Case Study

Bias-Corrected CHIRP Satellite Rainfall for Water Level Simulation, Lake Ziway, Ethiopia

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Abstract: Applicability of satellite rainfall products must be explored since rain gauge networks have limitations to provide adequate spatial coverage. In this study, Climate Hazards InfraRed Precipitation (CHIRP) satellite-only product was evaluated for rainfall-runoff modeling whereas the simulated runoff served as input to simulate the water levels of Lake Ziway from 1986 to 2014. CHIRP dataset was bias-corrected using power transformation and used as input to Hydrologiska Byråns Vattenbalansavdelning (HBV) model to simulate streamflow of Meki and Katar catchments. Results showed that gauged catchments of Meki and Katar contributed 524 and 855 mm to the annual lake inflow, respectively. The estimated runoff from ungauged catchments is 182 mm that amounts to approximately 8.5% of the total lake inflow over the period 1986–2000. The results of lake level simulation show good agreement from 1986 to 2000, but deteriorating agreement after 2000, which is mainly attributed to errors in water balance terms and human-induced impacts. For the period 1986–2000, the water balance closure error for the lake was 67.5 mm per year, which accounts for 2.9% of the total lake inflow from rainfall and river inflow. This study shows bias correction increases the applicability of CHIRP satellite product for lake water balance studies. **DOI: 10.1061/(ASCE)HE.1943-5584.0001965.** *© 2020 American Society of Civil Engineers.*

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Introduction

Accurate rainfall data at high spatial and temporal resolution is highly desirable for rainfall-runoff modeling. However, consistent rainfall measurements are not available or readily accessible in many less developed countries like Ethiopia (Ashenafi and Hailu 2014). Satellite rainfall products may complement rain gauge data. Therefore, satellite rainfall estimation algorithms are extensively being explored to produce reliable and accurate satellite rainfall estimates (SREs) that are meaningful for hydrological assessments. Evaluation studies on the accuracy of SREs show that estimates are subjected to systematic and random errors (Haile et al. 2013; Fuka et al. 2014; Habib et al. 2014; Bhatti et al. 2016). Hence, the systematic error (bias) should be removed before the products can be used for hydrological and water resources applications.

Satellite rainfall products have become available over the past decades at global coverage. Examples are the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al. 2007), Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al. 2004), Precipitation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; Sorooshian et al. 2000), and Climate Hazards Group (CHG) InfraRed Precipitation (CHIRP; Funk et al. 2015). Comparison studies have shown that the performance of these products varies considerably across geographic locations and over time periods.

Bias correction of satellite rainfall is advantageous as reported in recent studies. Krakauer et al. (2013) indicated that bias correction increases the match between rainfall amounts from satellite products and rain gauge records. Yuan et al. (2017) reported that the application of bias-corrected satellite rainfall product in runoff modeling resulted in substantial improvements in capturing both runoff volume and hydrograph pattern. Yong et al. (2014) found the use of bias-corrected rainfall product as model input instead of uncorrected products revealed better performance on rainfall-runoff simulation. Similar results were also reported by others (Ebert et al. 2007; Habib et al. 2014; Dembélé and Zwart 2016; Worqlul et al. 2018).

Subject to availability of products, studies have used products mostly at an application period of 10 years or shorter. Some satellite rainfall products are available for time periods longer than 10 years. Among these products, the CHIRP satellite-only product and CHIRP combined with stations observations (CHIRPS) are available at relatively high space-time resolutions (5.5 km, daily) (Funk et al. 2014, 2015).

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Several recent studies have investigated the accuracy of CHIRP and CHIRPS products across the world. For instance, Le and Pricope (2017) demonstrated the applicability of CHIRPS product for streamflow simulation over Nzoia basin, Western Kenya. The authors reported that the use of CHIRPS data as input into the hydrological model significantly improved streamflow simulation compared to rainfall from gauge observations. However, such results might be attributed to poor quality and inadequate rain gauge data coverage over the study area.

Duan et al. (2016) showed that CHIRPS performed better compared to eight high-resolution satellite rainfall products over Adiga basin (Italy). Hessels (2015) compared 10 satellite rainfall products over the Nile basin. Their findings suggest that CHIRPS is suited for water resources assessment studies. Dinku et al. (2018) evaluated CHIRP and CHIRPS satellite products and compared them against other two satellite products [i.e., ARC2 (African Rainfall Climatology V2) and TAMSAT (Tropical Application of Meteorology using SATellite)]. Authors reported that both CHIRP and CHIRPS products better performed than ARC2 and TAMSAT at decadal and monthly time scales.

Khandu et al. (2015) reported CHIRP performed relatively better in flat regions with elevation ranges from 150 to 1,500 m.a.s.l. Similarly, Shrestha et al. (2017) showed that CHIRP satellite-only product was found to better perform at lower elevation regions of Koshi basin in Nepal than CHIRPS product. Furthermore, studies indicated that products are also subjected to substantial biases. For instance, CHIRP underestimated the observed rainfall magnitude by 200–240 mm per month over Bhutan (Khandu et al. 2015). Their results also showed the bias correction of the CHIRP satellite significantly improved the accuracy of the products.

In Ethiopia, previous evaluation of satellite products for runoff simulation mostly focuses on the upper Blue Nile and Awash basin (Haile et al. 2013; Habib et al. 2014; Gebere et al. 2015). Similar studies are lacking over Central Rift Valley (CRV) lakes basin of Ethiopia for application in hydrological and water resources management. Dinku et al. (2014) reported that CHIRP satellite-only product better performed than CHIRPS over Ethiopia. Similar findings are reported in studies for the upper Blue Nile basin of Ethiopia (Ayehu et al. 2018). However, there is no study that demonstrated the applicability of CHIRP in data-scarce regions like Lake Ziway in Ethiopia with the objective to simulate lake water levels by lake water balance assessment. Therefore, the main objective of this study is to simulate river inflow and lake level using bias-corrected CHIRP satellite-only rainfall product. CHIRP will be used at daily temporal and $0.05° \times 0.05°$ spatial resolutions for the period 1984–2014.

To address the main objectives of this study, i.e., to simulate lake level and the lake water balance, long-term rainfall data series is needed. By lack of sufficient rain gauge data we selected CHIRP satellite rainfall products to complement and complete rainfall time series data. CHIRP data has the longest time series that goes back to 1981 and still is made available until near present time. An advantage of using CHIRP in this study is its fine spatial resolution ($0.05° \times 0.05°$) than other products (Dinku et al. 2014; Khandu et al. 2015; Shrestha et al. 2017). In addition, previous intercomparison and performance assessment of satellite products have shown that CHIRP product better performed in different regions as compared to other satellite products. Furthermore, CHIRP uses thermal infrared (TIR) data, which provide consistent time series data. Hence, in this study we selected to use CHIRP satellite-only rainfall estimate. The study area is Lake Ziway in the CRV Lake basin of Ethiopia. As such, this study will contribute to the applicability of CHIRP satellite product for estimating lake balance and lake level simulation in data-scarce regions.

Study Area

Lake Ziway subbasin is located in the CRV Lakes basin of Ethiopia. The subbasin has a total surface area of 7,022 km^2, of which the land surface covers 6,572.5 km^2. Lake Ziway is the highest of a chain of four lakes in the CRV basin with a surface area covering 445 km^2 and an island area of 4.5 km^2. The lake subbasin is situated between latitudes of 7°25′30″–8°34′30″N and longitudes of 38°12′00″–39°15′00″E (Fig. 1).

The topography of the sub basin is characterized by mountainous terrain over eastern and western margins, with an elevation variation from 4,200 to 1,600 m.a.s.l (Fig. 1). According to a bathymetric map of 2013, the maximum and average depth of the lake was 8 and 3 m, respectively, with an average volume of 1,148 Million Cubic Meter (MCM) at an average elevation of 1,636 m.a.s.l. The lake level rises during the rainy season (July to September) with highest levels in October, at the end of rainy season. Lowest water levels occur in December through March.

Meki and Katar catchments, which drain the western and eastern plateaus, respectively, provide a major inflow to Lake Ziway. The two catchments cover a total gauged area of 5,783 km^2, with an ungauged catchment area of 785 km^2. The lake outflow drains toward Lake Abijata via Bulbula River and is monitored at Kekersitu gauge station.

The mean annual temperature of the lake ranges from 18.2°C to 21.6°C, with tropical climate. The average annual rainfall of Lake Ziway varies between 454 and 995 mm as estimated for the period 1984–2014, while annual lake evaporation during the same period ranges from 1,775 to 1,969 mm. The average annual rainfall and evaporation from the lake is 746 and 1,870 mm, respectively for the specified period. The major land uses in the subbasin includes intensive agriculture cultivation land (both rain-fed and irrigated), wetland, and water bodies. Fig. 1 indicates the location of the study area including elevation variation, meteorological, and river gauge stations.

Datasets: Observed Data

Daily meteorological data from 20 rain gauge stations were obtained from the National Meteorological Agency (NMA) of Ethiopia. The data covers the period from 1984 to 2014. The dataset includes rainfall, maximum and minimum temperature, wind speed, relative humidity, and sunshine duration.

In this study, the quality of the observed rainfall was assessed using outlier, homogeneity, stationary, and consistency tests. The analysis showed that rainfall data of only 14 ground stations (6 for Meki and 8 for Katar catchments) were found complete and consistent for use in this study. After screening about 26% of missing records were identified. Missed data were filled using arithmetic and normal ratio methods mainly for potential evaporation estimation. For bias correction of the satellite product, only the available rainfall data of the selected stations were used while days with missing records were ignored.

The Ministry of Water, Irrigation, and Electricity (MoWiE) of Ethiopia provided the lake water level (at Ziway station), streamflow data at five stations (Meki at Meki town, Katar at Abura and Sagure, and Chiufa at Arata and Timala near Sagure), and lake outflow discharge (Kekersitu station at Bulbula River) (Fig. 1). Daily observations of water level and streamflow were made available to us for the period 1984–2014. Stations of small tributaries (such as Sagure, Chiufa, and Timala) had short records, and hence data from those stations were not considered.

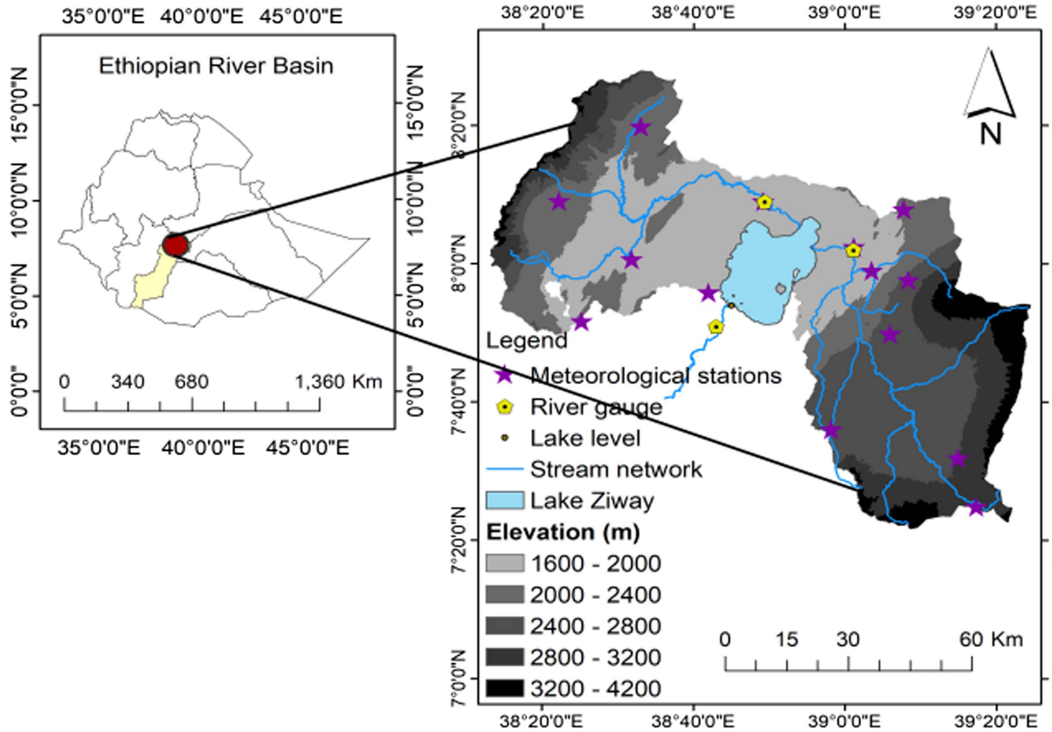

Fig. 1. Location map of Lake Ziway subbasin, including elevation, meteorological, lake level, and river gauge stations.

Digital Elevation Model (DEM) of advanced space-borne thermal emission and reflection (ASTER) radiometer global digital elevation model version 2 (GDEM V2) was downloaded from a freely available data source (https://lpdaac.usg.gov.dataaccess). The DEM has a spatial resolution of 30×30 m and was used to delineate the watershed. Land use/land cover data was obtained from MoWiE for the year 1992 and 1996. MoWiE also provided the lake bathymetric data of 1984 and 2013 and are used in this study.

Satellite Rainfall Product

CHIRP data is a near real-time product which is available since 1981 up to the present time. The data covers the region that is situated between 50°S and 50°N latitude and all longitudes (Funk et al. 2014, 2015).

CHIRP estimates precipitation data in two stages based on two global geosynchronous TIR archives i.e., the 1981–2008 globally gridded satellite from National Oceanic and Atmospheric Administration (NOAA) and the 2000-present NOAA CPC dataset. First, optimal temperature threshold for Cold Cloud Duration (CCD) of a given region was defined as a percentage of pentads (or five-day averages at $0.05° \times 0.05°$) with respect to their long-term (1981–2012) climatology. Then, a regression relationship is developed to translate CCD values into estimates of precipitation depth. This produces CHIRP satellite-only gridded precipitation dataset. In our study area, the precipitation is only in the form of rainfall. Thus, this study will use the term rainfall instead of precipitation. The CHIRP rainfall satellite data can be obtained freely from http:chg.geog.uscb.edu/data. Refer to Funk et al. (2015) for more details about CHIRP satellite rainfall estimate.

Methods: Bias Correction of CHIRP Satellite Product

The accuracy of CHIRP rainfall product was evaluated using gauge rainfall as a reference. First, a comparison of satellite and gauge rainfall amounts through visual inspection of scatter plots was performed. Then, performance indicators of relative bias (BIAS) and mean error (ME) were estimated to evaluate bias of CHIRP satellite estimates at monthly average time scale. For a more detailed performance assessment of CHIRP satellite product at various spatio-temporal scales, refer to Goshime et al. (2019).

The ME describes the average difference between satellite estimate and rain gauge observations. BIAS represents the systematic error of the satellite-based rainfall estimate as a percentage of the observed rainfall. A positive ME and BIAS indicates an overestimation, whereas a negative value indicates underestimation by the satellite. The ME and BIAS are expressed by

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(S_i - G_i) \tag{1}$$

$$\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(S_\mathrm{i} - G_\mathrm{i})}{\sum_{i=1}^{n} G_i} \times 100\% \tag{2}$$

where G_i and S_i = rainfall values from gauged-based and satellite product, respectively; and n = number of rainfall pair time series in the sample.

In this study, a nonlinear power transformation bias correction method was applied to remove the systematic error in CHIRP satellite estimates. For bias correction 14 rain gauge stations were available after screening. The nonlinear power equation reads

$$P_c = aP_o^b \tag{3}$$

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where P_c = bias-corrected CHIRP rainfall amount; P_o = uncorrected CHIRP rainfall amount; and a and b = bias factors.

The approach was selected as it accounts for the first and second statistical moment (mean and standard deviation) of rainfall time series and following (Lafon et al. 2013; Pratama et al. 2018). However, it is noted that there is no sufficient evidence in the scientific literature that guide best selection of a bias correction method. A power transformation bias correction has been applied for satellite rainfall bias correction at various previous studies. For instance, Leander and Buishand (2007) and Terink et al. (2010) applied power law for European river basins. The authors reported that a nonlinear bias correction revealed better performance than commonly used linear bias correction method. Gumindoga et al. (2019) applied power law in comparison with other methods for bias correction of CMORPH rainfall estimates in the Zambezi River basin. We also refer to recent studies (Wagesho et al. 2013; Goshime et al. 2019) that applied a nonlinear power bias correction method for the Rift Valley Lakes basin of Ethiopia. Therefore, we have chosen to apply a power transformation bias correction method to remove the systematic errors of the CHIRP satellite estimate.

The bias factors are determined iteratively until the statistics (mean and coefficient of variation) of the satellite estimates match with the observed rainfall amount at a monthly time step. First, daily data of both data sources were arranged for each month over the period from 1984–2000. Then, the values of a and b were estimated using the Excel solver function at selected 14 grid pixels that overlay the locations of the rain gauge stations.

The bias correction algorithm was verified for an independent period from 2001 to 2007. The verification was conducted to evaluate the applicability of the bias factors outside the bias correction data periods. The bias-corrected rainfall estimate was compared against observed rainfall amount using a plot of average monthly aggregate values for Meki and Katar catchments. The bias factors were spatially interpolated to other CHIRP grid pixels, which did not contain rain gauges, using Inverse Distance Weighting (IDW) method across the watershed. A similar approach was also adopted by Yong et al. (2010). Finally, the interpolated bias factors (a and b) were used in Eq. (3) to estimate bias-corrected satellite rainfall data.

HBV Rainfall-Runoff Modeling

The potential evapotranspiration (PET) was estimated using Penman-Monteith (Allen et al. 1998) and Hargreaves method (Hargreaves and Allen 1985) at four principal stations (Ziway, Kulumsa, Bui, and Merero). To correct for overestimation of Hargreaves estimate, we established a linear regression relationship (i.e., $y = mx + c$) between Penman-Monteith and Hargreaves values at the four mentioned stations.

The slope of the regression line (c) and its intercepts (m) at the four stations were transferred to the location of the seven ordinary stations (recording only temperature and rainfall) using the IDW method. Next, the error of the PET estimates from the Hargreaves method was corrected at the seven stations using the estimates of Penman-Monteith method. The catchment average areal PET was then computed from 11 stations in the watershed from an estimate of Penman-Monteith using Theissen polygon, which was then used as input to the hydrological model. The potential evapotranspiration estimation approach applied in this study is based on the study of Ayalew (2010) who applied a simplified regional potential evapotranspiration estimation method for Abbay River basin in Ethiopia. The author evaluated at 23 selected meteorological stations based on available maximum and minimum temperature. The authors reported that the method revealed satisfactory results and recommended as alternative approach to estimate PET in ungauged areas. Similar work has been done in South Africa by Pike (1988) and in Tanzania by Moges et al. (2003).

The Hydrologiska Byråns Vattenbalansavdelning (HBV) model has been widely applied in various countries for runoff simulation, climate change, and water accounting studies (Bergström 1992). The HBV model was selected due to its performance in simulating streamflow in a different Ethiopian river basin (Rientjes et al. 2011; Worqlul et al. 2015). Furthermore, operational and scientific applications of this model have been reported from more than 50 countries around the world (Johansson 2013). The HBV model reads rainfall, temperature, PET, and land cover (forest, field, and water) as main inputs. Observed streamflow data is used as reference data for model calibration.

The model consists of four subroutines for precipitation, soil moisture, runoff routine, and routing routine. Precipitation routine controls precipitation either to be simulated as snow or rain depending on a specified temperature threshold value. Precipitation is only in the form of rainfall in the Lake Ziway subbasin.

The soil moisture controls the formation of runoff (both direct and indirect). Direct runoff occurs when the simulated soil moisture (SM) in the soil moisture reservoir exceeds the maximum field capacity (FC). The indirect runoff in the system is expressed using power relationship as follows:

$$R = IN \times \left(\frac{SM}{FC}\right)^{BETA} \tag{4}$$

where R = indirect runoff (mm); IN is water infiltrating amount (mm); SM is soil moisture storage (mm); and FC is the field capacity at maximum soil moisture (mm). $BETA$ is a parameter that accounts for a nonlinearity of indirect runoff from the soil layer.

In SM routine, the actual evapotranspiration (E_a) equals the PET when the actual SM exceeds a certain threshold which is defined by LP. LP is a dimensionless parameter that represents the limit for potential evaporation. When water is available in the upper zone, percolation (PERC) will occur to the lower zone at approximately constant rate. PERC represents a constant percolation rate that occurs when water is available in the upper storage zone.

At runoff routine three parameters such as capillary transport (C_f) to the SM reservoir, percolation to the baseflow reservoir and runoff relationships are governed in the model. Capillary transport is determined as a function of maximum SM storage, FC, and maximum capillary flow (CFLUX), which is a calibrated model parameter. The relationship reads

$$C_f = CFLUX \times \left(\frac{FC - SM}{FC}\right) \tag{5}$$

Excess water is transformed from the SM zone to runoff. The summation of runoff from the upper and lower storage zones yields the total runoff. The runoff from the upper and lower storages reads:

$$Q_u = K_u \times UZ^{(1+Alfa)} \tag{6}$$

$$Q_l = K_4 \times LZ \tag{7}$$

where Q_u and Q_l = runoff components from the upper and lower storage zones, respectively; UZ = actual storage in the upper zone; LZ = actual storage in the lower zone; and K_u and K_4 = storage (recession) coefficients in the upper and lower zone, respectively. *Alfa* is a measure of the nonlinearity of the flow in the upper storage zone.

Table 1. Selected model parameters for calibration including their description and plausible range

Parameter	Description	Unit	Minimum	Maximum	Initial value
Alfa	Coefficient for non-linearity of flow	—	0	1.5	0.6
BETA	Exponent in drainage from soil layer	—	1	4	2.5
CFLUX	Maximum capillary flow	mm	0	2	0.5
FC	Field capacity	mm	100	1,500	200
K4	Recession coefficient for lower zone	d^{-1}	0.001	0.1	0.01
Khq	Recession coefficient for upper zone	d^{-1}	0.005	0.5	0.1
LP	Limit for potential evaporation	—	0.1	1	0.9
PERC	Percolation capacity	mm d^{-1}	0.01	6	0.5

We selected eight parameters (Alfa, BETA, CFLUX, FC, LP, K4, Khq, and PERC) for calibration based on recommendations in the literature (Wale et al. 2009; Rientjes et al. 2011) and HBV model documentation. Initial values of these model parameters were specified based on HBV model documentation (Johansson 2013). In Table 1, selected model parameters and their ranges are shown. For more detail descriptions of the HBV model reference is made to Lindström et al. (1997) and Johansson (2013).

Model Calibration and Evaluation

Sensitivity analysis was conducted to find the parameters for which model response is sensitive to aid model calibration. The default model values of the parameters were used in the model as reference to decide the sensitive model parameter. Parameter values were then varied within their allowable range by changing the value of one parameter at a time by a constant increment. The parameter for which the model is sensitive was determined based on Nash-Sutcliffe efficiency (NSE) and relative volume error (RVE) objective functions following Dessie et al. (2014).

In this study, the HBV model was initialized for the study area with a two-year warm-up period (1984–1985). The model was then calibrated for the period 1986 to 1991 using bias-corrected CHIRP rainfall input. This calibration period was selected since water abstraction for this period is limited. The calibration period covered normal, flood, and dry weather periods so the calibrated model is considered as representative to simulate lake streamflow inflows.

The model performance was evaluated in terms of visual inspection of the hydrographs and quantitatively through objective functions. Two objective functions were used to assess the model performances which are NSE and RVE. NSE is a measure of a degree of match between the pattern of simulated and observed hydrographs. The equation reads

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{sim,i} - Q_{obs,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - \overline{Qobs})^2} \tag{8}$$

where Q_{sim} and Q_{obs} = simulated and observed daily streamflow, respectively ($m^3 s^{-1}$) and the overbar symbol denotes the mean of the statistical values; i = time step; and n = number of days in the sample. NSE is a dimensionless value, ranges from $-\infty$ to 1, a value of 1 indicates a perfect fit.

RVE measures the average tendency of the simulated runoff to be larger (overestimation) or smaller (underestimation) than the observed values. The equation reads

$$RVE = \left[\frac{\sum_{i=1}^{n}(Q_{sim,i} - Q_{obs,i})}{\sum_{i=1}^{n} Q_{obs,i}}\right] \times 100\% \tag{9}$$

RVE ranges between $-\infty$ and ∞, but the model performs best when a value of 0 is generated. A value between -5% and $+5\%$ indicates that a model performs very well while a value between $\pm 5\%$ and $\pm 10\%$ indicates that a model has reasonably good performance.

The performance of the calibrated model was validated using the rainfall input for the period 1996 to 2000. Again, NSE and RVE were used to evaluate performance for the validation period. The streamflow data recorded from 1992 to 1995 was not considered either for calibration or validation due to incomplete data records.

Next, three (3) rainfall datasets were constructed, namely gauge, uncorrected CHIRP, and bias-corrected CHIRP rainfall to evaluate the effect of bias correction on streamflow simulation. The calibrated model parameters from bias-corrected CHIRP satellite rainfall inputs were used in all model simulation. Note that parameter recalibration was not performed for a model with different rainfall inputs. The simulated streamflows from 1996 to 2000, which is outside the calibration period for the three datasets, were compared to observed streamflow as a reference to assess the effect of bias correction of CHIRP satellite estimates.

Lake Water Balance and Lake Level Simulation

This study followed (Wale et al. 2009; Rientjes et al. 2011) who assessed water balance closure of Lake Tana, Ethiopia. The inflow and outflow from all sources were estimated at daily time step and estimated net inflow at daily time step (t) as follows:

$$\frac{\Delta V}{\Delta t} = [(R(t) - E(t))] \times A(h) + Q_{in}(t) - Q_{out}(t) + G_{in}(t) - G_{out}(t) + \varepsilon(t) \tag{10}$$

where $\Delta V/\Delta t$ represents net inflow volume over time ($m^3 d^{-1}$); R and E = lake rainfall and evaporation, respectively ($m d^{-1}$); Q_{in} = lake streamflow inflow ($m^3 d^{-1}$); Q_{out} = lake streamflow outflow ($m^3 d^{-1}$); G_{in} and G_{out} = groundwater inflow and outflow, respectively ($m^3 d^{-1}$); $A(h)$ = lake surface area in m^2 as a function of water level; and ε = closure error in water balance arising from errors in the data or other terms in ($m^3 d^{-1}$). The water balance closure term is an error term that cannot be accounted for directly, and hence it is estimated as water balance flux that closes the lake water balance.

Due to lack of piezometric groundwater data underneath and around the lake, the groundwater component was ignored in the water balance as shown in other studies as well (Vallet-Coulomb et al. 2001; Ayenew 2007; Seyoum et al. 2015; Desta et al. 2017). These studies argued that significant interaction is unlikely to occur due to the very shallow nature of the lake with flat topography and substantial sediment loads of inflowing rivers. As such, we neglected the groundwater contribution in the lake water balance of this study. Therefore, Eq. (10) is simplified as follows:

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$$\frac{\Delta V}{\Delta t} = [\{R(t) - E(t)\} \times A(h) + Q_{in}(t) - Q_{out}(t)] \quad (11)$$

where all water balance terms have been defined in Eq. (10).

The daily areal rainfall over the lake was estimated from bias-corrected CHIRP satellite data. The bias correction was applied according to power transformation between satellite and gauge rainfall data series as described in preceding section. The water evaporation from the lake was estimated using the Penman method (Penman 1948). This method was selected as it combines the energy balance and water vapor transfer. Its input data includes surface air temperature, relative humidity, wind speed, and sunshine hours. First, open water evaporation was estimated at three stations Ziway, Ogolcho, and Arata, which are situated close to the lake. Then, average lake evaporation was estimated using Thiessen polygon. The surface albedo in this study is assumed 0.06 following Vallet-Coulomb et al. (2001) for Lake Ziway and Dessie et al. (2015) for Lake Tana in Ethiopia.

The calibrated HBV model was applied to simulate the streamflow over the simulation period 1986–2014 from the gauged area of the two major tributaries. The ungauged part of the subbasin accounts for 18% of the total subbasin area. The streamflow contribution from ungauged catchment was estimated using the area-ratio method. This method was selected due to its simplicity. Furthermore, only about 38% of Lake Tana is gauged whereas a large parts of (almost 82%) the Lake Ziway catchment is gauged at major Meki and Katar Rivers. Therefore, applying other methods for estimating lake inflow from ungauged areas is intricate by the lack of river gauging stations that constrain the application of advanced regionalization applied in Wale et al. (2009) and Rientjes et al. (2011) for the Lake Tana basin area.

The outflow of Lake Ziway is measured at Kekersitu station which is situated at the head of Bulbula River. Incomplete records in lake outflow during the analysis period were filled by using a regression relationship between lake water level and outflow discharge. A similar approach was applied in other studies for Lake Ziway (Vallet-Coulomb et al. 2001), Lake Tana (Kebede et al. 2006), Lake Victoria (Nicholson and Yin 2001), and Lake Malawi (Kumambala and Ervine 2010). The regression relationship between water level and outflow discharge reads

$$Q_{ou} = \alpha(H - H_o)^{\beta} \quad (12)$$

where Q_{out} = simulated lake outflow; H = lake water level; H_o = water level at zero reference datum; and α and β = constants. The parameters α and β were estimated from the regression relationship between the lake level and outflow.

The relationship between lake level and outflow were established for a period in which complete data was available for the period 1987 to 2007. From the relationship, values of 1.73 and 3 were adopted for α and β, respectively. In this study, a reference datum level of 1,635 m.a.s.l was used for lake level simulation.

For lake level simulation a spreadsheet water balance model was developed to simulate the lake volume as follows:

$$V_{lake}(t) = V_{lake}(t-1) + \Delta V \quad (13)$$

where $V_{lake}(t)$ = lake volume at day t; $V_{lake}(t-1)$ = lake volume at previous day (t − 1); and ΔV represents net inflow volume as estimated using Eq. (11).

The updated lake volume was then converted to lake level using the bathymetric relation between lake level and volume. Finally, comparison of the match of the simulated lake level was evaluated by comparing against observed counterparts. Note that in the present study, human-induced impacts such as water abstraction are not considered in the rainfall-runoff and water balance model. Hence, major deviation of the simulated lake level from observed lake level was assumed to indicate the magnitude of human-induced impacts. A number of studies have shown that temporal variation between the model simulated and observed lake level can vary as a result of climate change, human activities, or both (Wang et al. 2010; Peng et al. 2013; Seyoum et al. 2015; Zhou et al. 2018). Furthermore, reference was made from previous studies that evaluated the extent of land use and land cover changes between 1973 and 2014 in the study area (Desta et al. 2017).

Results: Evaluation of CHIRP Satellite Product

The scatter plot between the daily gauge observation and CHIRP satellite-only estimates are shown in Fig. 2. The data plots are shown for selected stations covering the period from 1984 to 2007. The scatter plot demonstrates that there is strong disagreement between the two data sets. Only a few data points are spread along the 45° slope line, indicating a poor correlation between the CHIRP satellite-only product and the rain gauge data. The data points are mostly below the diagonal line, indicating an underestimation of observed rainfall.

Several data points are spread along the x-axis, indicating that CHIRP missed observed rainfall. Rainfall amounts up to 80 mm per day were missed by CHIRP. Similarly, there are several data points spread along the y-axis, indicating the satellite product reported false rains.

Table 2 shows the percentage of relative bias (BIAS) of CHIRP monthly rainfall at six (6) selected rain gauge stations. The satellite product has a significant bias, which is time and location specific. We note that overestimation dominates at Ziway and Ogolcho, whereas underestimation dominates at Kulumsa and Assela stations. This phenomenon is presumably related to the location of the stations at relatively low and high altitude regions, respectively. Khandu et al. (2015) reported similar results over Bhutan where CHIRP underestimated over higher elevation regions. Overall, CHIRP has a large bias that reaches up to 73% at rainy seasons. In terms of ME, the monthly difference between CHIRP satellite-only and observed rainfall reaches up to 13 mm. Thus, overall bias is large which indicates that the uncorrected CHIRP product cannot serve as input to a rainfall-runoff model. Therefore, bias correction was applied to improve the accuracy of the product. The bias correction was first performed using the satellite and gauge data from 1984 to 2000 at 14 selected stations.

Figs. 3(a and b) summarize the monthly aggregate rainfall from the gauge, CHIRP bias-corrected and uncorrected satellite-only product for Meki and Katar catchments, respectively. The comparisons were performed for the verification period 2001–2007. The bias-corrected CHIRP estimates captured the pattern of the annual cycle of the observed rainfall. Overall, this study indicates that bias correction has significantly minimized the systematic error in CHIRP rainfall estimates as the bias-corrected and observed rainfall amounts are equal for bias correction period from 1984 to 2000. The bias correction successfully reduced the bias of the satellite data even when validated outside the bias correction period 2001–2007 (Fig. 3). However, there is still some disagreement between the bias-corrected and gauge data for the validation period. The disagreement was during the rainy reason, which is most likely related to the bias of CHIRP satellite rainfall at seasonal scale. Such disagreement can be caused by the ineffectiveness of the bias correction algorithm to capture the difference in rainfall characteristics in the bias calibration and validation period. Note that the period 2001–2007 was relatively wetter than the period 1984–2000.

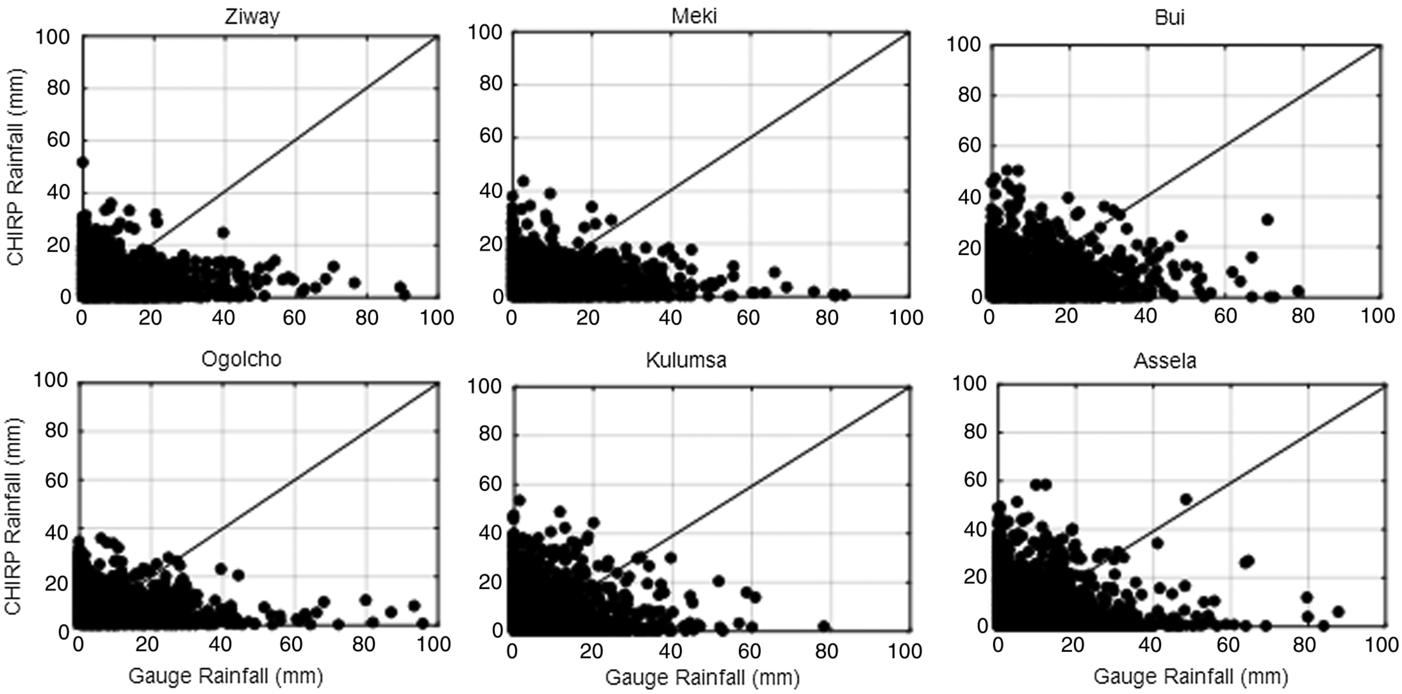

Fig. 2. Scatter plots of daily CHIRP satellite-only rainfall estimates against gauge rainfall at six selected main weather stations from 1984 to 2007.

Table 2. Monthly percentage bias between CHIRP satellite-only versus gauged rainfall from 1984 to 2007

Stations	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Ziway	33.0	17.3	30.2	16.4	−0.4	0.8	−2.9	22.2	22.9	26.2	63.7
Meki	10.0	−8.4	2.5	31.9	0.0	0.4	−13.7	2.0	28.0	29.5	35.8
Bui	−3.5	−43.2	−2.2	16.7	9.8	−11.9	−11.3	3.5	24.8	60.7	42.4
Ogolcho	30.7	3.5	−12.5	−8.9	6.3	1.3	9.1	68.3	−6.3	−21.2	8.0
Kulumsa	−25.3	−30.3	−20.7	−29.2	−31.8	−13.3	73.1	61.3	−7.2	−39.3	−25.9
Assela	0.4	−4.4	−23.2	−41.1	−25.1	−17.1	3.0	0.6	−31.0	−48.0	−47.1

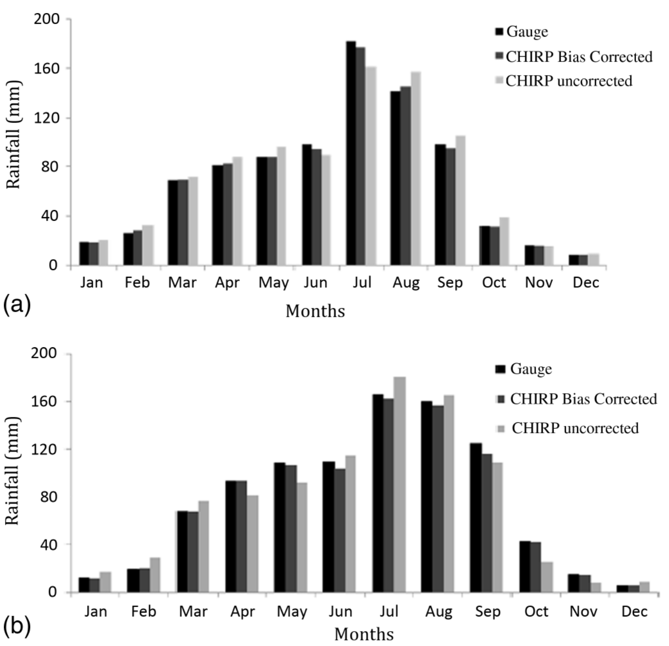

Fig. 3. Comparison of monthly average rainfall amount for CHIRP bias-corrected, uncorrected (satellite-only), and gauge time series from 2001 to 2007: (a) Meki catchment; and (b) Katar catchment.

We should therefore be very cautious in using the bias correction method outside the bias calibration period. As a result, we have recalibrated the parameters of the power law equation for the entire period 1984–2014.

Model Calibration and Sensitivity

The result of sensitivity analysis indicated that the HBV model of the study area is most sensitive to volume controlling parameters (FC, BETA, and LP). The shape controlling parameters (K4 and Khq) were found to have less effect on streamflow simulation. Parameters Alfa, CFLUX, and PERC showed to have least effect. Similar findings were reported in Dessie et al. (2014) and Worqlul et al. (2018) over upper Blue Nile basin in Ethiopia.

In Table 3 the calibrated parameter values of the HBV model for Meki and Katar catchments are tabulated. Note that the values of all parameters are within their allowable ranges as specified in the HBV manual. Values of K4, Khq, and Alfa are almost equal for the two catchments. However, most sensitive parameters (FC, BETA, and LP) values show a noticeable difference between the two catchments. The possible reason for this might be the differences in a rainfall-runoff relationship as affected by variation in rainfall, topographic, and physiographic properties among catchments.

Fig. 4 shows a comparison of simulated and observed streamflow hydrograph for the calibration period (1986–1991) for Meki

Table 3. Calibrated values of HBV model parameters using bias-corrected CHIRP satellite data

Parameter	Alfa	BETA	CFLUX	FC	K4	Khq	LP	PERC	hq
Unit	—	—	mm	mm	d^{-1}	d^{-1}	—	$mm\,d^{-1}$	—
Meki	0.8	1.96	0.010	860	0.10	0.10	0.5	1.15	0.83
Katar	1.1	3.05	0.005	820	0.10	0.12	0.7	2.75	1.13

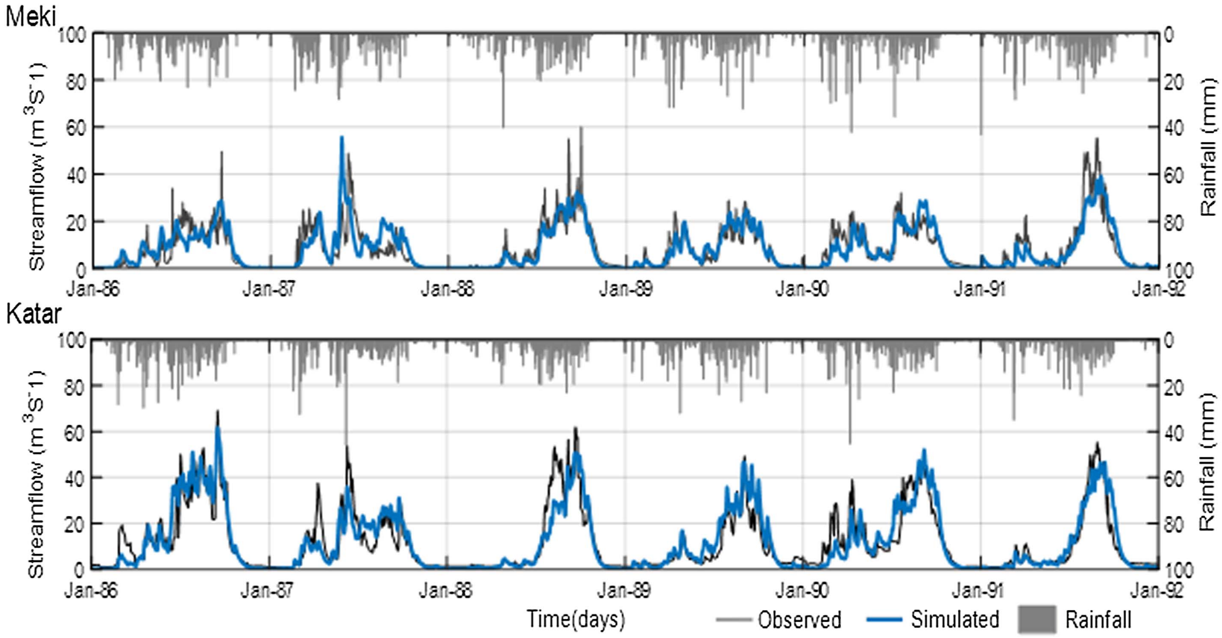

Fig. 4. Model calibration result of Meki and Katar catchments (1986–1991) using bias-corrected CHIRP rainfall as model input.

and Katar catchments. The model reasonably captured the pattern of the observed hydrograph of both catchments. The peak and baseflow were reasonably captured with the exception of a few high magnitude peak discharges.

Fig. 5 shows a comparison of the simulated and observed hydrograph for the validation period (1996–2000) for Meki and Katar catchments. There is good agreement between the simulated and observed hydrographs in terms of pattern, volume, and baseflow.

The HBV model performance is satisfactory when evaluated quantitatively using NSE and RVE (Table 4). The model performance is comparable for Meki and Katar catchments during both the calibration and validation periods. The NSE values are 0.71 and 0.80 whereas RVE values are −1.47% and −1.28% for Meki and Katar, respectively, for the calibration period. Note that the model performance efficiency slightly deteriorated in the validation period as compared to the calibration period. However, its performance is still very good for the validation period, indicating that the model can be applied to study rainfall-runoff relations in both catchments.

Effects of Bias Correction on Streamflow Simulation

The simulated streamflow hydrographs are compared using gauged, uncorrected, and bias-corrected CHIRP rainfall as model inputs for Meki catchment (Fig. 6). The outputs of the streamflow from the three datasets were compared with observed streamflow as a reference. The model missed some observed peak flows when rain gauge data were used as model input. There is also a noticeable difference between the observed and simulated hydrographs when uncorrected CHIRP satellite-only rainfall is specified as model input. The hydrographs indicated that the model performance showed improvement when using bias-corrected CHIRP satellite rainfall as model input. The pattern and volume of simulated hydrograph were better matched with the observed counterparts.

Fig. 7 presents the simulated streamflow for Katar catchment when using gauged, uncorrected, and bias-corrected CHIRP rainfall data. The figure demonstrates that the bias-corrected CHIRP product improved the performance of streamflow simulation. The values of bias correction are shown for Meki than Katar as the model performance significantly deteriorated in terms of pattern and magnitudes (peak and low flows) when uncorrected satellite-only rainfall served as model input instead of the bias-corrected rainfall estimates. Overall, the study results indicate that CHIRP bias propagates to streamflow simulation via the HBV model. From both plots (Figs. 6 and 7), this study indicated that bias-corrected CHIRP satellite better captured the volume and pattern of observed hydrograph than the uncorrected satellite-only dataset.

The simulated hydrograph was also evaluated using values of the objective function from gauged, uncorrected and bias-corrected CHIRP satellite as model inputs (Table 5). The results revealed better performance in terms of NSE and RVE when bias-corrected CHIRP rainfall data serves as model input. Note that the error of the uncorrected CHIRP satellite rainfall propagated into the HBV simulation as this input resulted in 10% more volumetric error in streamflow compared to the bias-corrected CHIRP satellite for the validation period.

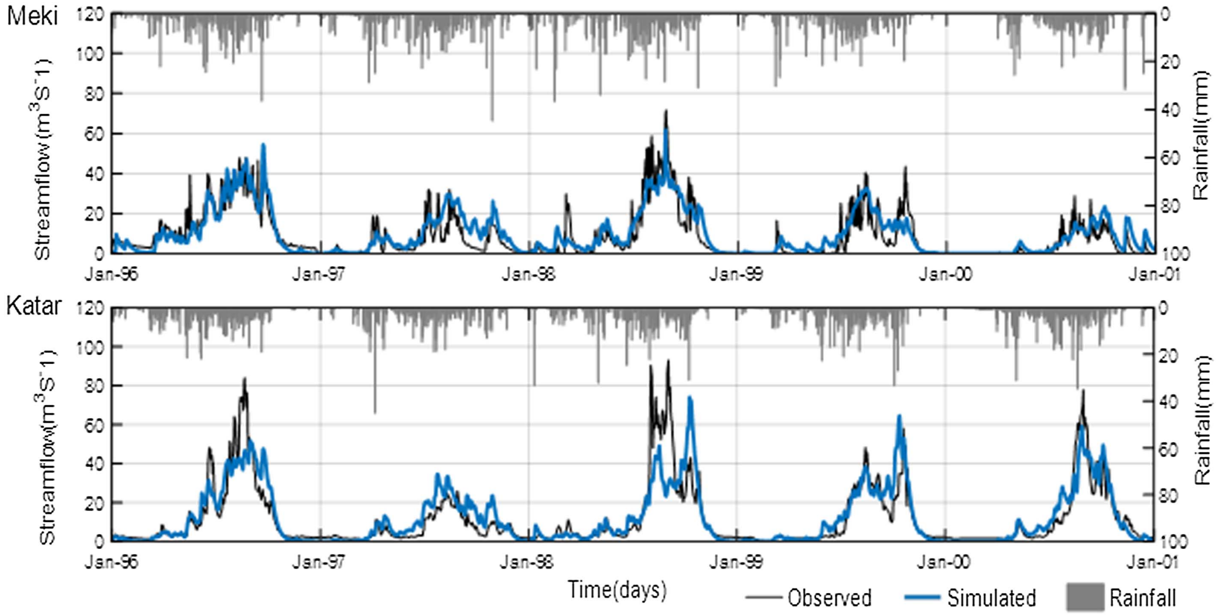

Fig. 5. Model validation results of Meki and Katar catchments (1996–2000) using bias-corrected CHIRP rainfall as model input.

Table 4. Performance of HBV model in terms of the objective functions for the calibration (1986–1991) and validation (1996–2000) periods

Catchment	Objective functions	Calibration	Validation
Meki	NSE (–)	0.71	0.67
	RVE (%)	−1.47	3.84
Katar	NSE (–)	0.80	0.76
	RVE (%)	−1.28	3.04

Lake Level Simulation and Temporal Variation of Water Balance Components

Fig. 8 presents daily estimate of Lake Ziway water balance components for a period from 1986 to 2014. The figure indicated that variation of climatic seasonality over each water balance component. The fluctuation/variability of the observed lake level is more distinct than the long-term gradual change. The level reduced for the period from 2000 to 2005 and recovered afterwards. We note that the year 1995, 2002, 2005, and 2011 was relatively a drier year both in terms of rainfall and discharge. It is plausible that the lower lake levels in 2000 to 2005 are the result of relatively lower river inflows being drier years. The decrease of the water levels in Lake Ziway would also imply that less water is being discharged into the Bulbula River. As it expected there is a direct relation between the water level and the outflow into the Bulbula River. In years with relatively low lake levels (2002 to 2005 and 2009) the outflow has also been low and decreased dramatically.

After determining the daily water balance terms, Eq. (13) was used to simulate changes in lake volume by the net inflow volume.

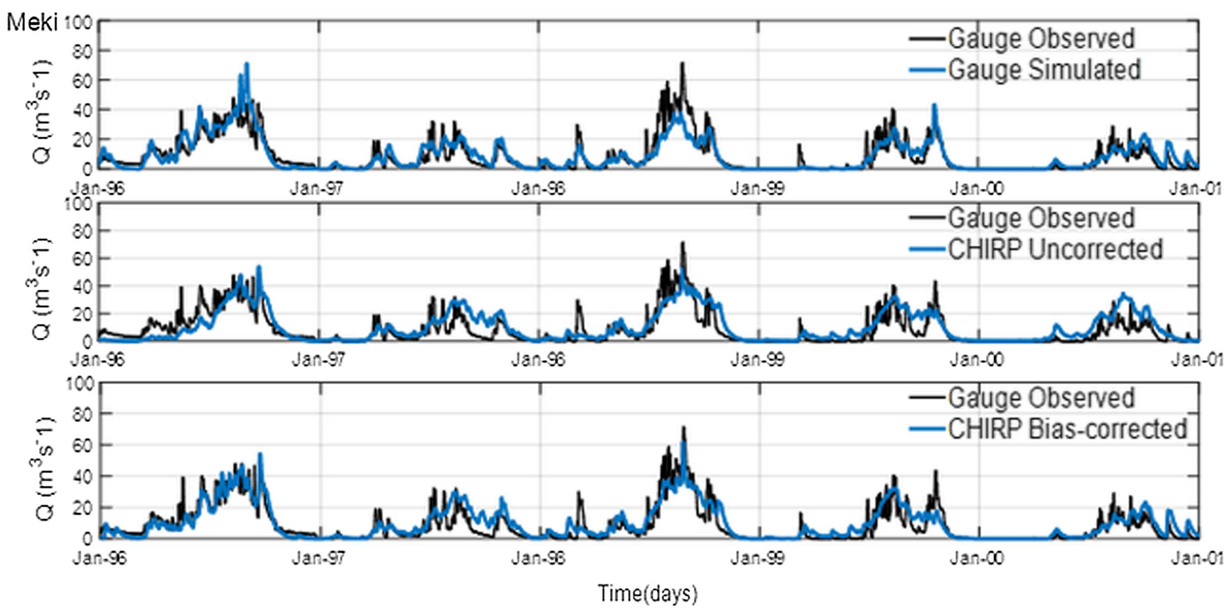

Fig. 6. Comparison of observed and simulated streamflow hydrograph for Meki catchment from 1996 to 2000 based on Gauge, CHIRP uncorrected, and CHIRP bias-corrected rainfall inputs.

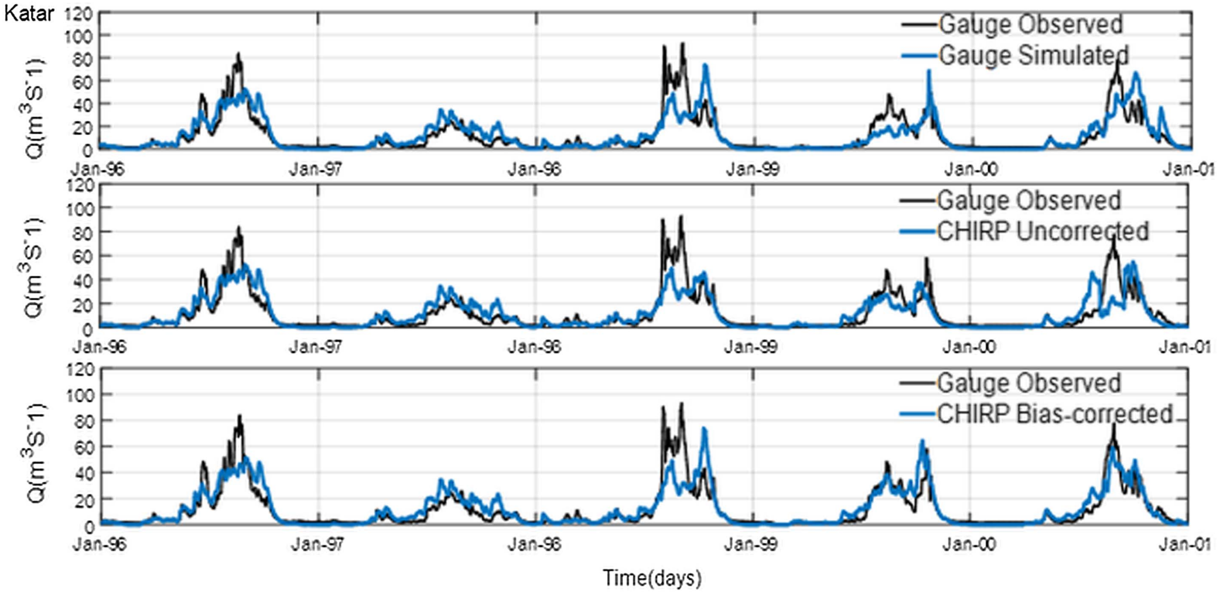

Fig. 7. Comparison of observed and simulated streamflow hydrograph for Katar catchment from 1996 to 2000 based on Gauge rainfall, CHIRP uncorrected, and CHIRP bias-corrected rainfall inputs.

Table 5. Comparison of model objective functions between the simulated (based on gauge-only, uncorrected, and bias-corrected CHIRP dataset) to observed streamflow

Catchment	Objective function	Gauge	CHIRP uncorrected	CHIRP bias corrected
Meki	NSE (−)	0.65	0.60	0.67
	RVE (%)	3.56	14.2	3.84
Katar	NSE (−)	0.70	0.64	0.76
	RVE (%)	2.91	12.8	3.04

The updated lake volume was transformed into a new lake level using area-elevation-storage relationships. The simulated lake levels were compared with observed lake levels. Fig. 9 shows a time series of simulated and observed lake level on a daily time scale from 1986 to 2014.

The simulated lake water level shows a better agreement with the observed water level from 1986 to 2000. However, the deviation between the two water levels continuously increased from 2000 onwards. The observed lake level declined while the simulated level increases for the period 2001–2014. This could be most likely attributed to an error in any of the water balance terms and human-induced activities that cannot be represented in model simulation. According to (Seyoum et al. 2015), human-induced activities mostly apply for the period 2001–2014. Furthermore, the uncertainties related to bias correction of the satellite, lake inputs obtained by the HBV model, lake outflow obtained by water level-flow relationships, and overall the cumulative impact might contribute the disagreement between the simulated and observed lake level.

We also refer to Desta et al. (2017) who evaluated the extent of land cover changes (conversion of woodlands into agricultural lands and settlement areas) for the period 1973–2014 in Lake Ziway catchment areas. Authors reported that agricultural lands and settlement areas together increased from 57% in 1973 to 75% in 2014 of the total area. As such impact could contribute to a mismatch between observed and simulated lake levels. Overall, on average 0.90 m annual decline of simulated water level was revealed in the simulation period 2001–2014. The daily maximum simulated water level deviated from the observed level by up to 2.28 m for both 2013 and 2014 period.

The bias-corrected CHIRP satellite estimates account for an average annual lake rainfall of 755 mm year^{-1} for the period 1986–2014. The average annual evaporation of the lake is estimated at 1,875 mm year^{-1} for the same period. In Table 6 the summary of Lake Ziway water balance components for the period 1986–2014 are shown. Evaporation from the lake is considerably larger as it is 2.5 times the rainfall amount over the lake. The gauged catchment contributes 1,404 mm year^{-1} to the lake inflow whereas the ungauged catchment contribution is 184 mm year^{-1} which constitutes 8.6% of the total lake inflow from rainfall and river inflow. Lake Ziway outflow is 386 mm year^{-1} which constitutes 16.5% of the total lake inflow. Overall, the closure term in this study over the simulation period 1986–2014 indicates a water balance error of 82 mm year^{-1} that accounts for 3.5% of the total lake inflow from rainfall and river inflow.

Fig. 10 presents the monthly average simulated water balance components of Lake Ziway from 1986 to 2000 (baseline condition). The plot indicates that lake inflows (rainfall and river inflow) mostly occur during the wet season (i.e., June–October), with the highest inflow in August. Lowest contribution to the inflow occurs for four months (November–February). The lake outflow due to evaporation was greater than the river outflow. The larger outflow through Bulbula River occurs from September to January while lower river outflow occurs from February to July.

Table 7 shows the mean monthly and annual water level fluctuation for 2013 and 2014. The result indicates a maximum mean monthly variation of 2.04 m in 2013 (August) and 2.24 m in 2014 (July) during the rainy season. The deviation is small between September and December. The average annual water level variation is 1.78 m and 1.97 m in 2013 and 2014, respectively.

Fig. 11 shows the deviation of the simulated lake volume from observed volume for the period 2001–2014. The difference in lake volume increased with time except for 2007, which was a drought

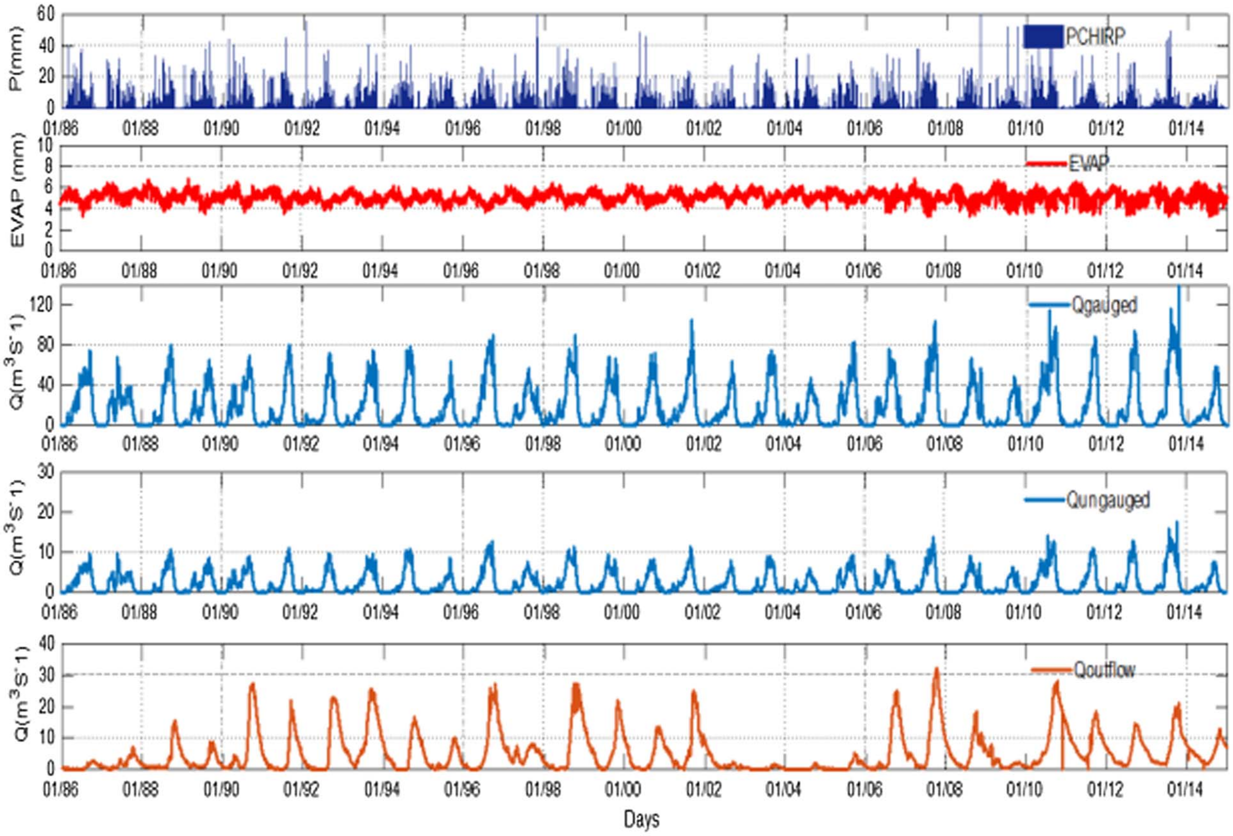

Fig. 8. Daily estimates of water balance terms of Lake Ziway from 1986 to 2014.

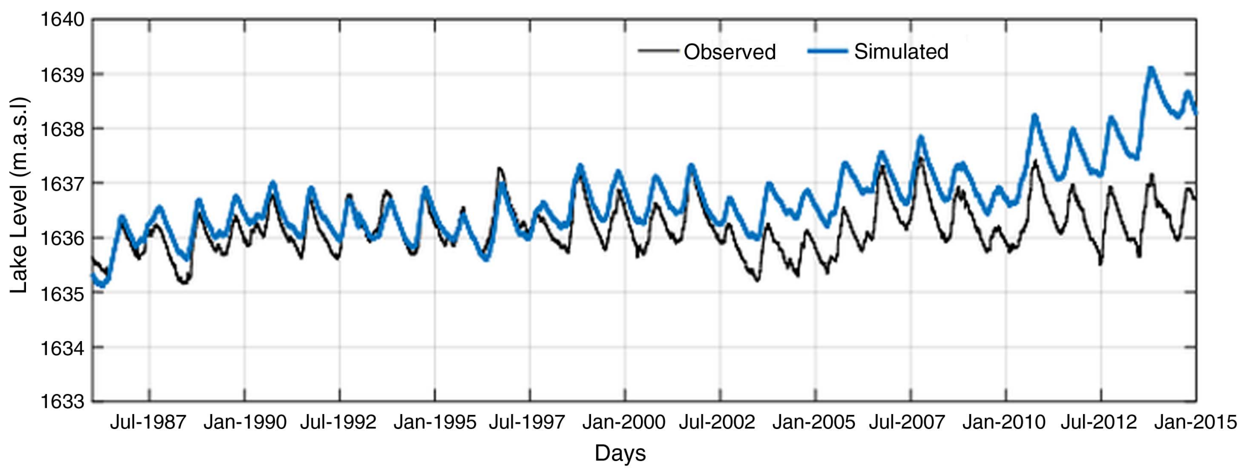

Fig. 9. Comparison of observed and simulated Lake levels from 1986 to 2014.

Table 6. Lake Ziway water balance components simulated for the 1984–2014 period

Water balance components	mm year^{-1}	MCM year^{-1}
Lake areal rainfall	755.1	336.0
Lake evaporation	1,875.1	834.4
Gauged river inflow	1,404.0	624.8
Ungauged river inflow	184.8	82.2
Outflow discharge	386.9	172.2
Closure term	81.9	36.4

year in the study area. The rate of increase was highest in 2012 and 2013. The highest average annual lake volume difference is 346 MCM in 2013 and 381 MCM in 2014, which is nearly 25% and 27.5% of the average lake volume from 1986 to 2000, respectively. The average annual volume difference from 2001 to 2014 is approximately 173 MCM, which accounts for 12.5% of the average volume of the lake from 1986 to 2000 (approximately 1,388.3 MCM). This large volume difference reveals the presence of increased human intervention by water abstraction from Lake Ziway

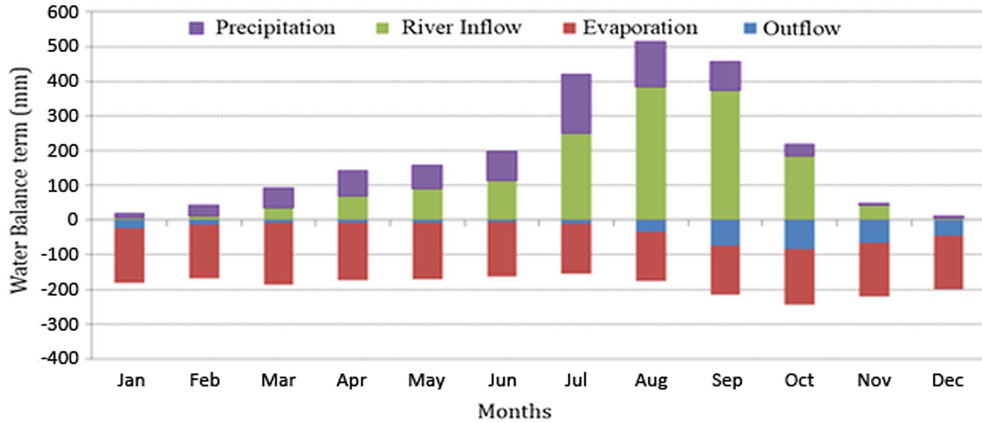

Fig. 10. Monthly average water balance components of Lake Ziway for a period from 1986 to 2000.

Table 7. Mean monthly and annual deviation of the simulated water level from observed levels in 2013 and 2014

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
2013	1.49	1.51	1.55	1.53	1.53	1.69	1.98	2.04	1.97	2.02	1.98	2.02	1.78
2014	2.09	2.04	2.00	1.96	2.14	2.23	2.24	2.06	1.85	1.75	1.69	1.63	1.97

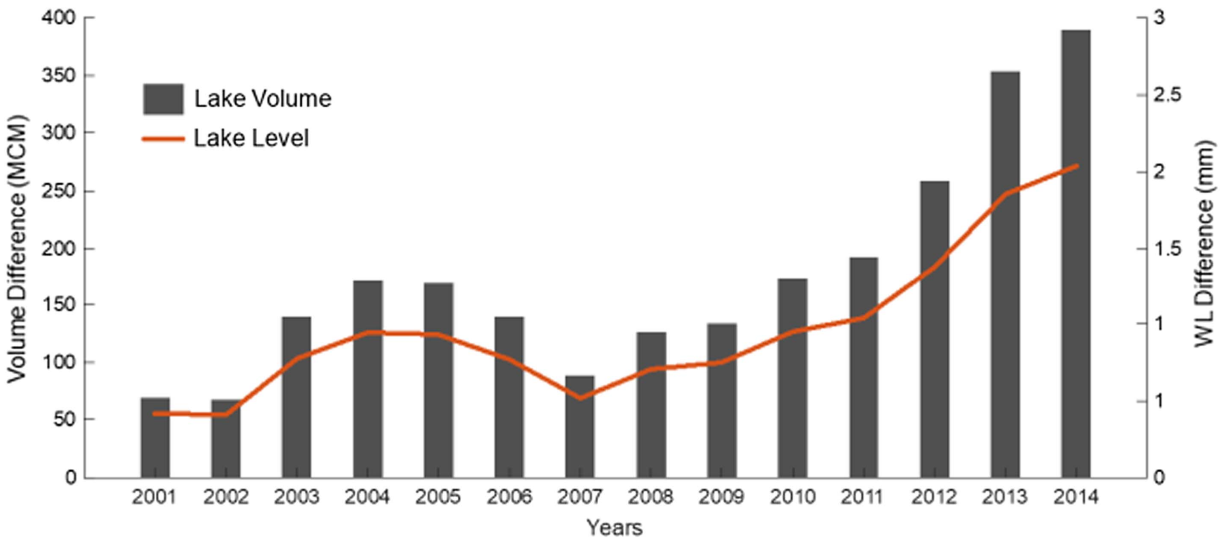

Fig. 11. Annual difference of simulated and observed volume and mean annual water level between 2001 and 2014.

and its tributaries. Similar findings are shown (Legesse et al. 2004; Seyoum et al. 2015) for Lake Abiyata situated within the same climatic zone and fed by the runoff from Lake Ziway outflow.

In this study, the lake water balance estimation was mainly from historic climatic conditions. However, it is reported that future climate change will affect the temporal distribution of rainfall and runoff in the CRV Lakes basin (Wagesho et al. 2013; Abraham et al. 2018). This further will affect the water balance components of the hydrological cycles such as rainfall, evaporation, and runoff of the lake area. Hence, for future water resources planning and management of the lake, the projected impacts of climate change and water abstraction needs to be considered.

Discussion: Comparison to the Previous Water Balance Studies

To compare water balance components of findings in this study to findings in previous studies in the study area, two hydrological regimes were constructed for periods 1986–2000 (baseline natural period) and 2001–2014 (human-induced period). This classification period was selected based on the finding of this study and reference was made from previous studies on Lake Ziway (Seyoum et al. 2015; Desta and Lemma 2017; Desta et al. 2017). To avoid the variation in water balance components among the studies with respect to the study period comparison was for baseline natural condition (1986–2000). This period

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Table 8. Comparison of Lake Ziway water balance components of this study with other previous studies (all terms are in mm)

Water balance terms	This paper (2019) baseline period	This paper (2019) human-induced Period	Vallet-Coulomb et al. (2001)	Ayenew (2004)	Jansen et al. (2007)
Study period	1986–2000	2001–2014	1969–1995	1970–1996	1990–2000
Lake areal rainfall	760.5	765.8	752.8	734.1	733.9
Lake evaporation	1,869.8	1,881.4	1,875	2,023.0	1,791.0
Gauged river inflow	1,379.3	1,408.6	1,474.1	1,492.0	1,476.4
Ungauged river inflow	181.6	186.2	112.4	109.1	85.4
Lake outflow	384.1	386.3	352.8	386.4	397.8
Closure term	67.5	92.9	111.5	−73.9	107.0

was selected as previous studies of water balance estimation were up to 2000.

The water balance analysis for the baseline natural period (1986–2000) resulted in an average annual lake rainfall of 760 mm year^{-1}, open water evaporation of 1,870 mm year^{-1}, river inflow from gauge and ungauged catchments constitutes of 1,561 mm year^{-1}, and outflow discharge from the lake of 384 mm year^{-1} (Table 8). Results of this study show that the Lake Ziway water balance error of 67.5 mm per year for the baseline natural condition that accounts for 2.9% of the total lake inflow from rainfall and river inflow. We note that the water balance components and water balance closure error for the human-induced period (2001–2014) is slightly attributed compared to the baseline condition. The variation in some water balance components reported in these more recent period points out more water abstraction from the lake and its tributaries. The water balance closure error for the human-induced period increased by 26 mm compared to the baseline condition, which results in a water balance closure error of 3.9% of the total lake inflow from rainfall and river inflow.

Under the baseline period (1986–2000) the average annual lake rainfall resulted in 760 mm year^{-1}. The lake average annual rainfall estimated in this study is higher than estimated in (Ayenew 2004; Legesse and Ayenew 2006; Jansen et al. 2007) (734 mm year^{-1}) but lower than estimated in Desta et al. (2017) (768 mm year^{-1}). However, the estimate better matches with an estimate in Vallet-Coulomb et al. (2001), which used three stations (Ziway, Meki and Abura) situated near to the lake. In most of the previous studies, lake rainfall estimation is only from Ziway town meteorological station which is situated close to the lake. In this study, lake areal rainfall estimation has benefited from the use of bias-corrected satellite rainfall on the lake surface.

The average annual lake evaporation is estimated at 1,870 mm year^{-1} for the period 1986–2000. This estimate is significantly lower than as estimated in Ayenew (2004) (2,023 mm year^{-1}) and Desta et al. (2017) (1,920 mm year^{-1}) but higher than Melesse et al. (2009) (1,662 mm year^{-1}) and Jansen et al. (2007) (1,791 mm year^{-1}). Evaporation estimate in this study is similar to the result obtained in Vallet-Coulomb et al. (2001) (1,870 mm year^{-1}) who also used the Penman method. In most of the previous studies, evaporation was estimated at monthly time step for meteorological time series from Ziway station only. In this study, the analysis is at daily time step with two additional stations (Ogolcho and Arata) at the lake shore. Hence, lake evaporation computations benefited from the additional air temperature data of stations near the lake. The differences in the estimated lake evaporation among the studies arise from this fact and other aspects concern the difference in estimation methods.

Simulated river inflow from major tributaries for the baseline period indicates 1,379 mm runoff inflow to Lake Ziway (38% of Meki and 62% of Katar), whereas the contribution of the ungauged catchment is 182 mm (8.5% of the total lake inflow from rainfall and river inflow) (Table 8). The river inflow to the lake estimated in this study is lower than reported in (Ayenew 2004; Jansen et al. 2007). In this study, the runoff from the gauged catchments is simulated by the use of a rainfall-runoff model using bias-corrected satellite rainfall estimates as input. However, most of the previous studies used river gauges streamflow for a shorter period. The relative difference among the studies originates from the selected method for estimation of runoff and the dataset used. The lake outflow obtained in this study was closer to Ayenew (2004) but higher than estimated in Vallet-Coulomb et al. (2001). The result revealed higher lake outflow which is related to lake water levels. Hence, more water abstraction would lead to lower lake outflow.

Unlike other previous studies, this study applied improved rainfall data quality by correcting the bias of CHIRP satellite-only product with rain gauge dataset as a reference. Hence, we advocate the use of bias-corrected satellite product to overcome the data gap in water budget studies and to improve accuracy of the research findings. However, note that there are many sources of uncertainty in the estimation of each lake water balance component. This study assumed that lake-groundwater interaction is negligible. Another source of uncertainty is in the estimation of lake evaporation using the Penman method from observed data and lake rainfall from satellite rainfall and bias correction method. There is also error due to runoff simulation from gauged and ungauged catchments. Hence, we suggest that future studies consider uncertainties in the water balance by using improved approaches to represent each component. Also uncertainties by advanced model calibration approaches and use of more advanced bias correction algorithms should be considered.

Conclusions

In this study, the CHIRP satellite-only rainfall product was used to simulate lake level fluctuation using a combination of HBV rainfall-runoff modeling and a simple lake water balance model. The study area is the Lake Ziway subbasin, in the CRV Lakes basin of Ethiopia. In this study, the estimated lake rainfall and evaporation are expected to have better accuracy than previous studies (Ayenew 2004; Jansen et al. 2007; Melesse et al. 2009; Desta et al. 2017). That is, since (1) rainfall is estimated from bias- corrected satellite data using rain gauge data as a reference, and (2) three stations (Ziway, Ogolcho, and Arata) were considered for evaporation estimation whereas previous studies only used Ziway station. The following conclusions were drawn based on the findings of this study:

1. The bias of CHIRP satellite rainfall product is very large and accounts for 73% over estimation at rainy season. Bias is considered too high to allow for the direct use of CHIRP product in

HBV rainfall-runoff modeling that serves lake inflow simulation of Lake Ziway. However, the study has shown that the bias can be significantly reduced using a nonlinear power bias correction using rain gauge data as a reference. The bias-corrected CHIRP satellite product better captured the temporal pattern and magnitude of the observed rainfall than uncorrected product.
2. The bias-corrected CHIRP rainfall estimate was used as the HBV model input. The HBV model performed adequately when evaluated in terms of NSE and RVE objective functions for both the calibration and validation periods. Thus, the streamflow pattern, peak flows, and baseflow of the simulated hydrograph agreed with those of the observed hydrograph. A disagreement between the simulated and observed hydrographs noticeably increased when the uncorrected CHIRP rainfall served as model input. Small errors in CHIRP data were found to propagate to relatively larger errors in streamflow simulation by means of the HBV model.
3. Under baseline natural conditions (1986–2000), the inflow to the lake consists of 33% from rainfall over the lake, 59% from gauged catchments and 8% from ungauged catchments. This indicates that the gauged catchments are the major contributors to Lake Ziway inflow. Whereas the outflow consists of 83% evaporation and 17% outflow through Bulbula River. As such, evaporation over the lake surface is the major lake water loss term. Results of this study show a water balance closure error of Lake Ziway is 67.5 mm per year for the assessment period 1986–2000, which accounts for 2.9% of the total annual lake inflow by rainfall and river inflow. Since the estimation of each water balance term must be associated with aspects of uncertainty, further assessment on the accuracy of the lake water balance component is required.
4. The lake level simulation indicates good agreement between the simulated and observed lake levels for the period 1986–2000. However, there was an increasing disagreement from the year 2000 onwards, which most likely can be attributed to human-induced influences such as water abstraction. The maximum difference between simulated and observed lake levels occasionally reached up to 2.28 m in 2013. This suggests that the actual lake level in 2013 should have been at least 2.28 m higher than the observed level if there were no human-induced influences.
5. The observed lake volume is less than the simulated counterpart by up to 381 MCM in 2014, which accounts for 27.5% of the average lake volume under the baseline condition. This difference mainly results from human-induced influences. Overall, the water balance closure error for the period 2001–2014 is higher than the baseline natural condition, which could be by increased water abstraction from the lake itself and from its tributaries.

In general, this study shows that applying bias-corrected CHIRP rainfall products is effective to fill the data void in Lake Ziway water budget studies. Hence, in data-scarce regions, use of bias-corrected CHIRP data is feasible for lake water level simulation. The findings of this study indicate a significant human impact on lake level and volume. Therefore, the study suggests future studies to explore impacts by projected climate change and anticipated increasing lake water abstractions.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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References

Abraham, T., A. Woldemicheala, A. Muluneha, and B. Abateb. 2018. “Hydrological responses of climate change on Lake Ziway catchment, Central Rift Valley of Ethiopia.” *J. Earth Sci. Clim. Change* 9 (6): 474. https://doi.org/10.4172/2157-7617.1000474.

Allen, R. G., L. S. Pereira, D. Raes, and M. Smith. 1998. *Crop evapotranspiration: Guidelines for computing crop water requirements*. Irrigation and Drainage Paper 56. Rome: Food and Agriculture Organization.

Ashenafi, Y., and D. Hailu. 2014. “Assessment of the use of remotely sensed rainfall products for runoff simulation in the Upper Blue Nile basin of Ethiopia.” *Zede. J.* 31: 1–9.

Ayalew, S. 2010. “Developing simplified regional potential evapotranspiration estimation method for Abbay river basin” *EEA. J.* 27: 25–33.

Ayehu, G. T., T. Tadesse, B. Gessesse, and T. Dinku. 2018. “Validation of new satellite rainfall products over the Upper Blue Nile Basin, Ethiopia.” *Atmos. Meas. Tech.* 11 (4): 1921–1936. https://doi.org/10.5194/amt-11-1921-2018.

Ayenew, T. 2004. “Environmental implication of changes in the levels of lakes in the Ethiopian Rift since 1970.” *Reg. Environ. Change* 4 (4): 192–204. https://doi.org/10.1007/s10113-004-0083-x.

Ayenew, T. 2007. “Water management problems in the Ethiopian rift: Challenges for development.” *J. Afr. Earth Sci.* 48 (2–3): 222–236. https://doi.org/10.1016/j.jafrearsci.2006.05.010.

Bergström, S. 1992. *The HBV model: Its structure and applications.* Norrköping, Sweden: Swedish Meteorological and Hydrological Institute.

Bhatti, H. A., T. Rientjes, A. T. Haile, E. Habib, and W. Verhoef. 2016. “Evaluation of bias correction method for satellite-based rainfall data” *Sensors* 16 (6): 884. https://doi.org/10.3390/s16060884.

Dembélé, M., and S. J. Zwart. 2016. “Evaluation and comparison of satellite-based rainfall products in Burkina Faso, West Africa.” *Int. J. Remote Sens.* 37 (17): 3995–4014. https://doi.org/10.1080/01431161.2016.1207258.

Dessie, M., N. E. Verhoest, V. R. Pauwels, E. Adgo, J. Deckers, J. Poesen, and J. Nyssen. 2015. “Water balance of a lake with floodplain buffering: Lake Tana, Blue Nile Basin, Ethiopia.” *J. Hydrol.* 522 (Mar): 174–186. https://doi.org/10.1016/j.jhydrol.2014.12.049.

Dessie, M., N. E. Verhoest, V. R. Pauwels, T. Admasu, E. Adgo, J. Deckers, J. Poesen, and J. Nyssen. 2014. “Analyzing runoff processes through conceptual hydrological modeling in the Upper Blue Nile Basin, Ethiopia.” *Hydrol. Earth Syst. Sci.* 18 (12): 5149–5167. https://doi.org/10.5194/hess-18-5149-2014.

Desta, H., and B. Lemma. 2017. “SWAT based hydrological assessment and characterization of Lake Ziway sub-watersheds, Ethiopia.” *J. Hydrol. Reg. Stud.* 13: 122–137. https://doi.org/10.1016/j.ejrh.2017.08.002.

Desta, H., B. Lemma, and E. Gebremariam. 2017. “Identifying sustainability challenges on land and water uses: The case of Lake Ziway watershed, Ethiopia.” *Appl. Geogr.* 88 (Nov): 130–143. https://doi.org/10.1016/j.apgeog.2017.09.005.

Dinku, T. 2014. “Validation of the CHIRPS satellite rainfall estimate.” In *Proc., 7th Int. Precipitation Working Group (IPWG) Workshop*. Bologna, Italy: International Research Institute for Climate and Society, the Earth Institute at Univ.

Dinku, T., C. Funk, P. Peterson, R. Maidment, T. Tadesse, H. Gadain, and P. Ceccato. 2018. “Validation of the CHIRPS satellite rainfall estimates over eastern of Africa." *Q. J. R. Meteorol. Soc.* 144 (Nov): 1–21. https://doi.org/10.1002/qj.3244.

Duan, Z., J. Liu, Y. Tuo, G. Chiogna, and M. Disse. 2016. "Evaluation of eight high spatial resolution gridded rainfall products in Adige Basin (Italy) at multiple temporal and spatial scales." *Sci. Total Environ.* 573 (Dec): 1536–1553. https://doi.org/10.1016/j.scitotenv.2016.08.213.

Ebert, E. E., J. E. Janowiak, and C. Kidd. 2007. "Comparison of near-real-time rainfall estimates from satellite observations and numerical models." *Bull. Am. Meteorol. Soc.* 88 (1): 47–64. https://doi.org/10.1175/BAMS-88-1-47.

Fuka, D. R., M. T. Walter, C. MacAlister, A. T. Degaetano, T. S. Steenhuis, and Z. M. Easton. 2014. "Using the climate forecast system reanalysis as weather input data for watershed models." *Hydrol. Process.* 28 (22): 5613–5623. https://doi.org/10.1002/hyp.10073.

Funk, C. C., P. J. Peterson, M. F. Landsfeld, D. H. Pedreros, J. P. Verdin, J. D. Rowland, B. E. Romero, G. J. Husak, J. C. Michaelsen, and A. P. Verdin. 2014. *A quasi-global rainfall time series for drought monitoring*. Washington, DC: USGS.

Funk, C. C., A. Verdin, J. Michaelsen, P. Peterson, D. Pedreros, and G. Husak. 2015. "A global satellite-assisted rainfall climatology." *Earth Syst. Sci. Data* 7 (2): 275–287. https://doi.org/10.5194/essd-7-275-2015.

Gebere, S. B., T. Alamirew, B. J. Merkel, and A. M. Melesse. 2015. "Performance of high resolution satellite rainfall products over data scarce parts of Eastern Ethiopia." *Remote Sens.* 7 (9): 11639–11663. https://doi.org/10.3390/rs70911639.

Goshime, D. W., R. Absi, and B. Ledésert. 2019. "Evaluation and bias correction of CHIRP rainfall estimate for rainfall-runoff simulation over Lake Ziway watershed, Ethiopia." *Hydrology* 6 (3): 68. https://doi.org/10.3390/hydrology6030068.

Gumindoga, W., T. H. M. Rientjes, A. T. Haile, H. Makurira, and P. Reggiani. 2019. "Performance of bias-correction schemes for CMORPH rainfall estimates in the Zambezi River basin." *Hydrol. Earth Syst. Sci.* 23 (7): 2915–2938. https://doi.org/10.5194/hess-23-2915-2019.

Habib, E., A. T. Haile, N. Sazib, Y. Zhang, and T. Rientjes. 2014. "Effect of bias correction of satellite-rainfall estimates on runoff simulations at the source of the Upper Blue Nile." *Remote Sens.* 6 (7): 6688–6708. https://doi.org/10.3390/rs6076688.

Haile, A. T., E. Habib, and T. Rientjes. 2013. "Evaluation of the climate prediction center (CPC) morphing technique (CMORPH) rainfall product on hourly time scales over the source of the Blue Nile River." *Hydrol. Process.* 27 (12): 1829–1839. https://doi.org/10.1002/hyp.9330.

Hargreaves, G. H., and R. G. Allen. 1985. "History and evaluation of Hargreaves evapotranspiration equation." *J. Irrig. Drain. Eng.* 129 (1): 53–63. https://doi.org/10.1061/(ASCE)0733-9437(2003)129:1(53).

Hessels, T. M. 2015. *Comparison and validation of several open access remotely sensed rainfall products for the Nile Basin*. Delft, Netherlands: Delft Univ. of Technology.

Huffman, G. J., D. T. Bolvin, E. J. Nelkin, D. B. Wolff, R. F. Adler, G. Gu, Y., Hong, K. P. Bowman, and E. F. Stocker. 2007. "The TRMM multi-satellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor rainfall estimates at fine scales." *J. Hydrometeorol.* 8 (1): 38–55. https://doi.org/10.1175/JHM560.1.

Jansen, H. C., H. Hengsdijk, D. Legesse, T. Ayenew, P. Hellegers, and P. C. Spliethoff. 2007. *Land and water resources assessment in the Ethiopian Central Rift Valley : Project: ecosystems for water, food and economic development*. Alterra Rep. No. 1587. Wageningen, Netherlands: Wageningen Univ.

Johansson, B. 2013. *Integrated Hydrological Modelling System (IHMS) manual version 6.3*. Norrköping, Sweden: Swedish Meteorological and Hydrological Institute.

Joyce, R. J., J. E. Janowiak, P. A. Arkin, and P. P. Xie. 2004. "A method that produces global rainfall estimates from passive microwave and infrared data at high spatial and temporal resolution." *J. Hydrometeorol.* 5: 487–503. https://doi.org/10.1175/1525-7541(2004)005<0487:CAMTPG>2.0.CO;2.

Kebede, S., Y. Travi, T. Alemayehu, and V. Marc. 2006. "Water balance of Lake Tana and its sensitivity to fluctuations in rainfall, Blue Nile basin, Ethiopia." *J. Hydrol.* 316 (1–4): 233–247. https://doi.org/10.1016/j.jhydrol.2005.05.011.

Khandu, X., J. L. Awange, and E. Forootan. 2015. "An evaluation of high-resolution gridded rainfall products over Bhutan (1998–2012)." *Int. J. Climatol.* 36 (3): 1067–1087. https://doi.org/10.1002/joc.4402.

Krakauer, N. Y., S. M. Pradhanang, T. Lakhankar, and A. K. Jha. 2013. "Evaluating satellite products for rainfall estimation in mountain regions: A case study for Nepal." *Remote Sens.* 5 (8): 4107–4123. https://doi.org/10.3390/rs5084107.

Kumambala, P. G., and A. Ervine. 2010. "Water balance model of Lake Malawi and its sensitivity to climate change." *Open Hydrol. J.* 4 (1): 152–162. https://doi.org/10.2174/1874378101004010152.

Lafon, T., S. Dadson, G. Buys, and C. Prudhomme. 2013. "Bias correction of daily rainfall simulated by a regional climate model: A comparison of methods." *Int. J. Climatol.* 33 (6): 1367–1381. https://doi.org/10.1002/joc.3518.

Le, A. M., and N. G. Pricope. 2017. "Increasing the accuracy of runoff and streamflow simulation in the Nzoia Basin, Western Kenya, through the Incorporation of satellite-derived CHIRPS data." *Water* 9 (2): 114. https://doi.org/10.3390/w9020114.

Leander, R., and T. Buishand. 2007. "Resampling of regional climate model output for the simulation of extreme river flows." *J. Hydrol.* 332 (3–4): 487–496. https://doi.org/10.1016/j.jhydrol.2006.08.006.

Legesse, D., and T. Ayenew. 2006. "Effect of improper water and land resource utilization on the central main Ethiopian rift lakes." *Q. Int.* 148 (1): 8–18. https://doi.org/10.1016/j.quaint.2005.11.003.

Legesse, D., C. Vallet-Coulomb, and F. Gasse. 2004. "Analysis of the hydrological response of a tropical terminal lake, Lake Abiyata (main Ethiopian rift valley) to changes in climate and human activities." *Hydrol. Process.* 18 (3): 487–504. https://doi.org/10.1002/hyp.1334.

Lindström, G., B. Johansson, M. Persson, M. Gardelin, and S. Bergström. 1997. "Development and test of the distributed HBV-96 hydrological model." *J. Hydrol.* 201 (1–4): 272–288. https://doi.org/10.1016/S0022-1694(97)00041-3.

Melesse, A. M., W. Abtew, and T. Dessalegn. 2009. "Evaporation estimation of rift valley lakes: Comparison of models." *Sensors* 9 (12): 9603–9615. https://doi.org/10.3390/s91209603.

Moges, S. A., Z. Katambara, and Z. Bashar. 2003. "Decision support system for estimation of potential evapotranspiration in Pangani Basin." *Phys. Chem. Earth.* 28 (20–27): 927–934. https://doi.org/10.1016/j.pce.2003.08.038.

Nicholson, S. E., and X. Yin. 2001. "Rainfall conditions in equatorial East Africa during the nineteenth century as inferred from the record of Lake Victoria." *Clim. Change* 48 (2–3): 387–398. https://doi.org/10.1023/A:1010736008362.

Peng, S., W. Liu, W. Wang, Q. Shao, X. Jiao, Z. Yu, W. Xing, J. Xu, Z. Zhang, and Y. Luo. 2013. "Estimating the effects of climatic variability and human activities on streamflow in the Hutuo river Basin, China." *J. Hydrol. Eng.* 18 (4): 422–430. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000664.

Penman, H. L. 1948. "Natural evaporation from open water, bare soil and grass." *Proc. R. Soc. A: Math. Phys. Eng. Sci.* 193 (1032): 120–145. https://doi.org/10.1098/rspa.1948.0037.

Pike, A. 1988. "The use of temperature based evaporation equations in Southern Africa." In *Proc., Seminar Pietermaritzburg*. Durban, South Africa: Univ. of Natal.

Pratama, A. W., A. Buono, R. Hidayat, and H. Harsa. 2018. "Bias correction of daily satellite rainfall data using genetic algorithm." *IOP Conf. Ser.: Earth. Environ. Sci.* 149 (1): 012071.

Rientjes, T. H. M., B. U. J. Perera, A. T. Haile, P. Reggiani, and L. P. Muthuwatta. 2011. "Regionalisation for lake level simulation—The case of Lake Tana in the Upper Blue Nile, Ethiopia." *Hydrol. Earth Syst. Sci.* 15 (4): 1167–1183. https://doi.org/10.5194/hess-15-1167-2011.

Seyoum, W. M., A. M. Milewski, and M. C. Durham. 2015. "Understanding the relative impacts of natural processes and human activities on the hydrology of the Central Rift Valley Lakes, East Africa." *Hydrol. Process.* 29 (19): 4312–4324. https://doi.org/10.1002/hyp.10490.

Shrestha, N. K., F. M. Qamer, D. Pedreros, M. S. R. Murthy, S. M. Wahid, and M. Shrestha. 2017. "Evaluating the accuracy of Climate Hazard Group (CHG) satellite rainfall estimates for rainfall based drought monitoring in Koshi basin, Nepal." *J. Hydrol.: Reg. Stud.* 13: 138–151. https://doi.org/10.1016/j.ejrh.2017.08.004.

Sorooshian, S., K.-L. Hsu, X. Gao, H. V. Gupta, B. Imam, and D. Braithwaite. 2000. "Evaluation of PERSIANN system satellite–based estimates of tropical rainfall." *Bull. Am. Meteorol. Soc.* 81 (9): 2035–2046. https://doi.org/10.1175/1520-0477(2000)081<2035:EOPSSE>2.3.CO;2.

Terink, W., R. T. W. L. Hurkmans, P. J. J. F. Torfs, and R. Uijlenhoet. 2010. "Evaluation of a bias correction method applied to downscaled precipitation and temperature reanalysis data for the Rhine basin." *Hydrol. Earth Syst. Sci.* 14 (6): 687–703. https://doi.org/10.5194/hess-14-687-2010.

Vallet-Coulomb, C., D. Legesse, F. Gasse, Y. Travi, and T. Chernet. 2001. "Lake evaporation estimates in tropical Africa (Lake Ziway, Ethiopia)." *J. Hydrol.* 245 (1–4): 1–18. https://doi.org/10.1016/S0022-1694(01)00341-9.

Wagesho, N., M. K. Jain, and N. K. Goel. 2013. "Effect of climate change on runoff generation: Application to Rift Valley Lakes Basin of Ethiopia." *J. Hydrol. Eng.* 18 (8): 1048–1063. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000647,1048-1063.

Wale, A., T. H. M. Rientjes, A. S. M. Gieske, and H. A. Getachew. 2009. "Ungauged catchment contributions to Lake Tana's water balance." *Int. J. Hydrol. Process.* 23 (26): 3682–3693. https://doi.org/10.1002/hyp.7284.

Wang, J., Y. Hong, J. Gourley, P. Adhikari, L. Li, and F. Su. 2010. "Quantitative assessment of climate change and human impacts on long-term hydrologic response: A case study in a sub-basin of the Yellow River, China." *Int. J. Climatol.* 30 (14): 2130–2137. https://doi.org/10.1002/joc.2023.

Worqlul, A. W., E. K. Ayana, B. H. P. Maathuis, C. MacAlister, W. D. Philpot, J. M. Osorio Leyton, and T. S. Steenhuis. 2018. "Performance of bias corrected MPEG rainfall estimate for rainfall-runoff simulation in the upper Blue Nile Basin, Ethiopia." *J. Hydrol.* 556: 1182–1191. https://doi.org/10.1016/j.jhydrol.2017.01.058.

Worqlul, A. W., A. S. Collick, S. A. Tilahun, S. Langan, T. H. Rientjest, and T. S. Steenhuis. 2015. "Comparing TRMM 3B42, CFSR and ground-based rainfall estimates as input for hydrological models, in data scarce regions: The Upper Blue Nile Basin, Ethiopia." *Hydrol. Earth Syst. Sci. Discuss.* 12 (2): 2081–2112. https://doi.org/10.5194/hessd-12-2081-2015.

Yong, B., B. Chen, J. J. Gourley, L. Ren, Y. Hong, X. Chen, W. Wang, S. Chen, and L. Gong. 2014. "Intercomparison of the version-6 and version-7 TMPA rainfall products over high and low latitudes basins with independent gauge networks." *J. Hydrol.* 508 (Jan): 77–87. https://doi.org/10.1016/j.jhydrol.2013.10.050.

Yong, B., L. L. Ren, Y. Hong, J. H. Wang, J. J. Gourley, S. H. Jiang, and W. Wang. 2010. "Hydrologic evaluation of multisatellite precipitation analysis standard rainfall products in basins beyond its inclined latitude band: A case study in Laohahe basin, China." *Water Resour. Res.* 46 (7): 1–20. https://doi.org/10.1029/2009WR008965.

Yuan, F., L. Zhang, K. W. W. Win, L. Ren, C. Zhao, Y. Zhu, S. Jiang, and Y. Liu. 2017. "Assessment of GPM and TRMM multi-satellite rainfall products in streamflow simulations in a data-sparse mountainous watershed in Myanmar." *Remote Sens.* 9 (3): 302. https://doi.org/10.3390/rs9030302.

Zhou, Z., Y. Jia, Y. Qiu, J. Liu, H. Wang, C.-Y. Xu, J. Li, and L. Liu. 2018. "Simulation of dualistic hydrological processes affected by intensive human activities based on distributed hydrological model." *J. Water Resour. Plann. Manage.* 144 (12): 04018077. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000990.

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