP)	0.02	0.2	Replace	0.0252	0.0244	0.0242

validation period. No additional data on the water balance components, e.g., ET, were available for validation.

Spatial analysis

The major water balance components, such as surface runoff contribution to the stream channel, actual ET, and groundwater recharge from the beginning to the end of the period (calibration and validation periods) were extracted for each HRU on a monthly basis and aggregated on a seasonal basis. These data were mapped to the catchment areas to visualize the spatially distributed model output (Wagner & Waske 2016). The major water balance components were mapped in order to identify potential areas of groundwater recharge. Special attention was given to the impacts of agricultural crop units on groundwater recharge, ET losses as well as surface runoff generation. The groundwater recharge in SWAT can be divided into shallow and deep aquifer recharge (Gemitzi *et al.* 2017). In this study, groundwater recharge refers to the proportion of rainfall that enters the shallow aquifer before it is partitioned into shallow and deep aquifer recharge.

Statistical test

The annual hydrologic responses (surface runoff, ET, and groundwater recharge values) of different crop units were tested for significant changes using the Mann-Kendall

(MK) trend test. The MK test is a non-parametric test which has been widely used to test for significant change in time series (e.g., Gautam *et al.* 2010; Tekleab *et al.* 2013; Hawtree *et al.* 2015; Tigabu *et al.* 2018). Furthermore, the variabilities of water balance components among different crop units and between Gilgelabay, Gumara, and Ribb were tested using a one-way ANOVA test. This test is widely applied in hydrology (e.g., Zegeye *et al.* 2010; Anibas *et al.* 2011). A significance level of 5% was applied in this study. Our hypothetical assumptions are that changes in the major water balance components under different crop covers, dry and wet seasons, and between the three catchments were insignificant.

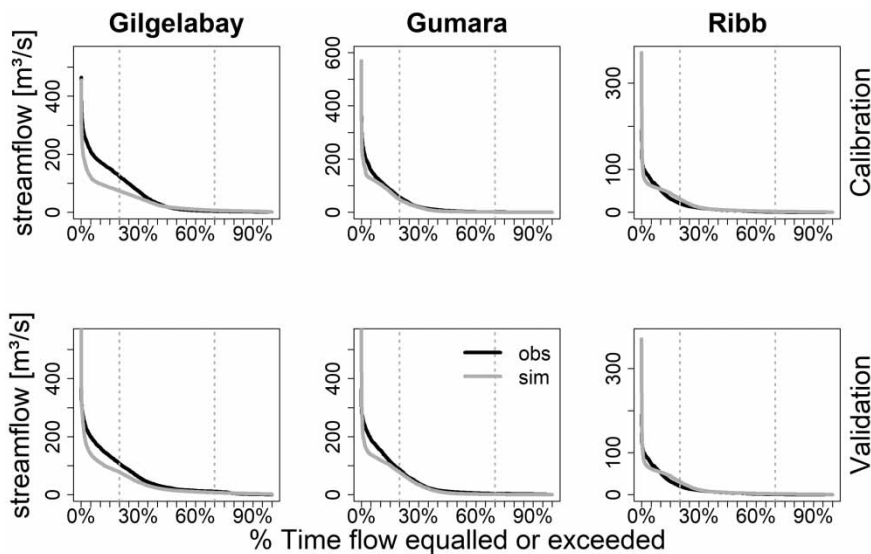
RESULTS

Model performance

The model output indicates satisfactory model performance at a daily time step, as the values of NSE, R^2 , and KGE were greater than 0.5 and the PBIAS values were in the range of $\pm 25\%$ in all three study catchments during both the calibration and validation periods (Moriasi *et al.* 2007; Table 4). At a monthly time step, the model performance was better in all catchments (Table 4). The good fit of observed and simulated streamflow was also indicated by the flow duration curves (Figure 3) and hydrographs

Table 4 | Daily and monthly model performance measures of different objective functions

Obj. function	Gilgelabay		Gumara		Ribb	
	Calibration (day/month)	Validation (day/month)	Calibration (day/month)	Validation (day/month)	Calibration (day/month)	Validation (day/month)
NSE	0.53/0.71	0.54/0.94	0.65/0.80	0.53/0.79	0.67/0.85	0.67/0.95
KGE	0.59/0.50	0.58/0.62	0.74/0.76	0.62/0.70	0.77/0.77	0.82/0.92
R ²	0.75/0.83	0.59/0.83	0.63/0.83	0.63/0.83	0.78/0.86	0.72/0.95
PBIAS	22.4/6.89	23.5/16.95	13.3/16.76	22.1/21.09	3.6/2.80	5/0.04
RSR	0.68/0.54	0.80/0.25	0.65/0.45	0.68/0.46	0.57/0.38	0.58/0.23

**Figure 3** | Flow duration curves of simulated (sim) and observed (obs) daily streamflow values for calibration and validation periods of the study catchments.

(Figure 4). The low and middle flows showed a good agreement between the observed and simulated values. On the contrary, the flow duration curve segment from 5% to 20% exceedance probability indicated an underestimation of streamflow by the model, especially in the Gilgelabay and Gumara catchments.

Impacts of agricultural crops on water balance components

General water balance

The water balance can be used to characterize a catchment. Rainfall is the only input variable of the water balance equation in our modeling approach. ET and water yield

are the main modeled output components of the water balance. In addition, we analyzed SURQ (surface runoff) and recharge. In all three catchments, more than 75% of the hydrological processes are taking place during the wet (summer) season. The simulated annual values indicated that the mean ET loss of the catchments accounts for 54% (Gilgelabay) and 44% (Gumara and Ribb) of the annual rainfall. Water yield from the HRUs accounted for about 45%, 53%, and 54% of the rainfall in Gilgelabay (759 mm), Gumara (783 mm), and Ribb (832 mm) catchments, respectively. The annual share of water yield from annual rainfall at the HRU level varied within each catchment (Figure 5) from 14% to 65% (Gilgelabay), 44% to 65% (Gumara), and 43% to 65% (Ribb). The groundwater return flow contributed more than 50% of the water yield in each catchment.

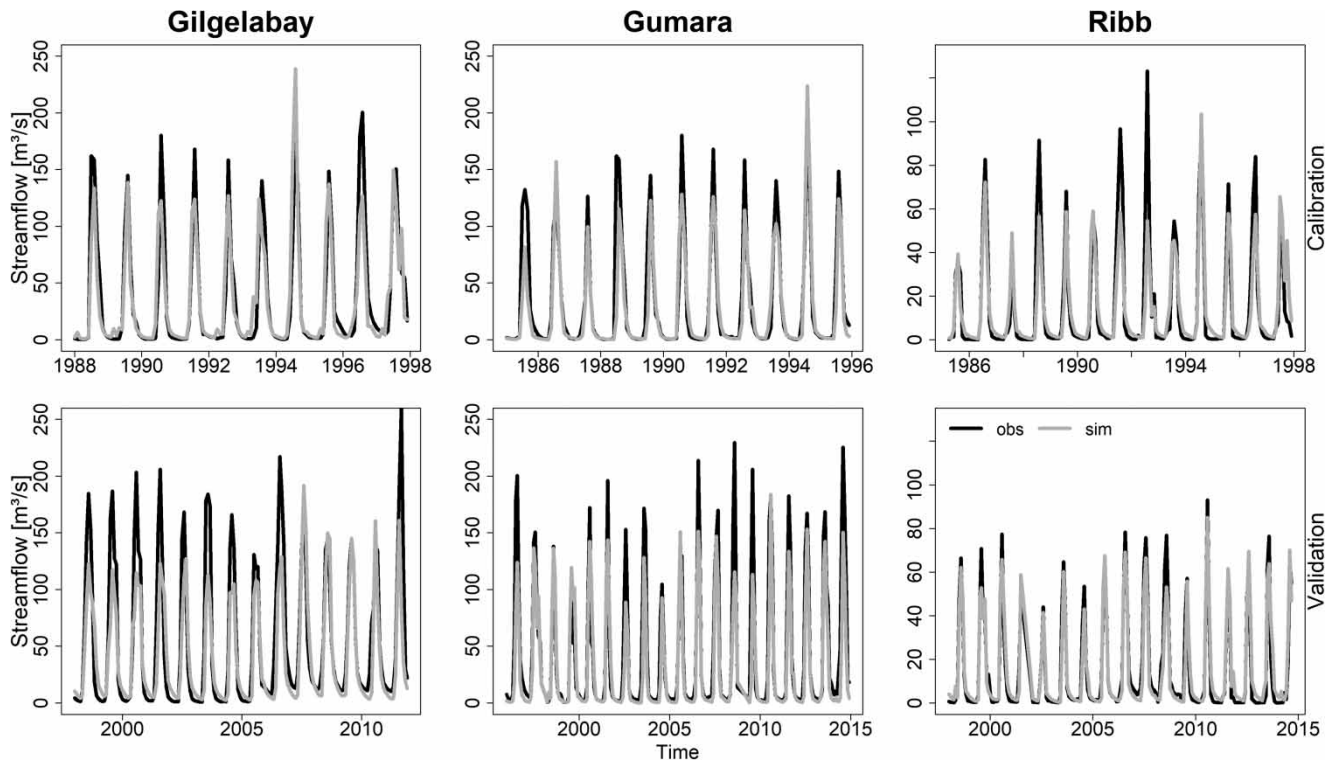


Figure 4 | Monthly time series plots of observed (obs) and simulated (sim) streamflow of Gilgelabay, Gumara, and Ribb for calibration and validation periods.

The water yield showed significant spatial variation in Gilgelabay and Ribb catchments with the southern and south-western part of Gilgelabay and eastern and north-eastern part of Ribb catchments experiencing high water yields. In Gilgelabay catchment, rainfall input was taken from four stations and the spatial patterns of ET and water yield followed the rainfall pattern (Figure 5). Whereas in Ribb catchment, spatial variations in ET and water yield were caused by the soil and land use variations. Additionally, other catchment properties such as slope affect the spatial variation in water yield. Except for some hot spots with higher water yields, the Gumara catchment had a relatively uniform spatial distribution of water yield when compared to the other two catchments. In general, high water yield corresponds to low ET loss and vice versa (Figure 5).

ET loss from different LULC units was generally similar in Gumara and Ribb catchments, although there were a few differences (Figure 6). Areas covered by natural and plantation forest are areas that have the highest ET and teff has the smallest amounts of average annual water

loss by ET in Gumara and Ribb catchments. Gilgelabay catchment differs from the other two with respect to ET loss due to variable rainfall input. In this case, medium density urban settlement areas have the highest and corn has the smallest absolute amount of ET. However, the percentage of ET from rainfall is lower for urban areas (56%) as compared to forests (60%). Other LULC units (forest, urban, wetland, range land, alfalfa, and rural residential) show different ET values also depending on the soil unit as well as slope class (Figure 6). The majority of the statistical test results showed that the variations in ET values among the crop and other land use classes were statistically significant. The differences in ET values among the different crops and other land use classes could be a result of differences in water uptake, available water capacity, and leaf area indices. However, there were a few exceptional cases that showed insignificant variations, for example, between corn and mixed crop land, barley and pea in Ribb catchment, between pea and mixed crop land in Ribb and Gumara, and between barley and wheat in Gilgelabay catchment.

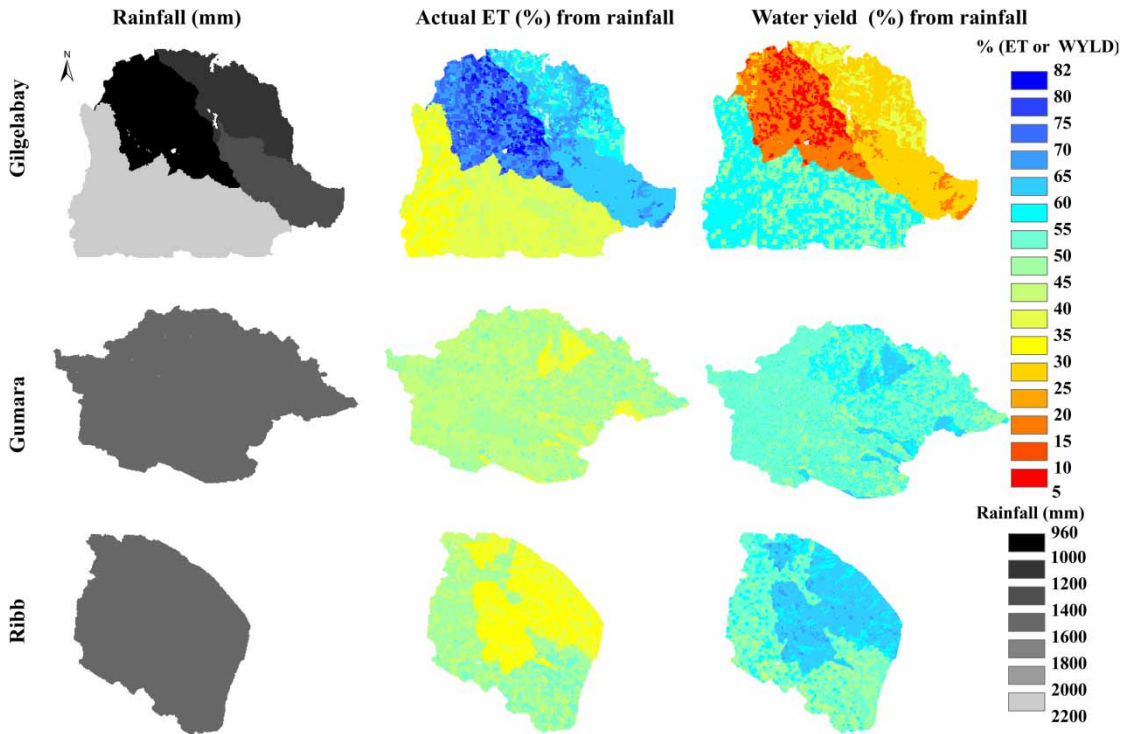


Figure 5 | Spatial distribution of annual rainfall, ET (%), and water yield (%) of Gilgelabay, Gumara, and Ribb catchments.

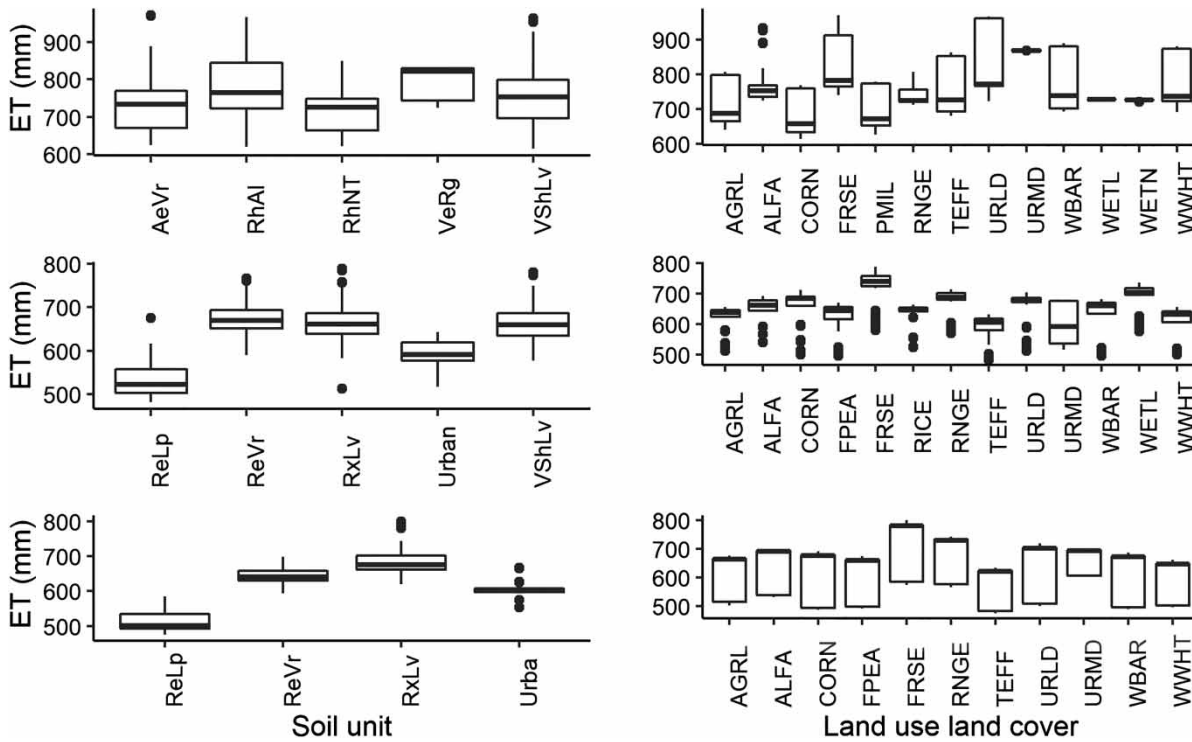


Figure 6 | Boxplots showing the annual mean actual ET of HRUs for different land use/land cover and soil units of Gilgelabay (first row), Gumara (second row), and Ribb (third row) catchments.

Additionally, ET values vary based on the spatial distributions of soil units in the Gumara and Ribb catchments. Low ET values are associated with Eutric Leptosol (Figures 2, 5, and 6) for both catchments due to the high infiltration capacity of this soil. High ET values cannot be linked to a single soil unit but appear on different HRUs. However, the mean ET values corresponding to Eutric Regosol (in Gilgelabay), Eutric Fluvisol (in Gumara), and Chromic Luvisol (in Ribb) indicated the highest values compared to the ET loss on other soil units in each catchment and Haplic Nitosol was associated with the lowest mean ET in Gilgelabay catchment (Figure 6). The inter-catchment comparison indicated that the annual ET losses in Gilgelabay catchment were significantly higher than in Gumara and Ribb catchments with differences varying between 104 mm and 133 mm. These can be explained by the significant variation of rainfall inputs between Gilgelabay and the other two catchments. On the contrary, the differences between Gumara and Ribb ranges from 2 mm to 26 mm were statistically insignificant.

Runoff analyses

Surface runoff varied considerably in time and space in the study catchments (Figure 7). In all three catchments, about 90% of the total surface runoff was generated during the summer months and the remaining 10% occurred during the other eight months. The runoff coefficients varied spatially among and within the three catchments due to changes in LULC and rainfall. The annual runoff coefficients (the ratio of total streamflow to rainfall) were 0.32, 0.43, and 0.46 in Gilgelabay, Gumara, and Ribb, respectively. The variability of surface runoff was linked to the LULC, soil type, topography of the area, as well as the associated model parameter values. HRUs covered by medium density urban settlements, farm settlements, and mixed cropland areas had a strong effect on increasing the magnitude of surface runoff. In the Gilgelabay catchment, the mean annual surface runoff of HRUs decreased from farm village, corn, mixed cropland, wheat, millet, barley, teff, permanent wetland, seasonal wetland, alfalfa, and range grassland to evergreen forest. Differences among

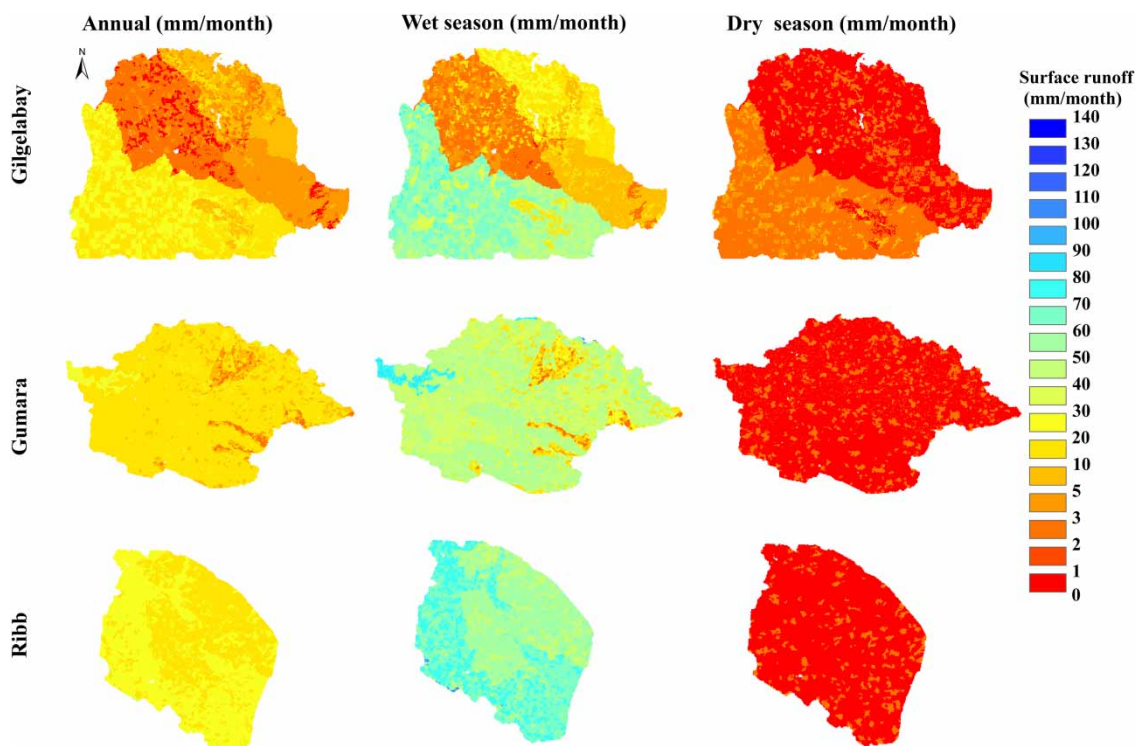


Figure 7 | Average surface runoff distribution for the year (all months), the wet season (June to September), and the dry season (October to May) for Gilgelabay, Gumara, and Ribb catchments.

some agricultural crops and other LULC classes were significant. For example, the changes between corn and other land use and crop classes (forest, wetland, grassland, millet, barley, wheat, and teff) vary from 14 mm to 83 mm and all of the changes were significant. Compared to other agricultural crop units, corn and teff had the highest and lowest response in runoff generation. These results can be explained by the lower runoff curve number value in the case of teff and vice versa in the case of corn. In Gumara and Ribb catchments, surface runoff on urban land cover was the highest. The effects of some of the LULC classes varied between the three catchments. For instance, teff, corn, and generic agriculture HRUs had a slightly different order with regard to the effect on runoff generation between the three catchments. In the Gilgelabay and Gumara catchments, the effect of teff on runoff generation was slightly weaker than corn, while in Ribb catchment teff had a stronger effect than corn (Figure 8). This implies that besides LULC, other HRU properties like soil, slope, and climate cause a combined effect on runoff response. Other LULC classes had similar effects on surface runoff response in

all the catchments (e.g., urban, forest, rural settlement, barley, and wheat). In addition to spatial variability, surface runoff varied seasonally (Figure 7 and Table 5). The annual pattern was mainly defined by the wet season and the surface runoff pattern in the dry season differed considerably from the annual and wet season pattern. Significant differences were observed between the three catchments regarding their runoff responses. Compared to Ribb and Gilgelabay catchments, the vast majority of annual and wet season runoff values of Gumara catchment were higher. The Ribb catchment also showed significantly higher runoff than the Gilgelabay catchment. Therefore, the Gumara catchment is highly susceptible for runoff, whereas Gilgelabay is less susceptible compared to the other two catchments.

Recharge analysis

Quantifying groundwater recharge from agricultural land is important to maintain sustainable water use all over the world. It is highly important in areas like the Lake Tana

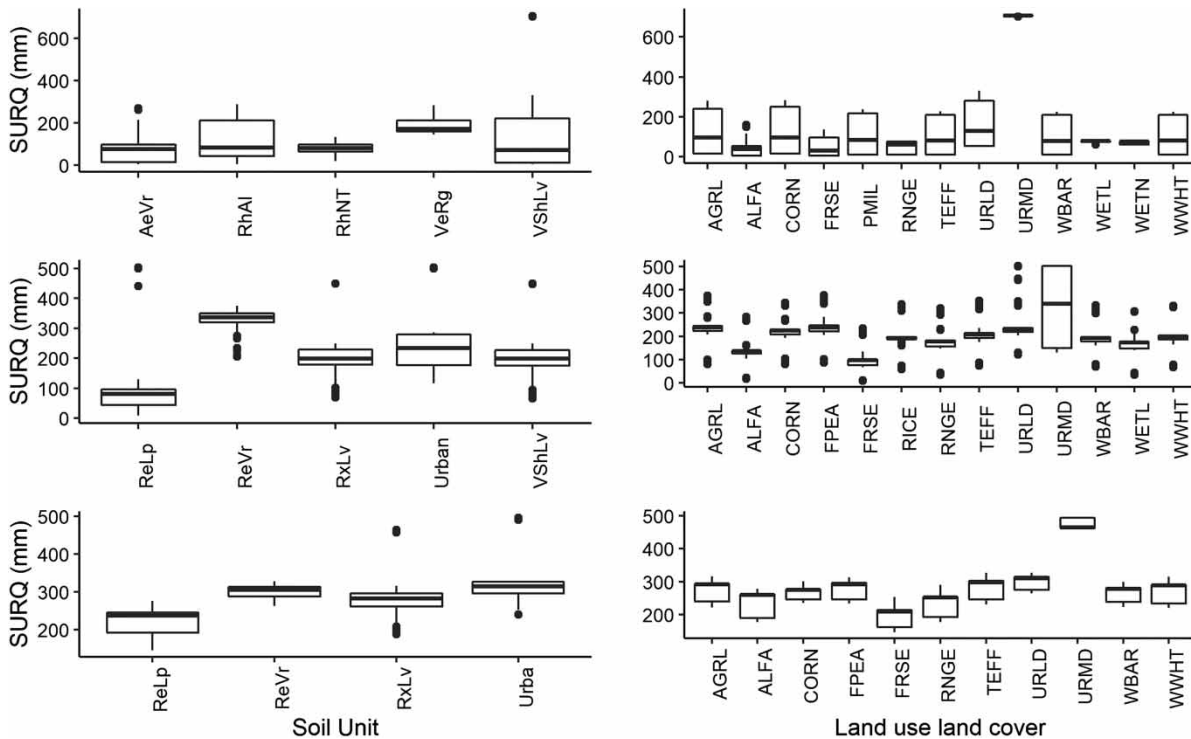


Figure 8 | Boxplots showing the annual surface runoff of HRUs for different land use land cover and soil units of Gilgelabay (first row), Gumara (second row), and Ribb (third row) catchments.

Table 5 | Annual and seasonal water balance components of the three catchments

	Gilgelabay			Gumara			Ribb		
	Annual	Dry season monthly average	Wet season monthly average	Annual	Dry season monthly average	Wet season monthly average	Annual	Dry season monthly average	Wet season monthly average
Rainfall (mm)	1,453.0	41.0	281.3	1,466.2	22.3	289.0	1,475.1	22.3	291.6
SURQ (mm)	108.8	1.1	24.9	190	1.8	44	265.9	1.9	62.7
ET (mm)	785.6	46.8	102.8	650.4	40.6	81.5	644.2	42.3	76.4
WYLD (mm)	648.0	22.5	118.0	728.0	13.0	156.0	752.0	11.0	166.0

basin, where most of the streams are perennial and get a substantial amount of their flow from groundwater discharge. There was a high degree of spatial and seasonal variation in groundwater recharge (Figure 9). Annual mean recharge (before partitioning into shallow and deep aquifer recharges) values were 561, 560, and 557 mm and the annual mean deep aquifer recharge values were 188, 135, and 115 mm for Gilgelabay, Gumara, and Ribb, respectively. Gumara catchment had the highest mean annual shallow aquifer recharge (457 mm) and Gilgelabay had the

lowest (373 mm). However, Gilgelabay had the highest average wet season monthly deep recharge (41 mm). LULC patterns had a strong influence on groundwater recharge rates with a contrasting effect on actual ET (Figures 5 and 9). In combination with soil properties and mean slopes, agricultural crops impacted the groundwater recharge response. The effect of LULC classes on groundwater recharge varied between the three catchments. In the Gilgelabay catchment, millet and corn had the highest and second highest recharge rates. However, the ranking

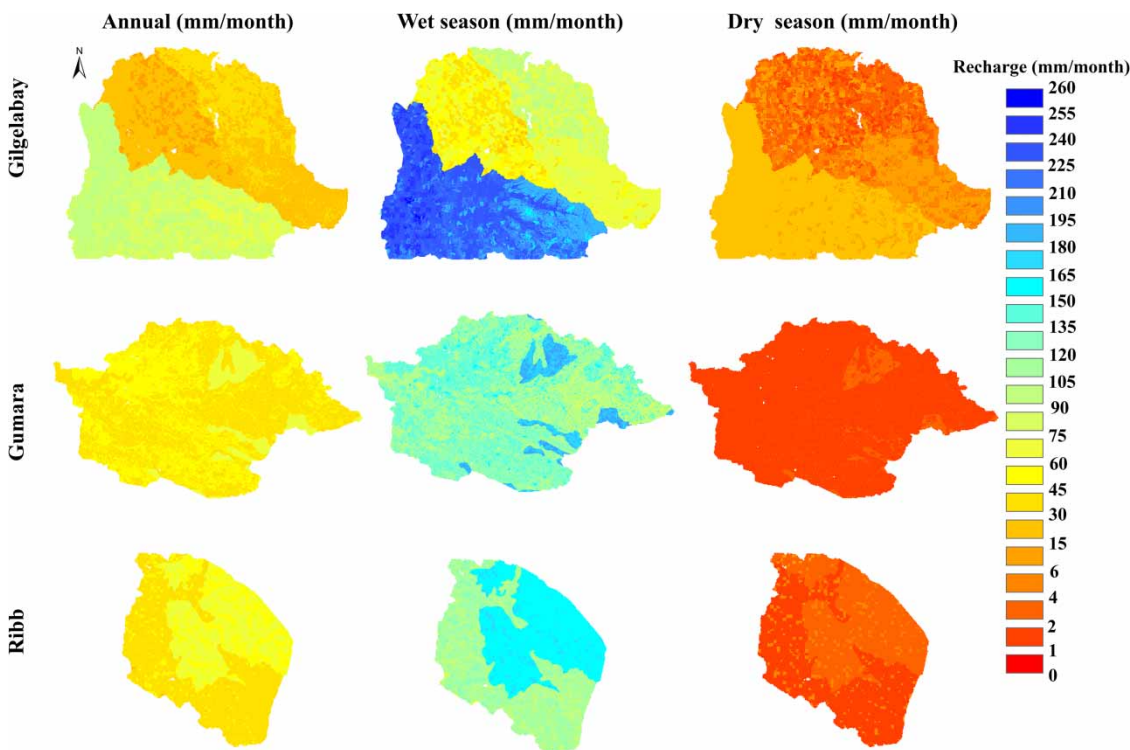


Figure 9 | Average groundwater recharge distribution of annual, wet season (June to September), and dry seasons (October to May) values (in mm) per month for Gilgelabay, Gumara, and Ribb catchments.

differed in terms of volumetric contribution. Nearly 50% of the total wet months recharge volume was contributed from corn- and teff-HRUs (corn, 29% and teff, 20%) as they covered a larger portion of the catchment (Table 1). These are mostly found in the south-western and western parts of the catchment that receive high amounts of rainfall (Figures 5 and 9). On the contrary, corn was among the LULC classes that had a low recharge rate in the case of Gumara (Figure 10). This indicated that other catchment properties also played a role in influencing recharge rates. In the Ribb catchment, agricultural areas covered by teff had the highest average annual (614 mm) recharge to the shallow aquifer. Urban areas had the lowest groundwater recharge in both Gumara and Ribb catchments (Figure 10). For the Gilgelabay catchment, the mean annual groundwater recharge in medium density urban areas was higher compared to other land uses due to the highest rainfall input, but its percent share of rainfall was the lowest of all LULC classes (26%). For other LULC, 28% to 44% of the rainfall recharged the shallow aquifer. As a whole, our

statistical test results indicated that there were significant variations in the rates of recharge among the different agricultural crops and other LULC classes between and within the three catchments. Therefore, our initial hypothetical assumption (no significance changes on the recharge rates among different land cover units) was rejected. For example, the recharge rates of forest areas were significantly lower than the recharge rates of agricultural areas (teff, barley, wheat, etc.) for all three catchments. Comparing recharge rates among the agricultural crop units showed that cereal crops (barley, corn, rice, teff, and wheat) had significantly higher recharge rates than leguminous (pea) and mixed cereal crop units. In addition to the LULC, the impact of soil units on recharge rate was obvious in all catchments. Areas covered by Eutric Regosols and Eutric Leptosols were identified as high groundwater recharge areas. In Gilgelabay catchment, areas covered by Eutric Regosols had the highest groundwater recharge rate whereas Haplic Nitisols had the lowest. In both Gumara and Ribb catchments, Eutric Leptosols had the highest average groundwater

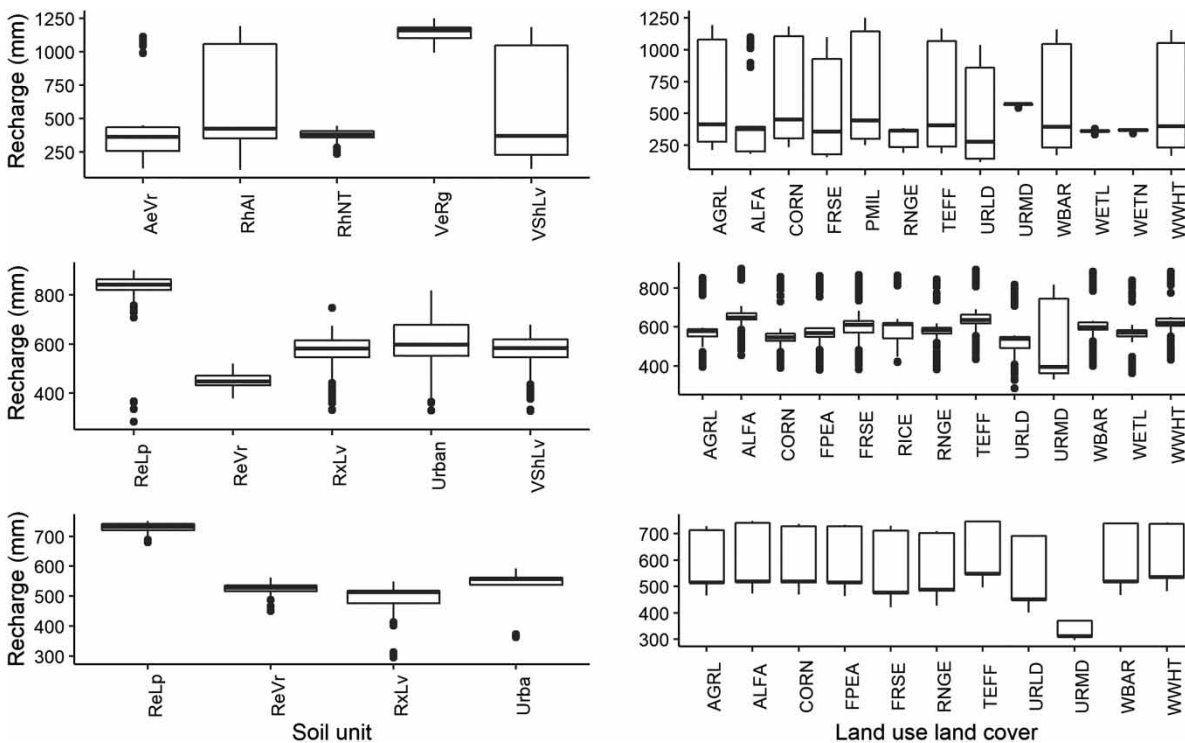


Figure 10 | Boxplots showing the annual groundwater recharge to the shallow aquifer for different LULC and soil units of Gilgelabay (first row), Gumara (second row), and Ribb (third row) catchments.

recharge, while Eutric Fluvisols and Chromic Luvisols had the lowest recharge (Figure 10).

Temporal analysis

Annual values of the hydrologic responses for dominant crop classes were analyzed. The inter-annual variabilities of these hydrologic responses are mostly driven by changes in the weather input (Figure 11). The annual values of water yield, ET, surface runoff, and groundwater recharge are a function of the temporal pattern of the rainfall inputs. As we used a static land use map for the modeling, most of the changes induced by agricultural crops are seasonal (Figures 7 and 9). The MK trend test was applied to test for significant changes on inter-annual variabilities of the hydrologic fluxes. The MK test results showed that there were no significant changes on the inter-annual variabilities of water balance components (p -value > 0.05). In general, ET is less affected by the inter-annual rainfall variability as compared to the other variables. However, a rainfall deficit (e.g., in 1991) has a stronger effect on ET than a rainfall surplus (e.g., 2006).

DISCUSSION

In this study, the impacts of agricultural crop units on the spatial and seasonal variation of the major water balance components were analyzed for the first time in the Gilgelabay, Gumara, and Ribb catchments of the Lake Tana basin, Ethiopia. The effects of HRU components (LULC, soil, and slope) on catchment water yield, ET, surface runoff, and groundwater recharge were assessed. A calibrated SWAT model was used to simulate the aforementioned water balance components from 1985 to 2014 assuming the recent temporal change on agricultural crop cover is minimal (CSA 2017). The dominant agricultural classes such as cereals, leguminous, and mixed cereals together with other land use classes were considered in the model. Our model performances were evaluated based on flow duration curves and hydrographs of simulated and observed streamflow values (Figures 3 and 4). The patterns of simulated and observed streamflows indicated consistency between each other for both calibration and validation periods. However, there are slight differences

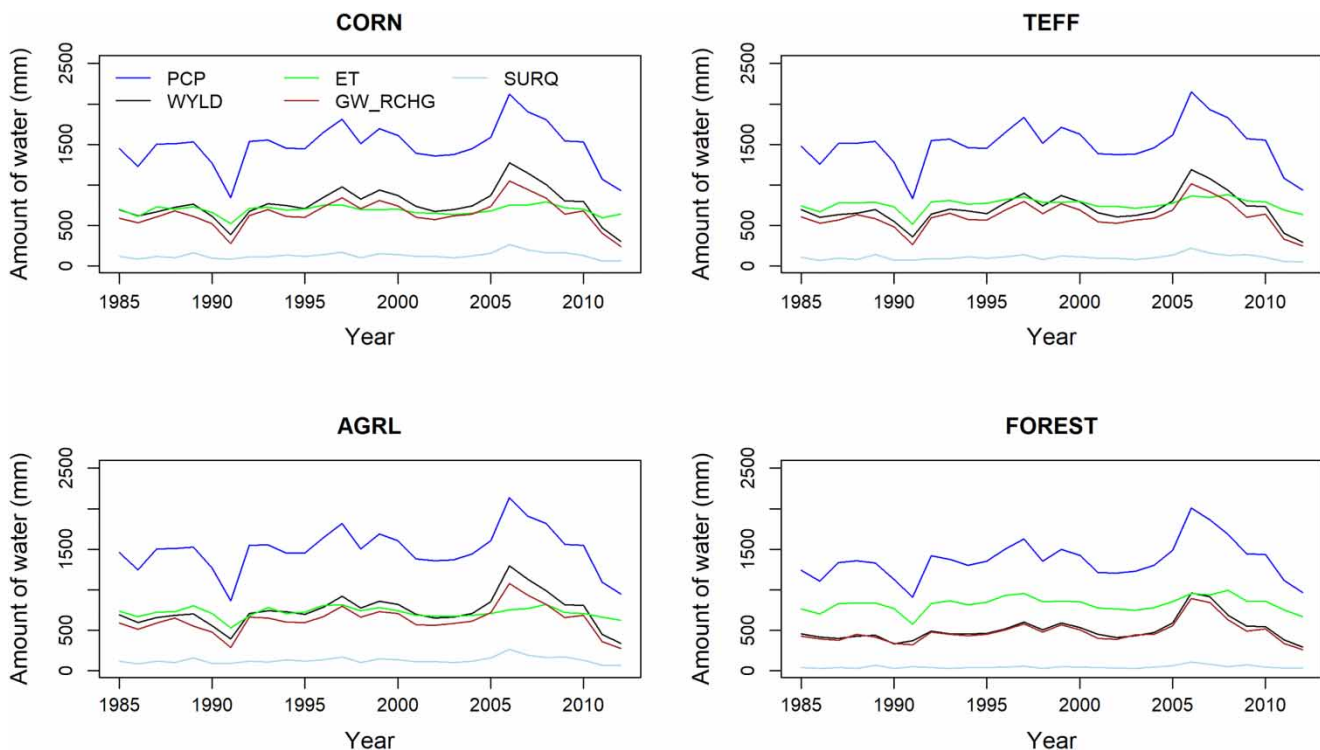


Figure 11 | Annual temporal distribution of rainfall (PCP), water yield (WYLD), actual evapotranspiration (ET), groundwater recharge (GW-RCHG), and surface runoff (SURQ) values under different LULC conditions in Gilgelabay catchment.

on the statistics of the model efficiencies reflecting the temporal dynamics of streamflow data (Fohrer *et al.* 2002). The model efficiencies were comparable with the results of Setegn *et al.* (2008) and Woldesenbet *et al.* (2017). However, our analysis of the flow duration curves indicates that there is a disparity between the measured and modeled high flows (between 5% and 20% exceedance probabilities with an RSR value 1.41) in the Gilgelabay catchment. This disparity on the high flow segment might be linked to the limitation of the curve number method, as the SCS-curve number method used in the SWAT model does not consider the duration and intensity of rainfall (Nie *et al.* 2011; Woldesenbet *et al.* 2017). The NSE for Gilgelabay catchment showed the lowest performance (0.53) compared to the other two catchments (Table 4), which also pointed to the disparity on the high flow segment of the FDC as NSE is known to give higher weights to high flows than to low flows (Guse *et al.* 2017). The underestimation of high flows can, to a lesser extent, be seen in the FDC for Gumara, whereas the FDC for the Ribb catchment indicates a much closer match.

The spatial and seasonal distribution of the modeled hydrological components groundwater recharge, surface runoff, water yield, and ET was analyzed. However, an independent validation of the spatial distribution of ET and water yield was not possible due to a lack of measured data. The accuracy of the derived patterns of ET and water yield relies on the model validity, which was tested with measured streamflow data at the catchment outlet using a multi-metric approach and flow duration curves. In addition, the seasonal development of the leaf area index was checked for all land use classes to provide further confidence in the model calculation. In our study, the Hargreaves method (Hargreaves & Samani 1985) was used to compute potential ET, which has been applied in several SWAT model studies in Africa (e.g., Setegn *et al.* 2008; Notter *et al.* 2012; Woldesenbet *et al.* 2017). In addition, Odusanya *et al.* (2019) compared the Hargreaves, the Penman–Monteith, and the Priestley–Taylor method in SWAT for a catchment in Nigeria, and found that the ET values computed using the Hargreaves method showed good agreement with satellite-based ET patterns. These studies provide further confidence in the accuracy of the derived ET patterns.

Likewise, the validity of the simulated surface runoff and groundwater recharge were not verified independently.

However, model outputs of the current study were compared to similar studies in the region. In this study, the runoff coefficients calculated from the simulated discharge were 0.32, 0.43, and 0.46 for Gilgelabay, Gumara, and Ribb, respectively. A study conducted on the effects of the floodplain on river discharges into Lake Tana by Dissie *et al.* (2014) reported that the runoff coefficient in the upper catchments of the Lake Tana basin vary between 0.23 and 0.81 with an average value of 0.5. The simulated runoff coefficients from our study are within this range. Furthermore, the ratios of average surface runoff to total streamflow found in our study were 0.23, 0.28, and 0.35 for Gilgelabay, Gumara, and Ribb, respectively. In support of these values are the findings by Jemberie *et al.* (2016), who reported that the average surface runoff to total streamflow ratio of the Lake Tana basin is 0.28.

In this study, the modeled water balance components showed a high degree of variation in their spatial and seasonal distribution. These spatial variations are due to variations in LULC types, soil permeability and porosity, and slope class of the area, as well as varying climatic input data. The seasonal variations are induced due to the temporal variation of rainfall and variation in the canopy coverage of the different crops during the wet and dry seasons. The water balance analysis indicates that different HRU components (LULC/crop, soil, and slope classes) do not equally affect the catchment's hydrology. The influence of slope is smaller when compared to soil and crop types. When the groundwater recharge and surface runoff generation were analyzed for different slope classes under the same land use (teff) and soil (Eutric Leptosol), the observed variation was about 1%. On the contrary, the groundwater recharge and surface runoff showed significant variations (from 47% to 50%) when Eutric Leptosols is changed to Haplic Luvisols for an HRU with teff and foot slope. Thus, variations in vegetation and soil types have a higher influence than slope in our simulation results. The changes in the water balance components were also significant between different agricultural crop units. Similarly, Li *et al.* (2019) reported a substantial impact on the hydrology of Wei River basin due to expansion of cropland. As an example, in the Gumara and Ribb catchments, the groundwater recharge over time in areas covered by teff was significantly higher than the groundwater recharge in areas covered

by other agricultural crops. In the Gilgelabay catchment, HRUs with agricultural area covered by millet have the highest average groundwater recharge followed by agricultural land covered by corn. These higher recharge rates on teff and millet crop cover areas might be linked to the lower water demand for evaporation as the water interception capacity and leaf area index values are lower than in other LULC units like forest and shrub lands. Moreover, forest cover and shrub land areas had less recharge compared to cropland because a larger amount of water was evapotranspired. The results are in agreement with the findings of [Nie *et al.* \(2011\)](#), who studied the impact of LULC change on the hydrology of the upper San Pedro watershed. Their scenario-based simulation indicated that the baseflow/percolation decreased when grassland was replaced by shrub land. A study by [Gumindoga *et al.* \(2014\)](#) on predicting streamflow for land cover changes in the Gilgelabay catchment also reported a higher groundwater recharge on agricultural areas than forest areas. Their findings are in agreement with the current study. The other crop types also exhibit different recharge rates based on the daily water needs and the phenological stage. Cereal crops like millet, teff, wheat, and barley show relatively good recharge due to less water interception and transpiration demand even in a full development stage when compared to mixed crops, pulses, and rice. Our results are in agreement with research findings of [Fohrer *et al.* \(2001\)](#), who reported that the baseflow was increased for an area covered with barley compared to forest cover due to the lower water interception capacity of barley in Germany. Therefore, it can be concluded that cereal crops such as teff, barley, wheat, and millet enhanced the groundwater recharge by reducing ET and surface runoff in the three catchments. Additionally, our runoff analysis results indicated that agricultural crops, such as pea increased runoff when compared to other agricultural crop, classes. Hence, an expansion of agricultural crops like pea affects the water availability in the region, which should be considered during decision-making processes.

The spatial dynamics of the hydrologic components for Gilgelabay catchment showed similar patterns to the differing rainfall input. The sub-basins located on the southern and south-western parts of the catchment have the highest amount of rainfall and are characterized as a high groundwater recharge and surface runoff zone ([Figures 5, 7, and 9](#)).

This part of the catchment, which accounts for about 15% of the total area, has the highest runoff response due to high rainfall intensity, steep slope classes, and Haplic Alisols. A secondary clay minerals assemblage domination is a typical feature of Haplic Alisols, which could cause high runoff response ([IUSS Working Group WRB 2015](#)). In the Gumara and Ribb catchments only one rainfall station was used, so that LULC and soil units have more influence on the spatial patterns of hydrologic components than rainfall. There is a high degree of spatial variability of the hydrological processes as the soil units change from Eutric Leptosols (mainly dominated by gravel and sand, and belongs to hydrologic soil group B) to texturally clay dominated Eutric Vertisols and Chromic Fluvisols, which belong to hydrologic soil group C and D, respectively. The northern and south-eastern parts of Gumara and Ribb catchments, which are covered by Eutric Leptosols (hydrologic soil group B), are relatively good groundwater recharge zones. The reason for this is that Eutric Leptosols are sand dominated and characterized by many coarse fragment soil particles ([IUSS Working Group WRB 2015](#)). The highest amount of surface runoff occurred on areas covered by Eutric Fluvisols (hydrologic soil group D). Thus, soil class boundaries are good benchmarks to map groundwater recharge zones in the catchments ([Figure 9](#)). With respect to LULC, agricultural areas covered by teff and wheat have the highest groundwater recharge potential due to their low leaf area index, which allows for more infiltration. Low density rural settlement areas are characterized by the lowest groundwater recharge and highest surface runoff. The higher surface runoff which is seen in settlement areas due to impervious surfaces is well supported by the literature: [Zhang *et al.* \(2016\)](#), who studied hydrological responses to land use change scenarios under constant and changed climatic conditions of the Heihe River basin, China, reported that developed lands produced higher runoff than cultivated and grassland and [Wagner *et al.* \(2016\)](#) linked an increase in urban area to an increase in water yield on the sub-basin level in a meso-scale catchment in India and, the increase in runoff to the onset of monsoon. The absolute values of ET decreased from forest cover to cultivated land for all three catchments due to the high canopy storage, leaf area index, and transpiration demand for forest cover compared to cropland ([Nie *et al.* 2011](#)). In

the case of the Gilgelabay catchment, urban and rural settlements have the highest average annual actual ET due to high rainfall input. However, their percentage shares from the total rainfall (urban, 40% and rural settlements, 56%) are still less than forest (60%) (Figure 6).

The overall mean annual ET loss from annual rainfall accounts for 54% in Gilgelabay and for 44% in Gumara and Ribb. Setegn *et al.* (2008) reported that more than 60% water is lost as ET. This variation could be due to the differences in the model setups and periods of simulation, as well as variation of the LULC data that were used. Setegn *et al.* (2008) used a single SWAT model for the whole Lake Tana basin with 10%, 20%, and 10% threshold values of LULC, soil, and slope, respectively, whereas the current study was carried out by setting up three independent models for Gilgelabay, Gumara, and Ribb catchments using highly refined LULC data (with no threshold limit for LULC, soil, and slope). Our findings showed significant dynamics of the hydrologic components between the wet and dry seasons. More than 90% of the groundwater recharge and surface runoff and about 49% of the ET took place during the wet season. This implies that the influence of rainfall for the hydrologic processes in the region is significant. The total streamflow values are dominated by the baseflow in all the three catchments (73%, 62%, and 60% of the total streamflow in Gilgelabay, Gumara, and Ribb, respectively). Setegn *et al.* (2008) reported a value of 59% for the Gilgelabay catchment. The higher baseflow contribution for the Gilgelabay catchment in this study may be due to the higher fitted values of SURLAG and ALPHA_BF, which affect the runoff and baseflow response. Moreover, baseflow is a function of catchment area, and geomorphological, geological, and hydrogeological parameters of the catchment (Wosenie *et al.* 2014). In this study, the effect of catchment area on baseflow contribution was reflected. The Gilgelabay catchment, which is the largest of the three, had the highest baseflow contribution, whereas the Ribb catchment, which is the smallest catchment, had the lowest baseflow contribution to streamflow. The annual deep groundwater recharge accounts for 13%, 9%, and 7% of annual rainfall for Gilgelabay, Gumara, and Ribb, respectively. The order of the amount of deep groundwater recharge is in agreement with the order of the fitted values for RCHRG_DP in our model (Table 3). These results

are in line with Wosenie *et al.* (2014), who reported that the Gilgelabay catchment had higher groundwater recharge rates than the Gumara catchment.

SUMMARY AND CONCLUSION

In this study, the impacts of agricultural crops and other LULC classes on the major water balance components were investigated in the Gilgelabay, Gumara, and Ribb catchment, Lake Tana basin, Ethiopia.

Our findings show that the spatial and seasonal values of ET in the Gilgelabay catchment were significantly different from the values in Gumara and Ribb. Likewise, the groundwater recharge and surface runoff values revealed significant spatial and seasonal variations between the three catchments. On the contrary, the ET values between Gumara and Ribb catchments showed insignificant variations. Compared to Gilgelabay and Ribb, the Gumara catchment showed high susceptibility for runoff, whereas Gilgelabay is less susceptible compared to the other two catchments. As well, the results showed that there were no significant differences in the inter-annual variabilities of ET, surface runoff, water yield, and groundwater recharge.

In summary, our findings highlight the significance of considering agricultural crop classes in the application of hydrologic models, which often rely on only one generic agricultural class. The vast majority of the agricultural crop classes had a significant effect on the water balance components. On the one hand, cereal crops had higher rates of groundwater recharge compared to others like leguminous and mixed crops. On the other hand, leguminous crops like peas had a significant impact on increasing runoff generation. Therefore, expansion of agricultural crops like pea may be discouraged as they favored surface runoff generation, which in turn, may lead to a higher erosion risk. In this regard, the present research approach could be extrapolated to similar catchments in Ethiopia and other African countries where agricultural land use dominates.

Moreover, for future impact assessment of agricultural crops on water balance components, a time series LULC could provide further insights into inter-annual impacts on the water resources. In addition, it is recommended to incorporate climate change in future assessments of groundwater

and surface water dynamics to derive sustainable solutions for the future.

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