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Evaluation of the WEAP model in simulating subbasin hydrology in the Central Rift Valley basin, Ethiopia

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Abstract

Background: The subbasin hydrologic behaviors have been altered by many natural and anthropologic factors such as climate change and land development activities. Model-based assessment can be used to simulate both natural hydrological processes, human-induced effects, and management strategies on water resources. For the Ketar subbasin, the WEAP (water evaluation and planning) hydrologic model was developed that aimed at (1) evaluating the application of the WEAP model in the Ketar subbasin, (2) evaluating the demonstration of the WEAP model using model efficiency evaluation criteria, and (3) simulating hydrological processes of the subbasin using the WEAP model.

Methods: WEAP-based soil moisture method (rainfall-runoff) hydrology routine is comprised of a lumped, one-dimensional, two-layer soil water accounting that uses empirical functions to designate evapotranspiration, surface runoff, interflow, and deep percolation for a sub-unit at root zone. A catchment is considered as the smallest hydrologic response unit. The catchment's surface hydrological balance is typically estimated by discretizing the catchment into multiple land uses for which water balance is estimated at root zone.

Results: The monthly measured and simulated streamflow statistics showed a positive strong relationship with R^2 of 0.82, NSE of 0.80, and IA of 0.95; and with R^2 of 0.91, NSE of 0.91, and IA of 0.98 for calibration and validation periods respectively. Similarly, the mean monthly measured and simulated streamflow showed an agreement with R^2 of 0.99, NSE of 0.97, and IA of 0.99, and R^2 of 0.94, NSE of 0.93, and IA of 0.93 for the periods of calibration and validation respectively.

Conclusion: The model has demonstrated the capability to represent the hydrologic dynamics of the subbasin both at monthly and mean monthly periods. In general, the overall model performance evaluation statistics show a very good agreement between measured and simulated streamflow at the outlet of the subbasin.

Keywords: Hydrologic processes, Model, Soil moisture method

Background

A proper understanding of subbasin hydrological processes is essential to estimate changes in the dynamic response of a hydrologic system in spatio-temporal dimensions. The earth's hydrological system encompasses

physical processes like precipitation, evapotranspiration (ET), overland flow, infiltration, recharge or discharge, and groundwater flow and their interactions in the atmosphere, land surface, and sub-surface that govern water movement, distribution, and change from one system to the other (Delfs et al. 2013; Niu et al. 2014). These could be largely influenced by meteorological parameters (precipitation, temperature, solar radiation, wind speed, and relative humidity), land surface properties, and soil parameters. To estimate hydrologic parameters, models are

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widely used. Hydrological models are simplified mathematical representation of a real-world system that is used to enhance the understanding, prediction of hydrologic processes (Pacheco 2015; Santos et al. 2014).

In the recent decade, hydrologic models play a very crucial role in properly characterizing subbasin properties by predicting target parameters based on input data. They provide a chance to estimate some variables that are difficult to measure in the field because of their inherent nature (may vary in spatio-temporal scale) (Wheater et al. 2010). Moreover, well-developed, calibrated, and validated models can be used for different applications such as impact evaluation of change in some of the input variables (e.g., land-use change, climate change, development activities are a few among others), and suitable for setting scenarios and analysis.

Generally, there are two classes of modeling techniques that are intensively used to estimate time series hydrologic parameters (Mohammadi et al. 2020a, b, c). These are the physical-based models and artificial intelligence (AI) models. Recently, the applications of artificial intelligence models have been widely and effectively used to predict hydrologic and meteorological parameters (Mohammadi et al. 2020a, b, c). The artificial intelligence models can estimate required parameters based on a series of input predictors without understanding the physical processes (Mohammadi et al. 2020a, b, c). In contrast to the artificial intelligence model, the physically based models are used to simulate time series hydrologic parameters through modeling the potential interactions among various factors (Fang et al. 2019; Wang et al. 2016). These groups of models have been widely practiced across the world; for instance, SWAT (Arnold et al. 1998) and the WEAP (SEI 2007) are a few among others.

Currently, the Central Rift Valley (CRV) basin has been facing challenges for satisfying ever-growing demands for water, domestic use, irrigation, and the requirement for environmental flow to maintain ecosystem health (Alemayehu et al. 2006; Ayenew 2007; Legesse and Ayenew 2006; Pascual-Ferrer et al. 2013). Consequently, competition has steadily tightened for Lake Ziway water abstraction among many water users (Pascual-Ferrer et al. 2014). Besides, the sustainability of water resources has become more challenged under potential impacts of human-induced changes such as land development and climate change. Effective water resources management depends on a thorough understanding of the quantity and quality of available water in the subbasin (Lorenz and Ziegeweid 2015).

Therefore, a model-based assessment can be used to simulate both the natural hydrologic processes, human-induced effects, and management strategies on water resources (Dougherty et al. 2007; Lerner 2002; Scanlon

et al. 2007). Presently, water resources management is primarily used model-based scenario analysis to explore different alternatives. Water resources modeling is a requirement, and an essential part of scenario analysis in water resources management for which different generic software platforms can be used depending on the specific purpose (Ahmadi et al. 2018). In Ethiopia, several hydrological studies have been developed using physically based models (Desta and Lemma 2017; Legesse et al. 2003; Zeray et al. 2007). Specifically, in the CRV basin, some of these hydrological models have been conducted to evaluate the hydrologic response of the basin.

It is well known that basin hydrologic processes can be altered by changing land development and climate conditions. For instance, the hydrological response of the main Ethiopian Rift valley basin to land use and climate change on streamflow, as well as lakes level fluctuation was studied with physically based distributed Precipitation Runoff Modeling System (PRMS) model (Legesse et al. 2003, 2004, 2010). They have investigated the basin's hydrologic processes (ET, surface runoff, interflow, baseflow components, and evaporation of lakes). Another study with Soil Water Assessment Tool (SWAT) model was used by Zeray et al. (2007) to assess the impact of climate change on Ziway Lake water level. The same model was developed to assess the hydrologic processes and distributed water balance of the Ketar subbasin (Desta and Lemma 2017). However, integrated hydrological and water resource models have not been done to date. In this effect, water evaluation and planning (the WEAP) model was selected to be implemented in the CRV basin. The WEAP modeling software, developed by the Stockholm Environment Institute (SEI) was used as a basis for building the hydrology component. It is water resources modeling system that includes options to simulate both the natural rainfall-runoff processes and the management of implemented water system (Yates et al. 2005). Previously, the WEAP has been successfully applied to agricultural and urban catchments for the simulation of climate, land use, and population growth in many parts of the world (Höllermaier et al. 2010; Joyce et al. 2006; Mehta et al. 2013; Purkey et al. 2008).

Therefore, this study aimed at (1) evaluating the application of the WEAP model in the Ketar river subbasin, (2) evaluating the demonstration of the WEAP model using model efficiency evaluation criteria, and (3) simulating hydrological processes of the subbasin using the WEAP model.

Methods

Description of the Ketar subbasin

The Ketar River subbasin is located in the central part of the main Ethiopian Rift Valley basin (Fig. 1) with a drainage area of 327,160 hectares. It supports more than 675,000 residents' livelihoods that mainly rely on subsistent farming.

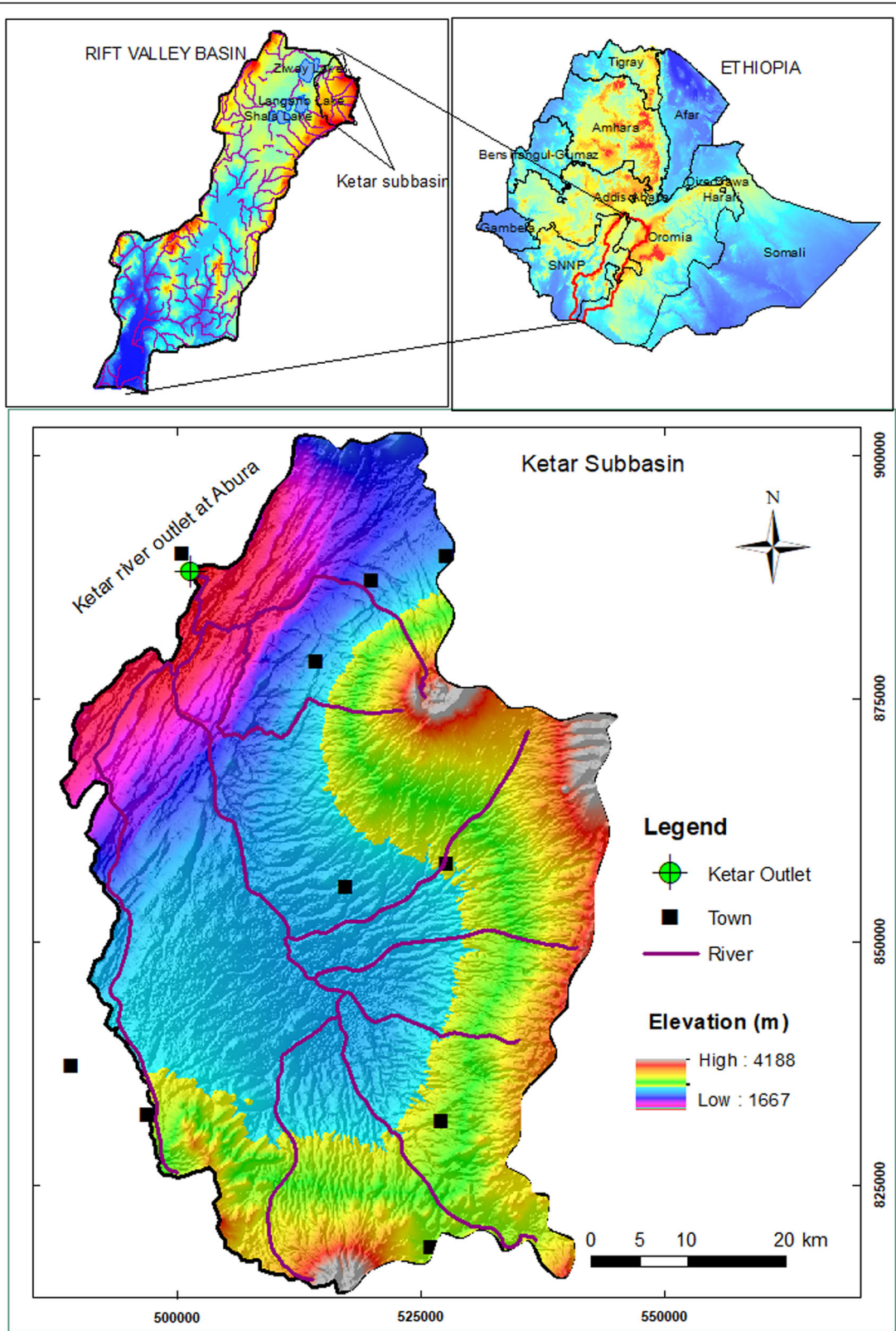


Fig. 1 Geographical location of the Ketar subbasin

The Ketar upstream subbasin is one of the main feeders of water to the Lake Ziway. Eventually, the overflow from Lake Ziway has a major share in sustaining Lake Abijata. The subbasin can be divided into three physiographic regions: the rift floor (<1750 masl), the transitional escarpment (1750–2000 masl), and the highlands (>2000 masl). Similarly, the climatic conditions characterizing the rift floor, the escarpment, and the highlands differ greatly. Mean annual rainfall over the entire basin is around 900 mm, showing high spatial variations as no more than 700 mm/year and as high as 1200 mm/year in the rift floor and highlands respectively. There is also temporal variability of total rainfall around 59% occurs during the rainy season (June–September), the remaining 28%, and 13% fall during months of Match–May and October–February respectively (Pascual-Ferrer et al. 2014).

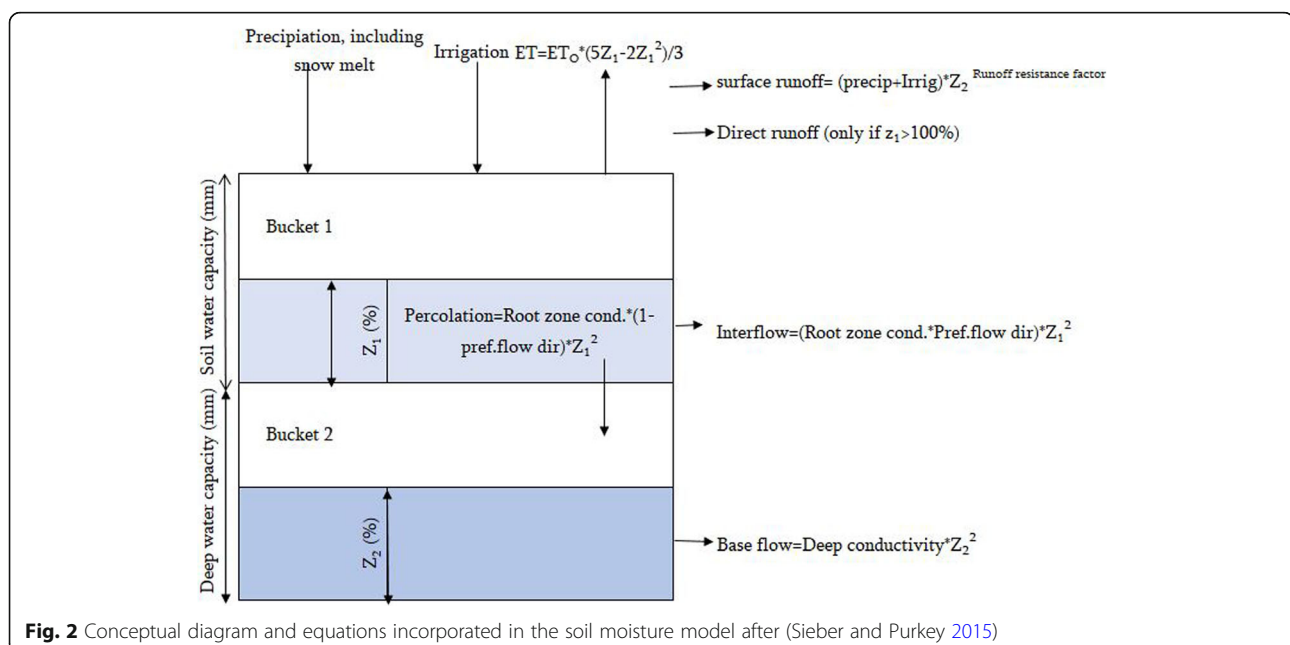
The mean annual temperature is about 15°C in the highlands and around 20°C in the rift and actual ET varies from around 900 mm/year in the highlands to 650 mm/year in the rift (Ayenew 2003). The climate is humid to sub-humid in the highlands and semi-arid in the rift floor. The hydrology of the region is characterized by seasonal variations. Since precipitation is the only input of water that is available for ET, surface runoff, recharge to groundwater, and interflow, and in turn, it determines stream flow that mostly feeds the lakes.

Hydrologic model development

The WEAP hydrologic model was applied to evaluate the hydrologic behavior at the subbasin or land-use

level. It is a lumped continuous model that is based on rainfall-runoff method (soil moisture method). This takes into account a one-dimensional, 2-layer (or “bucket”) soil moisture dynamic accounting system that uses empirical functions to partition water into ET, surface runoff, sub-surface runoff (i.e., interflow), and deep percolation for a subbasin unit at the root zone (Eq. 1) and shown in Fig. 2 (SEI 2007). One of the most important input data is the climate dataset as precipitation, temperature, relative humidity, and wind speed. The subbasin has a unique climate dataset that is uniformly distributed across subbasin.

This method allows for the characterization of land use, climate, and/or soil type impacts to these processes. The Ketar subbasin is fractionally subdivided into a unique set of independent land use/land cover classes (j) which sums up 100% of the sub basin’s area. To reflect the lumped hydrologic response, LULC values from each fractional area within the subbasin are then summed, with the surface runoff, interflow, and base flow being linked to a river feature and ET being lost from the system. For each fractional area, j of N, a water balance is computed. When proper linking is made between the subbasin unit node and a groundwater node, the deep percolation within the subbasin unit can be transmitted to a surface water body as baseflow or directly to groundwater storage and finally, the water balance empirical equation was computed as follow (SEI 2007).



$$Rd_j \frac{dz_{1,j}}{dt} = P_e(t) - ET_0(t)K_{c,j}(t) \left(\frac{5Z_{1,j} - 2Z_{1,j}^2}{3} \right) - P_e(t)Z_{1,j}^{RRF_j} - f_j k_{s,j} Z_{1,j}^2 - (1-f_j)K_{s,j}Z_{1,j}^2 \quad (1)$$

Where $Z_{1,j} \in [0, 1]$ is relative soil water storage, a fraction of the total effective water storage in the root zone layer land use j [dimensionless], j is land use and land cover unit (e.g., cultivated land, forest land, shrub) and each subbasin has N fraction of land use and land cover units, Rd_j is soil water holding capacity of land use j [mm], P_e is effective precipitation [mm], $ET_0(t)$ is reference evapotranspiration [mm/day], $K_{c,j}$ is crop coefficient land use j ; RRF_j is runoff resistance factor of land use and land cover j , $P_e(t)Z_{1,j}^{RRF_j}$ is the surface runoff, $f_j k_{s,j} Z_{1,j}^2$ is interflow from the first layer land use j , f_j is partitioning coefficient related to the land cover type, soil, and topography for the area j , that divides flow into horizontal f_j and vertical $(1-f_j)$ flows, and $K_{s,j}$ is saturated hydraulic conductivity of the root zone layer of land use j [mm/time].

In Eq. (1), the second term represents the reference ET; it is estimated using the Penman-Monteith equation modified for a standardized crop of grass, 0.12 m in height and with a surface resistance of 69 s/m. Continuing with Eq. (1), the $k_{c,j}$ is the crop/plant coefficient for each fractional land cover. The third term represents surface runoff, where RRF_j is the runoff resistance factor of the land cover. Higher values of RRF_j lead to less surface runoff. The fourth and fifth terms are the interflow and deep percolation terms, respectively, where the parameter $k_{s,j}$ is an estimate of the root zone saturated conductivity (mm/time) and f_j is a partitioning coefficient related to soil, land cover type, and topography that fractionally partitions water both horizontally and vertically.

Thus, total surface runoff (RT) and interflow, from each sub-catchment at time t is given as Eq. (2).

$$RT(t) = \sum_{j=1}^N A_j P_e(t) Z_{1,j}^{RRF_j} \quad (2)$$

The total interflow (IF), for each sub-catchment at time t , is given as Eq. (3).

$$IF(t) = \sum_{j=1}^N A_j f_j k_{s,j} Z_{1,j}^2 \quad (3)$$

When an alluvial aquifer is introduced into the model and a runoff/infiltration link is established between the watershed unit and the groundwater node and groundwater recharge (R) (volume/time) to the aquifer is computed as follows:

$$R = \sum_{j=1}^N A_j (1-f_j) K_{s,j} Z_{1,j}^2 \quad (4)$$

For applications where no return flow link is created from a catchment to a groundwater node baseflow emanating from the second bucket is computed as

$$S_{\max} \frac{dz_2}{dt} = \left(\sum_{j=1}^N (1-f_j) K_{s,j} Z_{1,j}^2 \right) - K_{s,2} Z_{2,j}^2 \quad (5)$$

Where the inflow to this storage, S_{\max} is the deep percolation from the upper storage given in Eq. (1) and $K_{s,2}$ is the saturated conductivity of the lower storage (mm/time), which is given as a single value for the subbasin, and therefore, does not include a subscript, j .

Actual evapotranspiration (ET) is also estimated using reference ET, crop coefficient (K_c), and soil water level in the modeling unit root zone given by Eq. (6).

$$ET = ET_0 \times K_c (5Z_1 - 2Z_1^2) / 3 \quad (6)$$

ET_0 is commonly known to be the amount of water from a land surface that would be lost to the atmosphere where water is adequate to meet the demand for atmospheric evaporation from the reference surface. ET_0 estimation uses standard climatological records of solar radiation (sunshine), air temperature, humidity, and wind speed above an extensive surface of green grass, shading the ground, and not short of water (Allen et al. 1998). The Penman-Monteith method to estimate ET_0 is expressed as:

$$ET_0 = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)} \quad (7)$$

Where, ET_0 is the reference evapotranspiration (mm/day), R_n is the net radiation at the crop surface (MJ/m²day), G is soil heat flux density (MJ/m²day), T is mean daily air temperature at 2 m height (°C), u_2 is the wind speed at 2 m height (m/s), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), $e_s - e_a$ is saturation vapor pressure deficit (kPa), Δ is slope vapor pressure curve (kPa/°C), and γ is the psychrometric constant (kPa/°C).

The WEAP model calibration and validation

Model calibration (parameter estimation) primarily aimed at obtaining a set of parameters applicable to the subbasin to reasonably represent the hydrology of the Ketar River at the Abura gauging station. It involves the automatic (Doherty 2010) and/or manual adjustment of model parameters to minimize the difference between observed and simulated values by tuning the model parameter values (Ingol-Blanco and McKinney 2013). In this study, the manual approach (trial-and-error) was used to fit as closely as possible; the simulated and

measured streamflow data. The WEAP embedded soil moisture method involves seven soil and land use-related parameters (Ingol-Blanco and McKinney 2013; Sieber and Purkey 2015) that can be used to re-calibrate the hydrologic model. These are crop coefficient (K_c), soil water capacity (S_w), deep water capacity (D_w), runoff resistance factor (RRF), the conductivity of root zone (K_s), conductivity of deep zone (K_d), preferred flow direction (f) and initial storage fraction at the beginning of simulation of upper soil layer (Z_1) and initial storage fraction at the beginning of simulation of lower soil layer (Z_2).

On the other hand, the main importance of implementing hydrologic models is to model subbasin hydrologic conditions. In this effect, the model validation process is essential to assess the validity of a model to simulate the hydrologic response of subbasin for conditions unlike that used during the calibration period (Legesse et al. 2003).

The WEAP model performance evaluation measures

The model performance was assessed using various techniques: (1) joint plots of the monthly and mean monthly simulated and observed hydrographs, (2) commonly used statistical methods. The coefficient of determination (R^2) (Krause et al. 2005); Nash-Sutcliffe coefficient of efficiency (NSE) (Nash and Sutcliffe 1970), index of agreement (IA) (Willmott 1981), root mean square error (RMSE), and RMSE-observations standard deviation ratio (RSR) (Singh et al. 2005) were used to measure the goodness-of-fit of a model as below:

$$R^2 = \frac{(\sum [X_i - \bar{X}][Y_i - \bar{Y}])^2}{\sum (X_i - \bar{X})^2 \sum (Y_i - \bar{Y})^2} \quad (8)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (X_i - Y_i)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (9)$$

$$IA = 1 - \frac{\sum_{i=1}^n (X_i - Y_i)^2}{\sum_{i=1}^n (|Y_i - \bar{X}| + |X_i - \bar{X}|)^2} \quad (10)$$

$$RSR = \frac{\sqrt{\sum_{i=1}^n (X_i - Y_i)^2}}{\sqrt{\sum_{i=1}^n (X_i - \bar{Y})^2}} \quad (11)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}} \quad (12)$$

Where X_i , Y_i , \bar{X} , \bar{Y} , and n denote the i th measured monthly discharge data, the i th simulated monthly discharge data, the mean of the measured monthly discharge data, the mean of the simulated monthly discharge data, and the total number of observation data respectively. These methods of model

performance evaluation metrics have successfully been implemented with the WEAP model (Barbaro and Zarriello 2006; Ingol-Blanco and McKinney 2013; McCabe and Legates 1999) for measured and simulated flows over the calibration and validation periods.

The WEAP model input data

To simulate the subbasin monthly hydrological processes with the WEAP hydrological model, meteorological data are required including monthly precipitation, temperature, wind speed, and relative humidity in addition to land use and soil layer depth, and geographic latitude data. Fifteen years (1991–2005) of monthly precipitation data were collected from 5 meteorological stations and used both model calibration and validation periods. To estimate the average areal precipitation (depth) across the subbasin, the Thiessen polygon method was used, and the station weight percentage is presented in Table 1. The average monthly temperature, relative humidity, and wind velocity data were obtained for the years 1991–2005 from National Meteorological Agency (NMA). The long-term average monthly precipitation, ET_0 , discharge, and temperature were shown in Fig. 3.

Besides climatic data, the land use and land cover (LULC) have also a significant role in determining the hydrologic processes for the subbasin. The land use and land cover maps were developed by MOWIE and the LULC types and their percentage is described in Table 2 and Fig. 4. The daily discharge data were obtained from the MOWIE for the Ketar River at Abura for the period of 1991–2005 and later summed to monthly time steps and pictorially presented in Fig. 3. Of which the monthly data from 1991 to 2000 and 2001 to 2005 were used for calibration and validation respectively. The missing data were filled by the linear interpolation method. Another important data input is the soil layer depth and hence the soil depth considered is 500 mm and 250 mm for the top and bottom layers respectively.

Table 1 Precipitation percentage weight of stations by Thiessen polygon method in the Ketar upstream

Station	Weighted percentage
Asella	13.7
Bekoji	35.73
Degaga	4.41
Ketar genet	34.63
Kulumsa	11.5
Sum	100

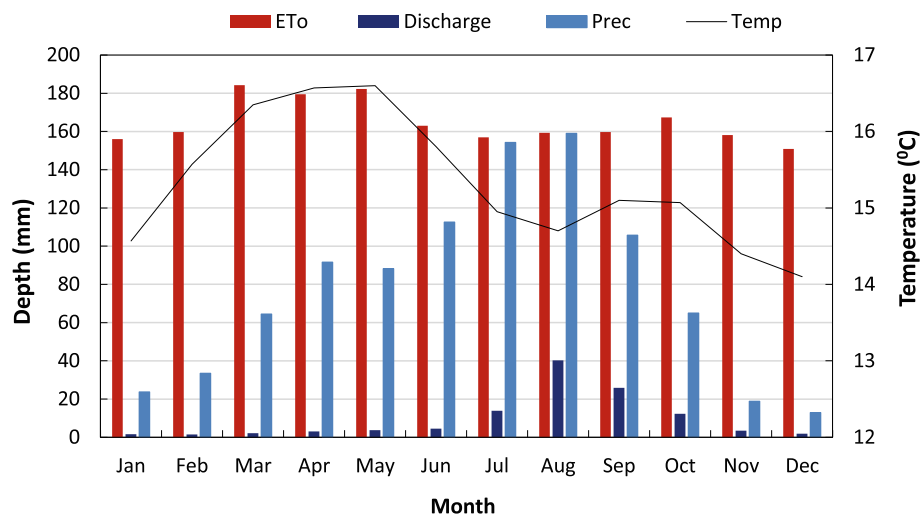


Fig. 3 Mean monthly temperature (Temp), evapotranspiration (ET₀), discharge, and precipitation (Prec)

Results and discussion

Model: calibration and validation

The monthly based climatic data such as precipitation, average temperature, relative humidity, sunshine hour, wind speed, land use, and soil parameters were used to simulate streamflow outputs. The model was calibrated to estimate land use and soil-related parameters using the manual (trial-and-error) method until a good fit is observed between the measured and simulated streamflow. Figure 5 shows a schematic diagram of flow chart for input and output, and modeling processes using the WEAP hydrologic model.

Table 3 shows a range of values for the estimated or calibrated model parameters. Figure 6a and b shows the observed and simulated monthly runoff for the Ketar River basin for the calibration and validation periods respectively. The monthly hydrographs of measured and simulated streamflow statistics presented in Table 4 showed a stronger agreement with R^2 of 0.82, NSE of 0.80, and IA of 0.95 for the calibration period. For the

validation period, there was a reasonably very good agreement between the measured and simulated streamflow during this period with R^2 of 0.91, NSE of 0.91, and IA of 0.98. On the other hand, the mean monthly measured and simulated streamflow as shown in Fig. 7a and Table 6 exhibited a strong agreement with R^2 of 0.99, NSE of 0.97, and IA of 0.99 for the calibration period. Figure 7b showed that for the mean monthly measured and simulated streamflow for the validation period, the achieved performance was with R^2 of 0.94, NSE of 0.93, and IA of 0.93 for the mean monthly period.

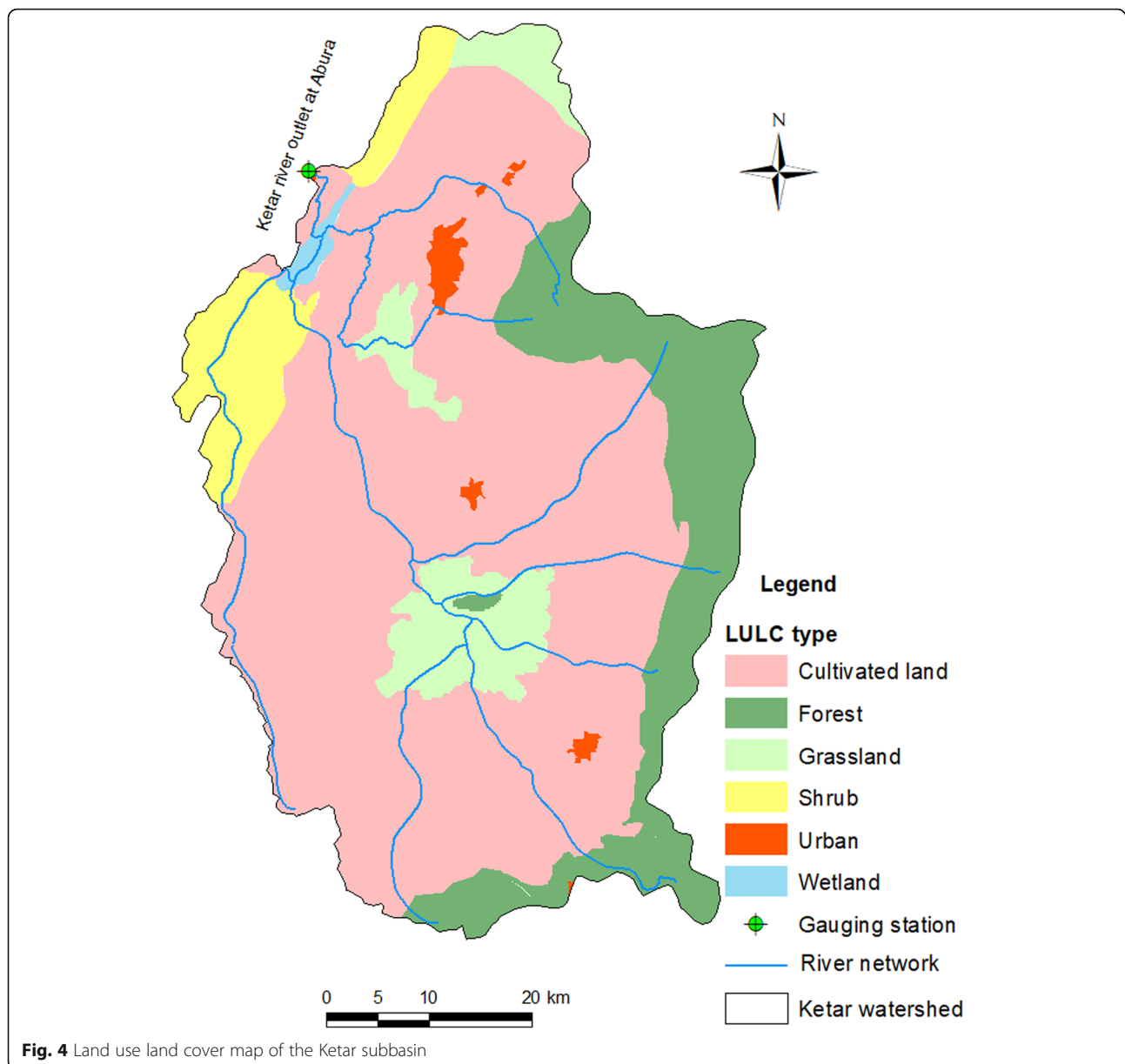
Model performance evaluation

The efficiency of the model performance was tested using statistics from the model simulated output and measured streamflow data. According to Santhi et al. (2001), Van Liew et al. (2007), the values of R^2 that are greater than 0.5 are acceptable with higher values indicating less error variance. For monthly hydrographical data, NSE values range between $-\infty$ and 1.0 and values between $0.75 < \text{NSE} \leq 1$ and $0 \leq \text{RSR} \leq 0.5$ rated as very good; $0.65 < \text{NSE} \leq 0.75$ and $0.5 < \text{RSR} \leq 0.6$ as good; $0.5 < \text{NSE} \leq 0.65$ and $0.6 < \text{RSR} \leq 0.7$ as satisfactory; and $\text{NSE} \leq 0.5$ and $\text{RSR} > 0.7$ rated as unsatisfactory for monthly data (Moriassi et al. 2007). Another model performance evaluation is the IA that can be used as a standardized measure of the degree of model prediction error and with values range from 0 to 1; the value of 1 indicates a perfect agreement and 0 indicates no agreement at all between the measured and simulated values (Willmott 1981).

For the calibration period, the model performance was achieved to simulate streamflow with R^2 , NSE, IA, and RSR values of 0.82, 0.8, 0.95, and 0.44 respectively. According to Moriassi et al. (2007), this result has shown a

Table 2 Land use and land cover data of Ketar subbasin in 2003

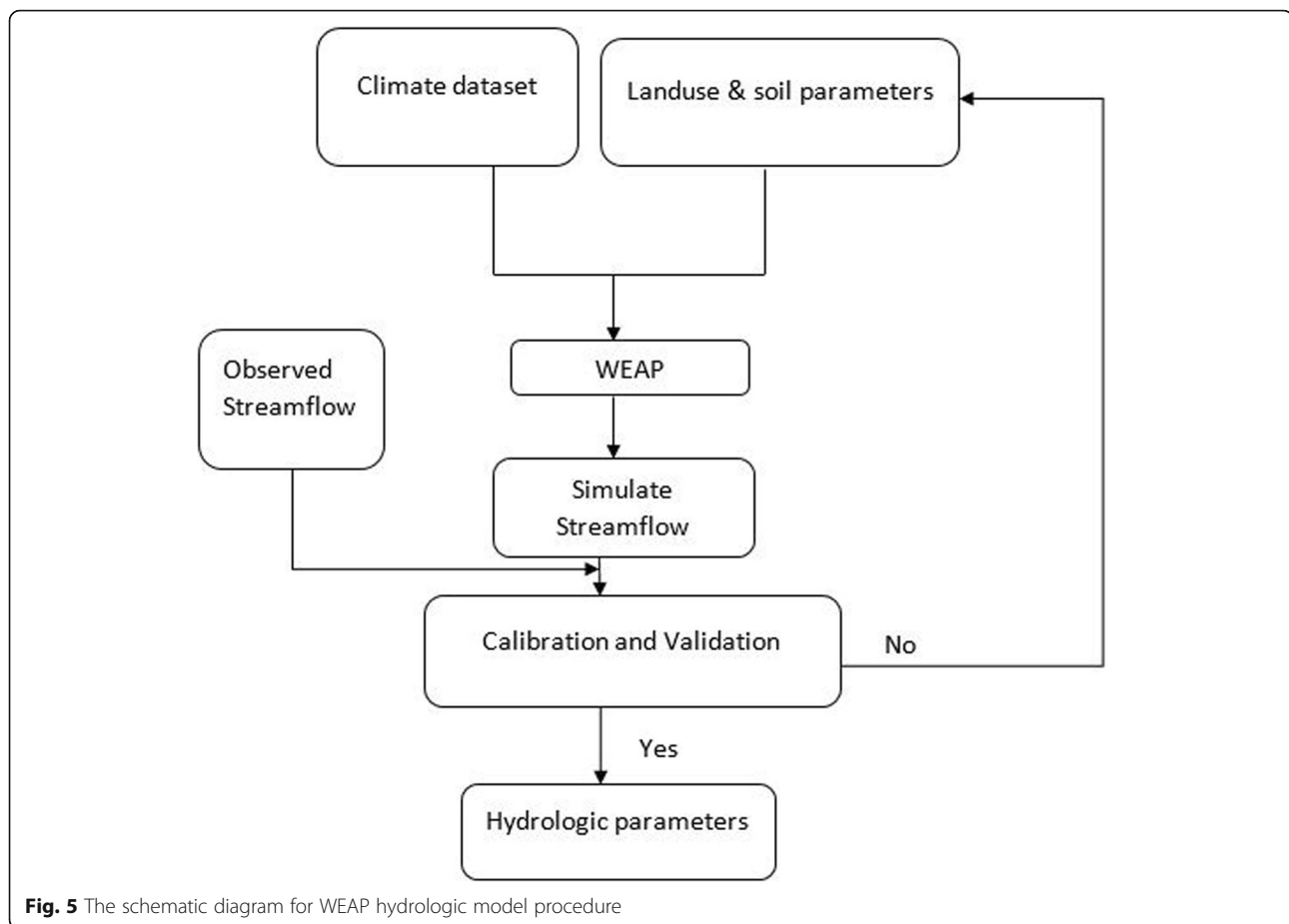
Land use/land cover	Ketar subbasin area	
	Hectare	Percentage
Cultivated land	210,841.5	64.4
Grassland	1628.7	4
Forestland	11,564.1	20
Shrubland	96,150.5	9.4
Barren land	6732.2	2.1
Waterbody	190.0	0.1
Wetland	54.3	0.0
Total area (hectare)	327,161	100



very good agreement between monthly measured and simulated streamflow in the Ketar River subbasin. Likewise, for the validation period, there was a reasonably good agreement between the measured and simulated flows with R^2 of 0.91, NSE of 0.91, IA of 0.98, and RSR of 0.3 during this period. On the other hand, the mean monthly measured and simulated streamflow (Table 4) shows a stronger agreement with R^2 of 0.99, NSE of 0.97, IA of 0.99, and RSR of 0.15 for the calibration period. For the validation period, the model performance agreement indices were R^2 of 0.94, NSE of 0.93, IA of 0.93, and RSR of 0.25 for the mean monthly period. In general, the model was able to maintain a very good

agreement in reproducing the overall streamflow characteristics.

Similarly, previous studies have confirmed that the capability of the WEAP hydrologic model in reproducing catchment hydrology processes in a different part of the world (Table 5). Among these, Asghar et al. (2019) reported the WEAP hydrologic model to attain the NSE and R^2 values of 0.85, 0.86, 0.89, and 0.87 for the monthly calibration and validation periods between the measured and simulated streamflow in the central Indus basin, respectively. From five gauging stations in the Western Algeria watersheds, ranging values of NSE= 0.23–0.88, and R^2 =0.74–1.0 were achieved between



measured and simulated average monthly flows (Hamlat et al. 2013). To balance future water availability and demand, the WEAP model was applied in Benin (Höller-mann et al. 2010) obtained values $NSE=0.91$, $R^2=0.92$, and $NSE=0.78$ and $R^2=0.83$ for calibration and validation periods, respectively. To assess the potential impacts of climate and land-use change on irrigation water supply in the USA, the WEAP hydrologic model was developed by Mehta et al. (2013) and the model has demonstrated the capability with values of $NSE=0.91$, $R^2=0.92$, and

$NSE=0.78$ and $R^2=0.83$ at calibration and validation periods between measured and simulated flows data respectively.

Finally, Ingol-Blanco and McKinney (2013) developed the WEAP model to assess the hydrologic processes in Rio Conchos Basin, Mexico. Six gauging stations were used in the basin for model performance evaluation. Values of $NSE=0.65-0.87$; $R^2=0.92-0.97$, and $NSE=0.60-0.88$ and $R^2=0.92-0.97$ pertinence between measured and simulated flows were found respectively.

Table 3 Range of values for the estimated parameters used in the WEAP model for the Ketar River subbasin

Parameters	Definition	Range in values
Kc	Crop coefficient	0.34–1.05
SWC	Effective soil water capacity of the upper layer (mm)	500
DWC	Effective soil water capacity of the lower layer (mm)	250
RRF	Runoff resistance factor	2.5–405
RZC	Root zone rate of conductivity at full saturation (mm/month)	0.8–179
DC	Rate of conductivity of deep layer at full saturation (mm/month)	4–24
PF	Preferred flow direction	0.65
Z ₁	Initial storage fraction of upper layer at the beginning of the simulation (%)	28–50
Z ₂	Initial storage fraction of lower layer at the beginning of the simulation (%)	70

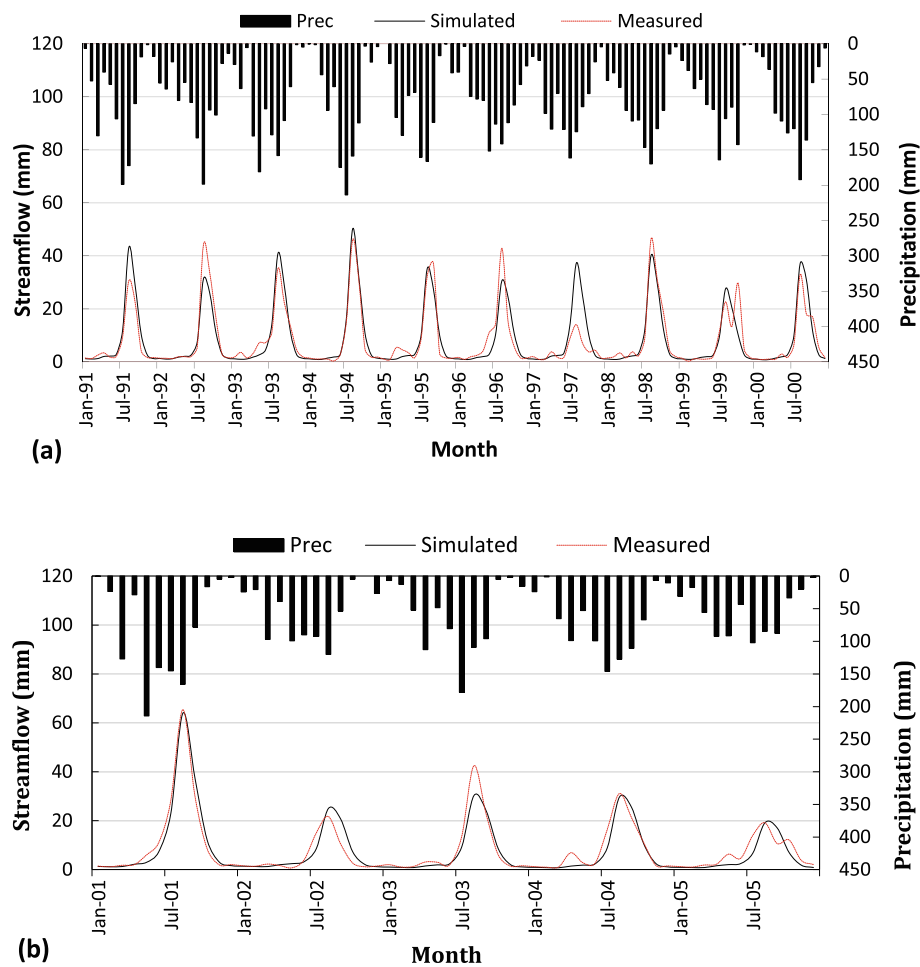


Fig. 6 Monthly hydrograph of measured and simulated streamflow of the Ketar River at Abura gauging station and monthly precipitation of the subbasin: **a** the calibration period and **b** the validation period

Hydrological processes

Precipitation is the only source of water input for the subbasin and it amounts to 930 mm annually in-depth. Over 60% of global precipitation is consumed by ET and it is tough to get accurate methods to determine it in less time and cost-effective (Mohammadi and Mehdizadeh 2020; Wang et al. 2019), since it is the major component of the hydrologic cycle affecting water resource availability and important in water resource development and management (Abtey and Melesse 2013). Long-term monthly values hydrological components of the Ketar subbasin are presented in Table 6. This study indicated that the ET loss was estimated to 799 mm/year. The remaining is the streamflow (runoff) components in order of their contribution are the interflow, baseflow, and surface runoff account 8 mm/year, 4.5 mm/year, and 1.3 mm/year respectively. ET loss accounts for 86% of overall precipitation available water. This result is consistent with the study by Jansen et al.

(2007) which indicated that 88% of precipitation is consumed by ET in the CRV basin of Ethiopia. In some months, ET exceeded the amount of precipitation in January, October, November, and December. On the contrary, in months ranging from March to August ET was less than the precipitation amounts and nearly equal in February and September. On the other hand, the remaining 14% of precipitation is the Ketar streamflow (runoff) which is comprised of 4.5%, 8%, and 1.3% baseflow, interflow, and surface runoff respectively.

Another study by Desta and Lemma (2017) using the SWAT model shows lower values as compared to the current study that ranges from 64–69% of precipitation lost to the atmosphere through ET. The relative proportion of the three components of the runoff (baseflow, interflow, and surface runoff) depends on the physical characteristics of the watershed, the land use, soil, topography, geomorphology, and geology characteristics.

Table 4 Summary of model performance statistics for measured and simulated the Ketar monthly and mean monthly streamflow at Abura gauging station

Statistics	Monthly	Mean monthly
Calibration period	1991–2000	
Drainage area (ha)	327,161	
Number of months	120	
Mean measured flow (m ³ /s)	13	12.52
Mean simulated flow (m ³ /s)	12.5	12.98
Standard deviation (SD) measured	17.8	16
Standard deviation (SD) simulated	17.2	18.2
Coefficient of determination (R^2)	0.82	0.99
Nash-Sutcliffe coefficient (NSE)	0.80	0.97
Index of agreement (IA)	0.95	0.99
Root mean square error (RMSE)	7.62	6.56
RMSE-observations standard deviation ratio (RSR)	0.44	0.15
Validation period	2001–2005	
Number of months	60	
Mean measured flow (m ³ /s)	10.4	10.4
Mean simulated flow (m ³ /s)	9.6	9.6
Standard deviation (SD) measured	14.5	13.1
Standard deviation (SD) simulated	14.4	13.3
Coefficient of determination (R^2)	0.91	0.94
Nash-Sutcliffe coefficient (NSE)	0.91	0.93
Index of agreement (IA)	0.98	0.98
Root mean square error (RMSE)	4.3	3.3
RMSE-observations standard deviation ratio (RSR)	0.3	0.25

The annual discharge (runoff) proportion of the Ketar River was estimated to 14% of annual precipitation. Subsequently, it is composed of 58% interflow predominantly from June to October and followed by 32% baseflow which sustained throughout the year, and 10% surface runoff that mostly occurs in July, August, and September. These results are consistent with the study by Legesse et al. (2003) using the PRSM model in the same subbasin. The same authors revealed that of the total annual flow, the interflow was about 60% and the most important component during the rainy season, while the baseflow was 30% that maintains the river runoff during the dry season. The same study explains an abundance of interflow and baseflow as compared to surface runoff associated with a presence of huge proportion of cultivated/grazing land in the subbasin that enhances infiltration in the soil zone and thereby lateral subsurface flow along subsurface channels, macro-pores, and fractures. Contrary to this, the less contribution of surface runoff to the streamflow is explained by the absence of significant impervious surfaces in the subbasin (Legesse et al. 2003).

Conclusion

The model performance evaluation statistics shows a very good agreement between measured and simulated monthly streamflow at the outlet for both the calibration and validation periods. The WEAP model outcome revealed that the lion's share of available water returns to the atmosphere via ET in the subbasin. The annual stream discharge is mainly composed of interflow that contributes a major part of flow during the wet season and is followed by the baseflow that is critical to sustaining the streamflow during the dry season. While considering water availability in a temporal context, more than 80% of the annual total runoff is concentrated in 4 months (July–October) and the remaining months largely depend on the baseflow contribution to the streamflow. This is because of the seasonality of rainfall in the catchment. However, in recent years, water requirement for irrigation particularly is increasing in the dry periods as a result of little precipitation in these months.

Therefore, the sustainable water availability of the Ketar stream throughout the year is largely dependent

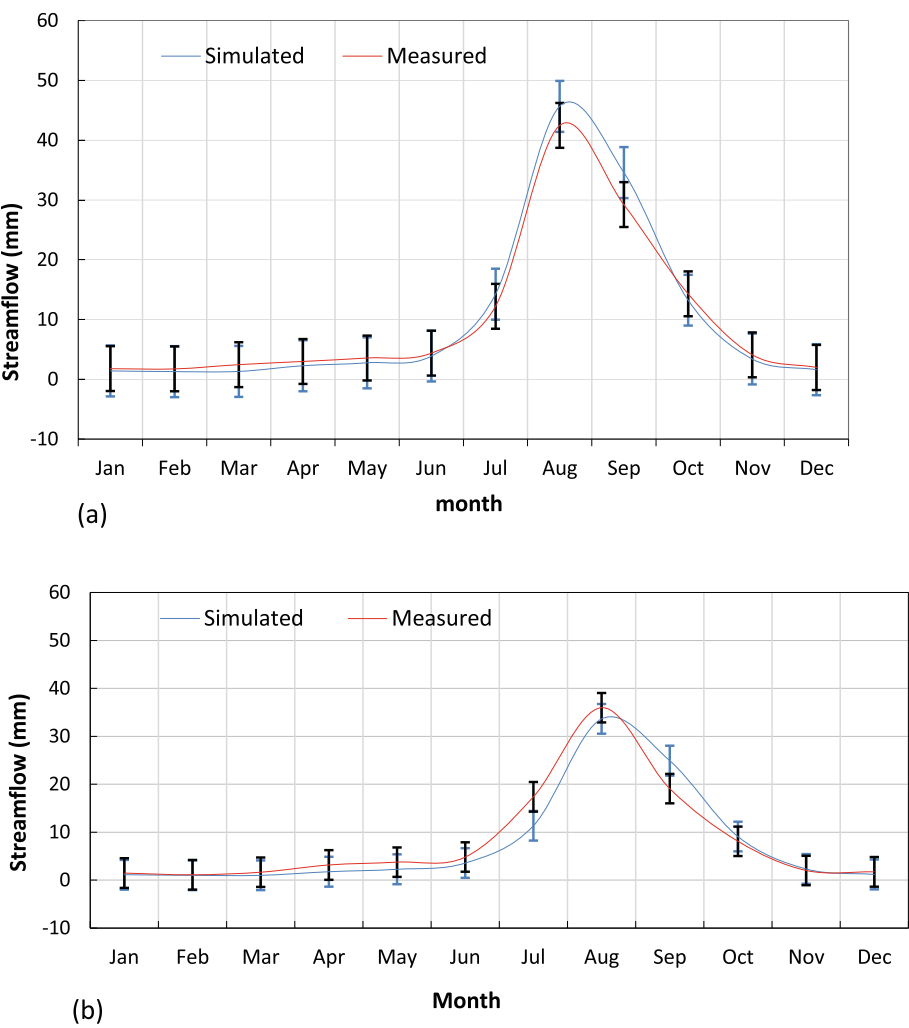


Fig. 7 Mean monthly hydrograph of measured, simulated flows of Ketar River at Abura gauging station for **a** the calibration and **b** the validation period; black line and green line error bars indicate the standard error of monthly measured and simulated flows respectively

Table 5 Comparison of WEAP hydrologic model performance evaluation with other similar studies elsewhere

Country of origin	Model accuracy statistics		Modeling periods	Reference
	R^2	NSE		
Ethiopia	0.82	0.8	Calibration	Present study
	0.91	0.91	Validation	
Pakistan	0.96	0.85	Calibration	(Asghar et al. 2019)
	0.87	0.89	Validation	
Algeria	0.74–1.0	0.23–0.88		(Hamlat et al. 2013)
Benin	0.92	0.91	Calibration	(Höllermaun et al. 2010)
	0.83	0.78	Validation	
USA	0.92	0.91	Calibration	(Mehta et al. 2013)
	0.83	0.78	Validation	
Mexico	0.92–0.97	0.65–0.87	Calibration	(Ingol-Blanco and McKinney 2013)
	0.92–0.97	0.60–0.88	Validation	

Table 6 Average monthly estimated depth of hydrologic components in the Ketar subbasin (in mm)

Month	Prec	ET	Baseflow	Interflow	Surface runoff	Runoff
Jan	23.7	29.7	1.7	0.1	0.0	1.8
Feb	33.5	30.0	1.6	0.1	0.0	1.7
Mar	64.5	39.4	1.4	0.3	0.0	1.7
Apr	91.7	57.8	1.8	0.9	0.0	2.7
May	88.3	72.4	2.2	1.0	0.0	3.2
Jun	112.6	83.9	2.5	1.6	0.2	4.3
Jul	154.3	83.9	3.4	8.2	2.7	14.3
Aug	159.0	99.6	7.5	30.6	7.8	45.8
Sep	105.8	96.8	10.2	22.6	1.9	34.7
Oct	65.0	105.1	5.4	8.2	0.0	13.6
Nov	18.9	66.0	2.6	1.1	0.0	3.7
Dec	12.9	34.6	1.8	0.1	0.0	2.0
Sum	930.2	799.3	42.2	74.7	12.5	129.5
Min	12.9	29.7	1.4	0.1	0.0	1.7
Max	105.1	105.1	10.2	30.6	7.8	45.8
Mean	77.5	66.6	3.5	6.2	1.0	10.8
%	100.0	86	4.5	8.0	1.3	14

on the baseflow, and anything that alters the hydrologic behavior of the subbasin may impact the amount and the sustainability of streamflow. Later, it may affect sequentially the downstream water users and water level of Lake Ziway and lastly Lake Abijata. The model can be used for further related to the impacts of climate change and land use/land cover dynamics on the subbasin hydrology that in turn affects the basin water availability.

Abbreviations

WEAP: Water evaluation and planning system tool; SWAT: Soil and Water Analysis Tool; PRSM: Precipitation and Runoff Simulation Model; Prec: Precipitation; ET: Evapotranspiration; masl: Meter above sea level; LULC: Land use and land cover

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Authors' contributions

The first author is currently conducting his Ph.D. research on model-based evaluation of water resources in the Central Rift Valley of Ethiopia. This work is a major part of the research in the completion of one of the objectives. Hence, he has made a significant role in all aspects of the research. He is researching under the very close supervision of the second author. The latter has involved from conception and design to analysis and interpretation of data. The author(s) read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors agreed and approved the manuscript for publication in *Ecological Processes*.

Competing interests

There is no conflict of interest.

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References

- Abtew W, Melesse A (2013) Evaporation and evapotranspiration: measurements and estimations. Springer, New York. <https://doi.org/10.1007/978-94-007-4737-1>
- Ahmadi A, Ohab-Yazdi SA, Zadehvaki N, Safavi HR (2018) A dynamic model of water resources management using the scenario analysis technique downstream of the Zayandehroud basin. *Int J River Basin Manag* 17(4):451–63. <https://doi.org/10.1080/15715124.2018.1505734>
- Alemayehu T, Ayenew T, Kebede S (2006) Hydrogeochemical and lake-level changes in the Ethiopian Rift. *J Hydrol* 316(1–4):290–300. <https://doi.org/10.1016/j.jhydrol.2005.04.024>
- Allen RG, Pereira LS, Raes D, Smith M (1998) Crop evapotranspiration: guidelines for computing crop water requirements. FAO irrigation and drainage paper no. 56, Rome
- Arnold J, Srinivasan R, Muttiah R, Williams J (1998) Large area hydrologic modeling and assessment part I: model development. *Am Water Resour Assoc* 34(1):73–89. <https://doi.org/10.1111/j.1752-1688.1998.tb05961.x>
- Asghar A, Iqbal J, Amin A, Ribbe L (2019) Integrated hydrological modeling for assessment of water demand and supply under socio-economic and IPCC climate change scenarios using WEAP in Central Indus Basin. *J Water Serv Res Technol* 68(2):136–148. <https://doi.org/10.2166/aqua.2019.106>
- Ayenew T (2003) Evapotranspiration estimation using thematic mapper spectral satellite data in the Ethiopian rift and adjacent highlands. *J Hydrol* 279(1–4): 83–93. [https://doi.org/10.1016/S0022-1694\(03\)00173-2](https://doi.org/10.1016/S0022-1694(03)00173-2)
- Ayenew T (2007) Water management problems in the Ethiopian rift: challenges for development. *J Afri Earth Sci* 48(2–3):222–236. <https://doi.org/10.1016/j.jfrsresci.2006.05.010>
- Barbaro BJR, Zarriello PJ (2006) A precipitation-runoff model for the Blackstone River Basin, Massachusetts, and Rhode Island, U.S. Geological Survey Scientific Investigations Report 2006–5213, p 95
- Delfs JO, Wang W, Kalbacher T, Singh AK, Kolditz O (2013) A coupled surface/subsurface flow model accounting for air entrapment and air pressure counterflow. *Environ Earth Sci* 69(2):395–414. <https://doi.org/10.1007/s12665-013-2420-1>
- Desta H, Lemma B (2017) Journal of hydrology: regional studies SWAT based hydrological assessment and characterization of lake. *J Hydrol Reg Stud* 13: 122–137. <https://doi.org/10.1016/j.ejrh.2017.08.002>
- Doherty, J. (2010) PEST, Model-Independent Parameter Estimation—User Manual. 5th Edition, with Slight Additions, Watermark Numerical Computing, Brisbane.
- Dougherty M, Dymond RL, Grizzard TJ, Godrej AN, Zipper CE, Randolph J (2007) Quantifying long-term hydrologic response in an urbanizing basin. *J Hydrol Eng* 12(1):33–41. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2007\)12:1\(33\)](https://doi.org/10.1061/(ASCE)1084-0699(2007)12:1(33))
- Fang W, Huang S, Ren K, Huang Q, Huang G, Cheng G, Li K (2019) Examining the applicability of different sampling techniques in the development of decomposition-based streamflow forecasting models. *J Hydrol* 568:534–550. <https://doi.org/10.1016/j.jhydrol.2018.11.020>
- Hamlat A, Erlih M, Guidoum A (2013) Simulation of water resources management scenarios in western Algeria watersheds using WEAP model. *Arab J Geosci* 6(7):2225–2236. <https://doi.org/10.1007/s12517-012-0539-0>
- Höllermaier B, Gieritz S, Dieckkrüger B (2010) Benin 2025-balancing future water availability and demand using the WEAP “Water Evaluation and Planning” system. *Water Resour Manag* 24(13):3591–3613. <https://doi.org/10.1007/s11269-010-9622-z>

- Ingol-Blanco E, McKinney DC (2013) Development of a hydrological model for the Rio Conchos Basin. *J Hydrol Eng* 18(3):340–351. [https://doi.org/10.1061/\(ASCE\)he.1943-5584.0000607](https://doi.org/10.1061/(ASCE)he.1943-5584.0000607)
- Jansen H, Hengsdijk H, Dagnachew L, Tenalem A, Hellegers P, Spliethoff P (2007) Land and water resources assessment in the Ethiopian Central Rift Valley, p 81
- Joyce B, Vicuña S, Dale L, Dracup J, Hanemann M, Purkey D, Yates D (2006) Climate change impacts on water for agriculture in California: a case study in the Sacramento Valley, p 85
- Krause P, Boyle DP, Båse F (2005) Comparison of different efficiency criteria for hydrological model assessment. *Adv Geosci* 5:89–97. <https://doi.org/10.5194/adgeo-5-89-2005>
- Legesse D, Abiye TA, Vallet-Coulomb C, Abate H (2010) Streamflow sensitivity to climate and land cover changes Meki River, Ethiopia. *Hydrol Earth Syst Sci* 14(11):2277–2287. <https://doi.org/10.5194/hess-14-2277-2010>
- Legesse D, Ayenew T (2006) Effect of improper water and land resource utilization on the central Main Ethiopian Rift lakes. *Quat Int* 148(1):8–18. <https://doi.org/10.1016/j.quaint.2005.11.003>
- Legesse D, Vallet-Coulomb C, Gasse F (2003) Hydrological response of a catchment to climate and land-use changes in Tropical Africa: case study south-central Ethiopia. *J Hydrol* 275(1–2):67–85. [https://doi.org/10.1016/S0022-1694\(03\)00019-2](https://doi.org/10.1016/S0022-1694(03)00019-2)
- Legesse D, Vallet-Coulomb C, Gasse F (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>
- Lerner DN (2002) Identifying and quantifying urban recharge: a review. *Hydrogeol J* 10(1):143–152. <https://doi.org/10.1007/s10040-001-0177-1>
- Lorenz DL, Ziegeweid JR (2015) Methods to estimate historical daily streamflow for ungaged stream locations in Minnesota. In: U.S. geological survey scientific investigations report, (2015–5181), p 18 Retrieved from <http://pubs.usgs.gov/sir/2015/5181/sir20155181.pdf>
- Mccabe GJ, Legates DR (1999) Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resour Res* 35(1): 233–241
- Mehta VK, Haden VR, Joyce BA, Purkey DR, Jackson LE (2013) Irrigation demand and supply, given projections of climate and land-use change, in Yolo County, California. *Agric Water Manag* 117:70–82. <https://doi.org/10.1016/j.agwat.2012.10.021>
- Mohammadi B, Ahmadi F, Mehdizadeh S, Guan Y (2020a) Developing novel robust models to improve the accuracy of daily streamflow modeling. *Water Resour Manag* 34(10):3387–3409.
- Mohammadi B, Guan Y, Moazenzadeh R, Jafar M, Safari S (2020b) Catena implementation of hybrid particle swarm optimization-differential evolution algorithms coupled with multi-layer perceptron for suspended sediment load estimation. *Catena* 198:105024. <https://doi.org/10.1016/j.catena.2020.105024>
- Mohammadi B, Mehdizadeh S (2020) Modeling daily reference evapotranspiration via a novel approach based on support vector regression coupled with the whale optimization algorithm. *Agric Water Manag* 237:106145. <https://doi.org/10.1016/j.agwat.2020.106145>
- Mohammadi B, Mehdizadeh S, Ahmadi F, Thi N, Lien T, Thi N, Linh T (2020c) Developing hybrid time series and artificial intelligence models for estimating air temperatures. *Stoch Environ Res Risk Assess* 7. <https://doi.org/10.1007/s00477-020-01898-7>
- Moriassi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans ASABE* 50(3):885–900
- Nash J, Sutcliffe J (1970) Riverflow forecasting through conceptual models, part I—a discussion of principles. *J Hydrol* 10(2):282–290. <https://doi.org/10.1080/00750770109555783>
- Niu GY, Paniconi C, Troch PA, Scott RL, Durcik M, Zeng X, Huxman T, Goodrich DC (2014) An integrated modeling framework of catchment-scale ecohydrological processes: 1. Model description and tests over an energy-limited watershed. *Ecohydrology* 7(2):427–439. <https://doi.org/10.1002/eco.1362>
- Pacheco FAL (2015) Regional groundwater flow in hard rocks. *Sci Total Environ* 506–507:182–195
- Pascual-Ferrer J, Candela L, Pérez-foguet A (2013) Ethiopian Central Rift Valley basin hydrologic modeling using HEC-HMS and ArcSWAT. *Geophysical Res Abstr* 15(1):10563
- Pascual-Ferrer J, Pérez-foguet A, Codony J, Raventós E (2014) Assessment of water resources management in the Ethiopian Central Rift Valley: environmental conservation and poverty reduction. *Int J Water Resour Develop* 30(3):572–587. <https://doi.org/10.1080/07900627.2013.843410>
- Purkey DR, Joyce B, Vicuña S, Hanemann MW, Dale LL, Yates D, Dracup JA (2008) Robust analysis of future climate change impacts on water for agriculture and other sectors: a case study in the Sacramento Valley. *Climatic Change* 87(S1):109–122. <https://doi.org/10.1007/s10584-007-9375-8>
- Santhi C, Arnold JG, Williams JR, Dugas WA, Srinivasan R, Hauck LM (2001) Validation of the SWAT model on a large river basin with point and nonpoint sources. *J Am Water Resour Assoc* 37(5):1169–1188. <https://doi.org/10.1111/j.1752-1688.2001.tb03630.x>
- Santos RMB, Sanches Fernandes LF, Moura JP, Pereira MG, Pacheco FAL (2014) The impact of climate change, human interference, scale and modeling uncertainties on the estimation of aquifer properties and river flow components. *J Hydrol* 519:1297–1314
- Scanlon B, Keese K, Flint A, Flint L, Gaye C, Edmunds M, Simmers I (2007) Global synthesis of groundwater recharge in semiarid and arid regions. *Hydrol Process* 20:3335–3370. <https://doi.org/10.1002/hyp.6335>
- Sieber J, Purkey D (2015) Water evaluation and planning system: user guide. Stockholm Environment Institute, U.S. Center, p 400 Retrieved from <http://www.weap21.org/WebHelp/index.html>
- Singh J, Knapp H, Demissie M (2005) Hydrologic modeling of the Iroquois River watershed using HSPF and SWAT. ISWS CR 2004-08. Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Hydrologic+Modeling+of+the+Iroquois+River+Watershed+Using+HSPF+and+SWAT#3>
- Stockholm Environment Institute (SEI) (2007) Water evaluation and planning system, WEAP, Stockholm Environmental Institute: Boston
- Van Liew MW, Veith TL, Bosch DD, Arnold JG (2007) Suitability of SWAT for the conservation effects assessment project: comparison on USDA agricultural research service watersheds. *J Hydrol Eng* 12(2):173–189. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2007\)12:2\(173](https://doi.org/10.1061/(ASCE)1084-0699(2007)12:2(173)
- Wang S, Huang G, Baetz B, Huang W (2016) Probabilistic inference coupled with possibilistic reasoning for robust estimation of hydrologic parameters and piecewise characterization of interactive uncertainties. *J Hydrometeorol* 17(4): 1243–1260. <https://doi.org/10.1175/JHM-D-15-0131.1>
- Wang S, Lian J, Peng Y, Hu B, Chen H (2019) Generalized reference evapotranspiration models with limited climatic data based on random forest and gene expression programming in Guangxi, China. *J Hydrol* 221: 220–230
- Wheater HS, Mathias SA, Li X (2010) Groundwater modeling in arid and semi-arid areas. Cambridge University Press, Cambridge, UK. <https://doi.org/10.1017/CBO9780511760280>
- Willmott CJ (1981) On the validation of models. *Phys Geogr* 2(2):184–194. <https://doi.org/10.1080/02723646.1981.10642213>
- Yates D, Sieber J, Purkey D, Huber-Lee A (2005) WEAP21 - a demand-, priority-, and preference-driven water planning model. Part 1: model characteristics. *Water Int* 30(4):487–500. <https://doi.org/10.1080/02508060508691893>
- Zeray L, Roehrig J, Alamirew D (2007) Climate change impact on Lake Ziway watershed water availability, Ethiopia. In: Paper presented at the conference on international agriculture research for development. The University of Bonn: Germany, pp 1–25

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