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Impact of climate change on surface water availability and crop water demand for the sub-watershed of Abbay Basin, Ethiopia

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Abstract

In the present study, climate change effects on surface water availability and crop water demand (CWD) were evaluated in the Birr watershed (a sub-watershed of Abbay Basin), Ethiopia. The Coordinated Regional Climate Downscaling Experiment (CORDEX)-Africa data output of Hadley Global Environment Model 2-Earth System (HadGEM2-ES) was selected under the representative concentration pathways (RCP) scenarios. The seasonal and annual streamflow trends in the watershed were assessed using the Mann-Kendall (MK) test and Sen's slope at 5% significance level. The surface water availability was assessed using the Hydrologiska Byråns Vattenbalansavdelning (HBV) model. The HBV model showed a satisfactory performance during calibration ($R^2 = 0.89$) and validation ($R^2 = 0.85$). The future water availability was simulated under climate change scenarios. The future projected streamflow indicates that minimum flow may decrease under RCP4.5 and RCP8.5 scenarios, revealing significant downward shifts in the years 2035 and 2055, respectively. Similarly, the 1 day and 7 days maximum flow under RCP8.5 and 90 days flow under RCP4.5 are expected to decrease significantly and a considerable shift may occur in the 2060s and 2030s, respectively. Contrarily, both the minimum and maximum flow may not change significantly under the RCP2.6 scenario. Current and future water demand for the maize crop was estimated using the CROPWAT. The result indicated that irrigation water requirement (IWR) for maize crop may be increased throughout the growing periods, especially, during the development stage. Therefore, this study may contribute to the planning and implementation of the sustainable water resources development strategies and help to mitigate the consequences of climatic change, especially on commonly grown crops in the region.

Keywords CWD · IWR · HBV model · Trend analysis · Climate change · Ethiopia

Introduction

Irrigated agriculture plays a significant role in achieving food security and improves the lifestyle of people in many parts of the world. However, climate change may have serious effects on crop water use, water resources potential, and availability in the future. Changes in climate variability and

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associated droughts have been a primary cause of food insecurity and famine in Ethiopia (Demeke and Zeller 2011). If climate change phenomenon occurs frequently, future water availability for crop water demand (CWD), domestic water consumption and agricultural production become more uncertain. Depending on the crop type and crop characteristics, CWD can be increased up to 250% by the end of the twenty-first century (Gondim et al. 2012). In developing regions, irrigation water requirement (IWR) can be increased by 50% for each degree of global warming, while in developed regions, it is expected to increase by 16% (Fischer et al. 2007).

Developing countries such as Ethiopia may be more susceptible to climate change (IPCC, 2007). Many researchers have shown that water resource of Ethiopia is very sensitive to climate change and variability (e.g., Chaemiso et al. 2016). FAO (2016) indicated that due to the frequent climate variability, about 10.2 million people in Ethiopia have

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become food insecure. Rainfed agriculture together with few irrigation practices supports half of the gross domestic product and 80% of the total employment in Ethiopia. This shows that Ethiopian agriculture is largely dependent on rain. Therefore, climate change may have a significant impact on agricultural yield.

Few research works conducted in the Abay (Blue Nile basin) have shown the effect of climate change on the water resources in general and precipitation in particular. Dile et al. (2013) indicated that the mean annual precipitation is expected to decrease by 30% during the period 2010–2040, while it may be increased by more than 30% during the period 2070-2100. The impact of climate change may cause a decrease in mean monthly flow volume between 0 and 50% during the years 2010–2040 but may increase by more than the double during 2070-2100 in the Gilgel Abbay River basin located in the Upper Blue Nile River basin, Ethiopia. Taye et al. (2015) have presented a review on implications of climate change on hydrological extremes in the Blue Nile basin, Ethiopia. The discrepancies among different study outputs were discussed. However, these study results were assessed based on Global Circulation Models (GCM) at a regional scale and considered the old IPCC scenarios (A2 and B2) which may not address local scale problems adequately.

Birr watershed is one of the sub-watersheds of the Abbay river basin and situated in the lower region of the basin. The majority of the people in the study area depend on rainfed agriculture system which has been strongly influenced by the climate variability in the last three decades. If the temporal and spatial variability of rainfall increases in case of changing the climate, there is a great probability that the rainfed agricultural system of this area may be subjected to the effects of climate (Bewket and Conway 2007). Gebrehiwot (2012) also reported the presence of a significant decreasing trend in both the total flow and maximum flow in the Birr watershed. Although the impact of climate change was estimated under the Special Report Emission Scenarios (SRES) (Nakicenovic and Swart 2000), the severity and magnitude of the impact at a watershed scale were not explored using the newly developed Representative Concentration Pathways (RCP) scenarios (van Vuuren et al. 2011). The previous studies were based on the historical patterns or trends of hydrometeorological variables such as precipitation, temperature, and streamflow over the past decade. These studies also provided incomplete information about hydrological changes across the watershed under the influence of climate change. Therefore, it is required to study the impact of climate change on surface water availability and CWD in the Birr watershed, Ethiopia.

The estimation of CWD is also important for the planning, design, and operation of irrigation and water resources systems. It gives important directions for the optimal water allocation policy formulation as well as decision making in the operation and management of irrigation systems (FAO 2002). Therefore, in the present study, the trend analysis was used to assess the variability of future climate. An increase or decrease in the climate variables could affect the general hydrologic cycle and hence water availability in a given region. Mann-Kendall (MK) and Sen's slope test were used to analyze the trend in seasonal and annual climatic variables. On the other hand, the semi-distributed Hydrologiska Byråns Vattenbalansavdelning (HBV)-96 model was used to compute an outflow in the watershed. Assessment of the trend in climatic variables and water availability could enable to study future CWD and supply conditions. Finally, future CWD of the major crop grown in the area (i.e., maize) at different crop growth stages was estimated under different climate change scenarios. The streamflow was assessed at the different time intervals to check whether water demand of the crop can be fulfilled or not under different climate change scenarios. Therefore, this study will help in making better water supply (availability) and CWD adaptation strategy in the future under climate change scenarios.

Materials and methods

Study area descriptions

Birr watershed is located in the northwestern region of Ethiopian highlands. It is located at 37°16'E to 37°40'30"E longitude and 10°40'N to 11°11'N latitudes (Fig. 1). Birr River is one of the tributaries of Abbay basin. The watershed area of Birr watershed is about 978 km². The basin has three distinctive seasons based on rainfall regime namely Kiremt (long rainy season during June to September), Belg (short rainy season during February to May) and Bega (a dry season which lasts from October to January) (Gebere et al. 2015). The highest annual average rainfall recorded is about 1391 mm around the north-eastern part of the basin, the lowest being 1026 mm in the southwestern tip close to the outlet of the basin. The average maximum temperature was varied between 25.6 and 30.9 °C and the minimum temperature was ranging from 10 to 15 °C. The elevation of the Birr watershed ranges from 1752 to 3502 m above mean sea level (m.a.s.l.) and an average altitude of 2562 m. The slope of the watershed indicates that about 40% of the area falls in 0-8% slope and 54% falls in the slope range of 8-30%(Fig. 2a). There are six types of soil groups found in the Birr watershed. The dominant soils are Haplic Alisol which covers (61.20%) followed by Eutric Fluvisol (21%), Haplic Luvisols (7.70%), Eutric Leptosols (0.42%), Haplic Nitisols (4.20%) and Eutric Vertisol (0.003%) (Fig. 2b). The main land cover types in Birr watershed are cultivated, grassland, plantation shrubland, wetland and natural forest. Among



Fig. 1 Location of the Birr watershed

these, cultivated area was found to be largest (64.7%), followed by grassland plantation (21.8%), plantation (6.3%), wetland (5.2%), shrubland (3.3%), and natural forest (0.03%) (Fig. 2c). Maize is the major staple crop grown in the watershed. The crop is usually grown in the Kiremt and Bega seasons.

Data used and data quality analysis

Hydrometeorological data were collected from the National Meteorological Agency (NMA) in Ethiopia for three stations located in the watershed (the year 1989 to 2015) such as Dembecha, Adet, and Laybirr. The daily data of streamflow of Birr river gauging station were collected from the Department of Hydrology, Ministry of Water, Irrigation, and Electricity (MoWIE), Ethiopia.

The present study utilized one of the 5th Coupled Model Inter-comparison Project (CMIP5) model (i.e., HadGEM2-ES model) outputs, which was used in several climate change impact studies in Ethiopia and found consistent with other GCMs (e.g., Niguse and Aleme 2015; Bhattacharjee and Zaitchik 2015; Urgaya 2016). The precipitation and temperature datasets under different RCP scenarios were derived from the HadGEM2-ES model output which was dynamically downscaled by CORDEX-Africa at a grid resolution of $0.5^{\circ} \times 0.5^{\circ}$ (approximately 55 km). These datasets were used for the two time periods (1951–2005: baseline period and 2006–2100: the future period) for three RCP scenarios (RCP2.6, RCP4.5 and RCP8.5). RCP2.6 and RCP4.5 represent low and medium stabilization emission scenarios, respectively. RCP8.5 represents the highest emission scenario without climate change policy (van Vurren et al. 2011). Three grid points were selected based on their proximity to the meteorological station in the Watershed. These datasets were used for estimating future CWD for maize crop and also climate change impacts on surface water availability. The land use/land cover data for the year 2008, digital elevation model (DEM) (30 m×30 m) and soil map of the Birr watershed were obtained from the GIS Department (MoWIE) (Figs. 1, 2).

The datasets for the period from 1989 to 2015 were subjected to initial quality checks such as missing and inconsistencies in the data. The normal ratio and station average methods were used to fill the missing rainfall data. The normal ratio method was used when normal annual rainfall at the nearby station differs from the missed station by more than 10%, otherwise, station average was used (Subramanya 2008). The consistency of rainfall data was tested by double mass curve analysis. The selected



C Land use/land cover map of the year 2008

Fig. 2 Spatial input database provided for the HBV model

stations in this study have not undergone any significant change during the period 1989–2015. The homogeneity test was performed using RAINBOW software for rainfall and streamflow data independently and confirms the presence of homogeneity among them. The bias correction in the projected climatic data was performed to minimize systematic error and adjust the observed daily precipitation and temperature datasets. The non-linear correction method was used to estimate the bias in the projected precipitation data (Leander and Buishand 2007). Similarly, the systematic biases were determined for temperature datasets for the baseline period using the methodology explained by Ho et al. (2012). More information about bias correction methodology adopted in this study can be found in Kahsay et al. (2017).

Methodology

The conceptual framework of the study is shown in Fig. 3 and discussed as follows:

Trend and shift detection analysis

In this study, trend analysis was carried out using the nonparametric Mann–Kendall (MK) test. The MK test is a statistical test widely used for the trend estimation in hydroclimatic time series (e.g., Yue and Wang 2004). The test has an advantage which can accommodate non-linear trends and data need not be normally distributed. This test has also low sensitivity to abrupt breaks due to inhomogeneous time series (Tabari et al. 2011). The null hypothesis (H_0) of MK test indicates that there is no trend and this is tested against the alternative hypothesis (H_1), which shows the existence of Fig. 3 Flowchart of the method-

ology adopted in this study



a trend (Onoz and Bayazit 2003). Additionally, more details about the MK test can be found in Pingale et al. (2016). XLSTAT 2015 trial version software was used to analyze the trend in the hydrometeorological variables using the MK test. The seasonal and annual streamflow trends were estimated at 5% level of significance over a period of time. The change point (shift) detection in hydro-climatic variables is needed to understand the climate change effects. The shift in the observed and simulated streamflow at different temporal scales was investigated using the Pettitt test (1979). This test considers a time series as two samples represented by a sequence of random variables x_1, \ldots, x_t and x_{t+1}, \ldots, x_T . The more details about the PMW test can be referred in Pingale et al. 2016.

Evaluation of climate change projections

Statistical techniques such as percent bias (PBIAS), the coefficient of variation (CV) and correlation coefficient (r) were used to evaluate model simulation outputs of rainfall with observed

climatic data for the Birr watershed. PBIAS is used to evaluate the systematic error in the rainfall. The optimal value of PBIAS is equal to zero and a low value indicates an accurate model simulation. Positive values show model underestimate the biases, while negative value indicates overestimation of the biases (Moriasi et al. 2007). The CV was computed for both observed and simulated rainfall to evaluate the degree of rainfall variability in replicating the observed rainfall by RCM data. According to NMSA (1996), when the degree of rainfall variability is small, the CV value is less than 20%; when it is moderately variable, CV ranges between 20 and 30% and when the degree of rainfall variability is large, CV is larger than 30%. The correlation coefficient was used to evaluate the linear relationships between the observed and model output datasets with a value of one representing perfect relationships. The PBIAS, CV, and r were estimated using the following equations:

$$PBIAS = \frac{(\overline{R}_{RCM} - \overline{R}_{obs})}{\overline{R}_{RCM}} \times 100$$
(1)

$$CV = \frac{\partial R}{\partial \overline{R}} \times 100$$
(2)

and

$$r = \frac{\sum_{i=1}^{N} (R_{\rm obs} - \bar{R}_{\rm obs}) (R_{\rm RCM} - \bar{R}_{\rm RCM})}{\sqrt{\sum_{i=1}^{N} (R_{\rm obs} - \bar{R}_{\rm obs})^2 (R_{\rm RCM} - \bar{R}_{\rm RCM})^2}}$$
(3)

where \overline{R} is the average rainfall over the basin; 'RCM' and 'obs' subscripts represent rainfall amount over the basin either from RCM simulation or observed datasets, respectively; ∂ indicates standard deviation between the RCM or observed rainfall and R represents individually estimated statistics either for RCM or observed rainfall amount. The HadGEM2-ES model output under RCP scenarios was used to assess the future scenario in this study. The analysis was carried out for near-term (2020–2049) and mid-term (2050–2079) projections with respect to the baseline period (1971–2000) for different RCP scenarios.

Determination of crop water demand (CWD)

$$CWD = K_c \times ET_o \tag{4}$$

where CWD is the crop water demand, K_c is the crop factor, and ET_o is the reference evapotranspiration.

Irrigation water requirement (IWR) can be estimated as the difference between water consumed by crops (CWD) and the effective rainfall (P_e).

$$IWR = CWD - P_e$$
⁽⁵⁾

In this study, the Hargreaves method (Hargreaves and Samani 1985) was applied to calculate future potential evapotranspiration which requires only air temperature and latitude:

$$ET_{o} = 0.0023(T_{mean} + 17.8)(T_{max} - T_{min}) \times 0.5R_{a}$$
(6)

where R_a is the water equivalent extraterrestrial radiation, mm/day; T_{mean} , T_{max} and T_{min} are the mean, maximum and minimum temperature

Model description

The conceptual HBV-96 model was used for simulation of runoff and outflow from the study watershed. The HBV model was developed in the early 1970s at the Swedish Meteorological and Hydrological Institute. This model is widely used in many countries in the World including Ethiopia (e.g., Abdo et al. 2009). The application of the HBV model is not limited to runoff simulation and hydrological forecasting. The model can also be used for water balance studies (Seibert2002). Additional details about the HBV model are described in Lindström et al. (1997), Seibert (2002) and Seibert and Vis (2012).

The indicators of hydrologic alteration (IHA) model were used in this study to estimate the 1 day, 7 days, 30 days and 90 days minimum and maximum flow under the selected climate change scenarios. This model was developed by the nature conservancy (TNC) for evaluating the characteristics of natural and altered hydrologic flow regimes. The IHA model can also be applied to daily hydrologic data such as streamflow, river stages, groundwater levels, or lake levels. Using the IHA model, the long periods of daily hydrologic data can be summarized easily according to ecologically relevant hydrologic parameters (Richter et al. 1997; Huh et al. 2005). Additional details about the IHA model are found in the user manual (The Nature Conservancy 2009). The essence of analyzing the 1 day, 7 days and 30 days periods of flow can be linked with the availability of water for a given crop. Irrigation interval for maize crop often varies between 1 and 7 days in critical growth stages while it may leverage for longer intervals in the other stages (initial and late stages). Therefore, flow volume in such time steps can provide an insight into the availability of sufficient water for the crop.

Model setup The HBV-96 model was provided with input data such as areal daily rainfall, potential evapotranspiration, and watersheds characteristic. The rainfall data from the year 1989 to 2015 was used from the three meteorological stations and areal rainfall was estimated using the Thiessen polygon method. The monthly potential evapotranspiration was estimated using the Hargreaves method, which is used as an input to the HBV model. The DEM of the study area was generated using Shuttle Radar Topography Mission (SRTM). Further, DEM was processed to extract the drainage area and its network for different sub-basins and elevation zones.

Model calibration and validation

For this study, the observed period is divided into three time periods to simulate the runoff. In the first stage, model warm-up was carried out for the year 1989. In the second stage, model calibration was undertaken for the period from 1990 to 1999 by minimizing the difference between the observed and computed streamflow. Finally, model validation was conducted for the periods between the years 2000–2005 with an independent set of data. The calibration and validation were carried out for daily time steps. The

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Table 1	The	parameters	of	the
HBV m	odel			

Parameters	Description	Range	Value
α	Used in equation $Q = K \times UZ^{(1+\alpha)}$, where Q is the reservoir outflow (mm); K is recession coefficient upper reservoir; UZ is the reservoir content upper reservoir (mm)	0.5–1.1	1.1
β	Exponent for discharge from the zone of soil	1–4	1.2
F _c	Maximum soil moisture storage (mm)	100-1500	1300
<i>Kh</i> _q	Resection coefficient for the upper response	0.005-0.2	0.11
K ₄	Resection coefficient for lower response	0.001-0.1	0.001
LP	Limited for potential evaporation	≤ 1	0.43
Perc	Percolation from the upper to lower response box	0.01-6	0.09
ecor	Evaporation correction	2.5	1.6
rcf	Rainfall correction	0.9	0.9

HBV-96 model was calibrated manually and several runs were made by fine tuning the model parameters to select the optimum values. The optimum value of each HBV-96 model parameters adopted through manual calibration procedures is shown in Table 1. For this specific study, h_q is found to be 4.52 mm/day. The quick flow was calibrated by changing Kh_q and α . The Kh_q results in higher peaks and exhibits more dynamic response in hydrograph, while α was used to fit the higher peaks into the hydrograph. The higher the value of α , the higher the peaks and quicker the recession flow (SMHI 2006). Base flow was adjusted with a K₄ parameter which describes the recession of base flow.

Model performance indicators

The model performance was evaluated using indicators like Nash and Sutcliffe coefficient of efficiency (NSE), the coefficient of determination (R^2), relative volumetric error (RVE) and the ratio of root mean square error to observed standard deviation (RSR). NSE is the normalized statistics and required to measure the relative magnitude of the residual variance as compared to the measured data variance (Nash and Sutcliffe 1970) and can be estimated by

NSE = 1 -
$$\frac{\sum_{i=1}^{n} (Q_{\text{obs},i} - Q_{\text{sim},i})^{2}}{\sum_{i=1}^{n} (Q_{\text{obs},i} - \overline{Q}_{\text{obs},i})^{2}}$$
 (7)

where $Q_{obs,i}$ is the observed discharge at the time step *i*, $\overline{Q_{obs,i}}$ is the average of the observed discharge, $Q_{sim,i}$ is the simulated discharge in the time step (m³/s) and *n* is the number of observations. The value of NSE ranges between $-\infty$ and 1.0 and NSE value equal to 1 shows perfect agreement. The values between 0.5 and 1.0 are generally viewed as an acceptable level of model performance. The NSE values less than and/or equal to zero (NSE \leq 0) reflect that the mean observed

value is a better predictor than the simulated value. This shows an unacceptable model performance (Santhi 2001).

 R^2 is the index of correlation of measured and simulated values. R^2 was estimated from

$$R^{2} = -\frac{\left[\sum_{i=1}^{n} \left(Q_{\mathrm{sim},i} - \overline{Q_{\mathrm{sim},i}}\right) - \left(Q_{\mathrm{obs},i} - \overline{Q_{\mathrm{obs},i}}\right)\right]^{2}}{\sum_{i=1}^{n} \left(Q_{\mathrm{sim},i} - \overline{Q_{\mathrm{sim},i}}\right)^{2} \sum_{i=1}^{n} \left(Q_{\mathrm{sim},i} - \overline{Q_{\mathrm{obs},i}}\right)^{2}}.$$
(8)

The value of R^2 ranges from 0 to 1. The more the value of R^2 approaches to 1, the better the model performance and R^2 values less than 0.5 indicate the model performance is poor in general. On the other hand, the higher value of R^2 reflects less error variance, and typical values greater than 0.6 are considered acceptable (Santhi 2001). The RVE was estimated using the following expression:

$$RVE(\%) = \frac{\sum Q_{obs} - Q_{sim}}{\sum Q_{obs}} \times 100$$
(9)

Average predicted value of the RVE ranges between $-\infty$ and $+\infty$. The model performance is very good for RVE "between" -5 and 5%, whereas the RVE between -10 to -5% and 5-10% indicates satisfactory model performance. The RVE function was used to quantify the volumetric error of the simulated streamflow.

RSR is used to indicate error index and was estimated using

$$RSR = \frac{RMSE}{STD_{obs}} = \left[\frac{\sqrt{\sum_{i=1}^{n} (Q_{obs,i} - Q_{sim,i})}}{\sqrt{\sum_{i=1}^{n} (Q_{obs,i} - \overline{Q_{sim,i}})}}\right]^{2}$$
(10)

where RMSE is the root mean square error and STD_{obs} is the standard deviation of observed datasets. The value of

Parameters	Annual rainfall (mm)	CV (%)	PBIAS (%)	RSR	r
Observed	1245	0.12	_	_	_
Corrected RCP	1238	0.10	-0.60	0.57	0.77
Uncorrected RCP	1210	0.80	2.79	0.89	0.56

Table 2 Performance evaluation of observed vs. RCP dataset

RSR ranging from 0 to 1 with lower values closer to zero shows the higher accuracy of the model performance, while its value approaching 1 indicates poor model performance.

Results and discussion

Performance of HadGEM2-ES model

In this study, the simulated mean annual rainfall using the HadGEM2-ES model was used and compared with observed mean annual rainfall. The observed, bias-corrected and uncorrected average annual historical rainfall was found to be 1245 mm, 1238 mm and 1210 mm, respectively. The simulation results show good agreement during the control period (1971–2000). However, it indicates a slight underestimation of simulation outputs with bias = -0.60% and good linear relationship (r = 0.77) for bias-corrected simulation data (Table 2). The underestimation of the results might be due to insufficient model resolution and topography which provides mechanical uplifting and thermal forcing to air parcels (Li et al. 2016). The result of the model performance and evaluation shows less agreement with high CV and bias as well as low values of correlation (r) (Table 2). The satisfactory model performance was also observed by RSR (=0.56). The average monthly rainfall, minimum and maximum temperature values also show a similar pattern with observed climate datasets over the watershed (Fig. S1a-c). However, there is a variation of rainfall during July and August months (Fig. 4a), while its performance is within the acceptable range (Table 2). This may be due to individual point regional scale predictors of rainfall variation, which is poorly resolved as compared to temperature (IPCC 2014). The result of downscaled maximum and minimum temperature shows that there is a satisfactory agreement with simulated temperature (Fig. S1b, c). The mean monthly absolute error (MAE) between the minimum and maximum temperature was found to be 0.45 °C and 0.50 °C, respectively. This result clearly reveals that the HadGEM2-ES outputs can be utilized for future projection of rainfall, maximum and minimum temperature in the Birr watershed in Ethiopia.

Trend analysis for the observed period

The MK test showed a decreasing trend in the annual rainfall of three stations in the Birr watershed at a 5% level of significance (Table 3). The change in precipitation magnitude was found to be higher in Adet station than in other two stations (Dembecha and Laybirr). It decreases by the magnitude of 8.19, 2.20 and 3.90 mm/year in Adet, Dembecha and Laybirr stations, respectively. However, Gebremicael et al. (2012) indicated that there is no significant trend in precipitation except Asosa station over the Upper Blue Nile during the last few decades. Similarly, Tekleab and Mohamed (2013) reported the presence of insignificant trends in both monthly and seasonal scale hydro-climatic variables in the majority of climate stations in the Abay basin. This discrepancy in the results may be mainly attributed due to climate variability and watershed characteristics.

A significant increasing trend was observed in the case of average temperature in the Adet and Laybirr except for Dembecha station at the 5% significance level (Table 3). The magnitude of the average temperature has increased to 0.031, 0.018 and 0.057 °C/year in Adet, Dembecha and Laybirr stations, respectively. This result is in good agreement with the previous study carried out in the Lake Tana basin (Addisu et al. 2015). The average maximum and minimum temperatures indicated insignificant increasing trend at 5% significance level. Similarly, the trend in annual average ET_o was observed using the MK test (Table 3). The test statistics revealed a statistically significant trend at Adet and Laybirr stations. The magnitude of Sen's slope test also shows that ET_o increases by 1.7 mm/year, 5.0 mm/year and 5.4 mm/ year in Dembecha, Laybirr and Adet stations, respectively (Table 3). This increase in average ET_0 has a negative impact on the present and future crop water demand in the watershed. ET_o shows the climatic demand of water by a reference crop which can also be expressed for the demand of water by a given crop by incorporating its crop coefficient (K_c) . Increased ET_o shows an increased demand for water or the stressed condition of crops when there is limited water available.

Future climatic projections under RCP scenarios

Precipitation

Average areal precipitation over the watershed may decrease in the future except for the Kiremt season (Table 4; Fig. 4a). In the 2020 (2020–2049), the maximum precipitation change may be decreased between 35.5% and 66.2% under RCP8.5 in the Belg season. With respect to this scenario, the areal average rainfall under RCP4.5 and RCP2.6 may decrease between 29–57% and 15.3–37.2%, respectively. Conversely, precipitation will increase during the Kiremt season



c Average potential evapotranspiration for RCP8.5

Fig. 4 Projected change of average precipitation, temperature, and potential evapotranspiration

under all RCP scenarios. Even if precipitation increases in the Kiremt season, the mean monthly precipitation may decrease significantly in Belg and Bega seasons. In the 2050s (2050–2079), precipitation is expected to decrease up to 47.6% and 82.7% under RCP8.5 during Belg and Bega season, respectively. The relative change in mean monthly precipitation may be much higher under RCP8.5 scenario than under RCP4.5 and RCP2.6 scenarios. This would be attributed to higher greenhouse gas (GHG) concentration under RCP8.5 scenario (Riahi and Nakicenovic 2007). These

Table 3 The MK test result for observed average precipitation, temperature and ET_{o}

Kendall's tau	S	Sen's slope	P value	Trend type
-0.194	-63	-8.2	0.17	Accept H_0
-0.05	-17	-2.2	0.72	Accept H_0
-0.15	- 50	-3.9	0.28	Accept H_0
0.354	115	0.031	0.011	Reject H_0
0.403	131	0.057	0.04	Reject H_0
0.108	35	0.018	0.458	Accept H_0
0.33	107	5.4	0.020	Reject H_0
0.24	77	5.0	0.045	Reject H_0
0.16	53	1.7	0.260	Accept H_0
	Kendall's tau -0.194 -0.05 -0.15 0.354 0.403 0.108 0.33 0.24 0.16	Kendall's tau S -0.194 -63 -0.05 -17 -0.15 -50 0.354 115 0.403 131 0.108 35 0.33 107 0.24 77 0.16 53	Kendall's tau Sen's slope -0.194 -63 -8.2 -0.05 -17 -2.2 -0.15 -50 -3.9 0.354 115 0.031 0.403 131 0.057 0.108 35 0.018 0.33 107 5.4 0.24 77 5.0 0.16 53 1.7	Kendall's tau Sen's slope P value -0.194 -63 -8.2 0.17 -0.05 -17 -2.2 0.72 -0.15 -50 -3.9 0.28 0.354 115 0.031 0.011 0.403 131 0.057 0.04 0.108 35 0.018 0.458 0.33 107 5.4 0.020 0.24 77 5.0 0.045 0.16 53 1.7 0.260

study results are in good agreement with similar studies performed for the Ethiopian regions for annual and seasonal scales (e.g., Niguse and Aleme 2015; Li et al. 2016). The increase or decrease in precipitation might be due to the combined effects of seasonal movement of the Inter-Tropical Convergence Zone (ITCZ), local land surface heating and topographic forcing (Li et al. 2016).

Temperature

Table 4 The changes in temperature, ET_o and precipitation

Unlike precipitation, the average temperature shows clear increasing trends for almost all months of the year in the near-term and mid-term periods (Fig. 4b). The maximum change in the average temperature of the intermediate

period may increase in Belg (Small) season under the RCP8.5 scenario. For this scenario, the temperature may increase by 4.2 °C and 4.8 °C in the Belg season for the near-term and mid-term periods, respectively. Similarly, under RCP4.5 and RCP2.6, the temperature may slightly increase between 2.1–3.3 °C and 0.8–1.2 °C, respectively. The average temperature in the Belg season will also increase from 2.9 to 3.9 °C for RCP8.5, from 0.3 °C to 1.6 °C for RCP4.5 and from 0.3 to 0.7 °C for RCP2.6 scenarios (Table 4).

In the 2020s (2020–2049), the average annual temperature may increase in all RCP scenarios. In the near-term, the average temperature may increase in Belg and Bega (dry) seasons and may slightly decrease during the Kiremt (main rainy) season. However, with respect to the control period, the average temperature is expected to increase in the Kiremt season. The maximum average increment in temperature can be anticipated under RCP8.5 in Belg season by the magnitude of 3.1 °C (0.4–1.4 °C) and 4.5 °C (0.2–0.7 °C). Similarly, the projected average temperature may be increased in both RCP4.5 and RCP2.6 scenarios during the Belg season. This result is in close agreement with the previous study by Gebre and Ludwig (2015), who used the HadGEM2-ES climate model for the Lake Tana basin. The report revealed that the average temperature under RCP8.5 and RCP4.5 strongly increases at 2070s than 2030s. The average temperature may be significantly increased in RCP8.5 than RCP4.5 scenarios. In 2070, the average temperature may be increased up to 7.1 °C and 4.5 °C for RCP8.5 and RCP4.5, respectively. Similarly, Elshamy et al. (2009) reported that the projected average temperature may be increased between 2 and 5 °C during the years 2081–2098. This study was based on the output

Variables	Temperatu	ure (°C)	ET _o (mm/	month)	Precipitation (%)	
Season/periods	2020s	2050s	2020s	2050s	2020s	2050s
Belg						
Feb	3.2	4.3	14.7	18.9	-46	-40.5
Mar	3.1	4.2	15.7	17.6	-66.2	- 82.7
Apr	4.1	4.5	17.2	18.7	-44.5	-56.2
May	4.5	4.8	18.8	19.7	- 35.5	-47.9
Kiremt						
Jun	2.6	2.8	5.6	4.1	32.2	25.1
Jul	0.8	1.3	2.9	2.2	35.2	31.9
Aug	0.2	0.6	1.6	2.0	47.5	31.5
Sep	1.2	1.1	5.1	7.1	25.7	20.7
Bega						
Oct	3.0	3.6	8.8	12.0	-21.5	-47.5
Nov	2.2	2.9	3.6	9.9	-31.6	-47.6
Dec	2.9	3.9	9.8	14.4	-13.3	- 19.6
Jan	2.9	3.8	10.5	13.5	- 30.2	-40.5

of 17 GCM models under an A1B scenario in the upper Blue Nile basin. From this study, it is clearly observed that the monthly and seasonal precipitation can be strongly decreased with increasing temperature under all RCP scenarios.

Evapotranspiration

The future potential evapotranspiration may be increased during the two time periods (i.e., 2020-2049 and 2050–2079). The results revealed that the potential evapotranspiration is higher in the second time series. Table 4 illustrates that the highest seasonal ET_o was occurred during the Belg season, while the lowest ET_o occurred in the Kiremt season during the observed period. The lowest ET_o may be expected under RCP2.6 for the different time series. This shows that ET_o has a significant difference between the current and future scenarios. The maximum ET_o in the 2050s can occur in Belg season, which may range between 14.7 and 18.8% under the RCP8.5 scenario. ET_0 under RCP2.6 may be changed between 9.4–11.6% and 11.2–12.9% in the near and mid-term periods, respectively (Fig. 4c). This result is also in close agreement with Elshamy et al. (2009), whose findings indicated that the total annual ET_0 may vary from 2 to 14% in the future. Similarly, Farag et al. (2015) reported that the projected ET_o varies from scenario to scenario and from season to season. The lowest (7.8%) and highest (22.9%) percentage of increase in the ET_o may also be expected under RCP2.6 and RCP8.5 scenarios in the Belg season, respectively. During the Bega season, all RCP scenarios show an increasing trend of ET_o in the future. Under RCP8.5, RCP4.5 and RCP2.6, ET_o may be changed from 3.6 to 10.5%, 3 to -5.1% and 2.5 to 5% during near-term, and 9.9% to -14.4%, 5% to -7% and 5.8% to -7.4% in the mid-term, respectively. However, ET_o is often limited seasonally by the availability of soil water in addition to temperature (Kurc and Small 2007; . Wilske et al. 2010). When the available soil water is limited, ET_o is taking below the potential rate and ET_o takes place at the potential rate when there is sufficient soil moisture (Allen et al. 1998).

Our study result is also in agreement with Hailu et al. (2016), who used CSMK3 and MPEH5 regional climate model for the ensemble project concerning the near future (2020–2039) and the far future (2000–2100) in Gilgel Abbay and Gumara watershed of the Upper Blue Nile Basin. The findings of the particular analysis indicated that annual ET_o may be increased by 15–24.2% in the dry season and 5.5–21.4% in the wet season. In the near and far future time periods, seasonal evaporation and crop evapotranspiration are expected to increase by about

2.9–10% and 6.8–24.5%, respectively. These results indicate that there is a general understanding of the increasing trends of ET_o in the future. Therefore, there may be a great percentage difference in seasonal and annual CWD in the future. Thus, unless sustainable development strategies to mitigate the consequences of climate change are not taken into account, agricultural activities such as irrigation water delivery and agricultural production may be severely affected.

Future CWD for the maize crop

Adequate water availability throughout the growing period of the crop is very important for obtaining maximum yield, because the vegetative growth is directly proportional to the water transpired (FAO 2006). Depending on climate characteristics, monthly and seasonal CWD of maize and IWR were estimated under the selected RCP scenarios during two time periods of near-term (2020-2049) and mid-term (2050-2079). The results reveal that the CWD in the middle-term is higher than the near-term time period. Future IWR and CWD of maize under RCP scenario can be increased during the Belg season in the mid and development stages (Fig. 5). This can be attributed to the high crop coefficient values throughout the growth stage. Additionally, increased temperature and thereby the increased ET in future climate scenarios yielded large CWD and IWR of the maize crop. The crop coefficient and crop canopy play a significant role to determine the CWD (FAO 2006). Similarly, the peak irrigation water demand might be occurred in the month of March being the hottest and driest month in the study area. Table 5 presents the relative change in CWD for various scenarios.

Under the RCP8.5 scenario, effective rainfall is likely to be decreased by 41% and 44% in the near and midterm periods, respectively. Therefore, the crop needs supplementary irrigation to compensate for this deficit of water. Consequently, the total IWR and CWD increase from 8.5 and 12.8% during the near-term and mid-term periods (Table 5). Both IWR and CWD may be expected to increase by 8.8–15.4% throughout the growing crop period. The CWD of maize may be more than the effective rainfall and additional water is required to compensate the evapotranspiration losses in future. Similarly, the total IWR and CWD of maize under RCP4.5 can be increased from 6.8 to 11.5% in the near-term and also in 2050s, and it may be changed from 8.8 to 16.9% in the mid-term periods. However, IWR and CWD under RCP2.6 exhibit a slight change from 5.7 to 7.4% and 7.1–10.5% in the near and mid-term periods, respectively (Table 5). Figure 5 illustrates monthly CWD and IWR of maize at different growth stages at Laybirr station. The results clearly show

Fig. 5 The IWR and CWD for maize crop at different growth stage at Laybirr station







Table 5	Change of CWR and
IWR of	maize at Laybirr station

CWD for maize	CWD/grov	wth period		Change of	Change of CWD (%)		
	CWR	IWR	P _e	CWR	IWR	P _e	
CWD							
Observed	363	295	78				
RCP4.5							
Near-term	394	333	61	8.5	12.8	-21	
Mid-term	399	349	50	8.8	15.4	-35	
RCP8.5							
Near-term	388	329	46	6.8	11.5	-41	
Mid-term	395	345	43.3	8.8	16.9	-44	
RCP2.6							
Near-term	384	317	68	5.7	7.4	-13	
Mid-term	389	326	63	7.1	10.5	- 19	





 Table 6
 List of objective functions and their values obtained during calibration

Objective function	Calibration	Validation
NSE	0.89	0.85
R^2	0.79	0.76
RVE (%)	-2.10	5.10
RSR	0.11	0.22

that the peak IWR and CWD of maize can be expected in the development stage in the month of March. Similarly, monthly CWD and IWR of maize were calculated at Adet and Dembecha stations (not mentioned for brevity).

Model calibration and validation

The HBV model was manually calibrated for the year 1990–1999 and validated for the years 2000–2005 (Fig. 6a, b). The observed and simulated flow shows that the performance of the model in simulating the base flow, rising and recession limb of the hydrograph is fairly good even though the model overestimates the flow in the years 1996 and 1997. The simulated flow in these years may have a

bV	a	lid	lat	tic	on
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larger degree of uncertainty since rainfall was highly variable in space and time (Dile et al. 2013). The model results are reasonably accurate for high flow. The objective functions which were used to evaluate the model performance are presented in Table 6. The statistical parameter indicates a good model performance in terms of capturing the observed streamflow volume (RVE = -2.1%), the pattern of streamflow hydrographs (NSE = 0.89), and relatively better agreement between the observed and simulated daily discharge (RSR = 0.11). The model also performs reasonably well in simulating the discharge during the validation period (Fig. 6b). The NSE, R^2 , RVE, and RSR were found to be 0.85, 0.76, 5.10, and 0.22, respectively.

Impact of climate change on future water availability

The impact of climate change on streamflow in the Birr watershed was evaluated based on the changes in temperature, evapotranspiration, and precipitation under RCP8.5, RCP4.5 and RCP2.6 scenarios (Table 7). The future streamflow was analyzed for two simulations time periods (i.e., near-term: 2020–2049) and mid-term: 2050–2079).

Table 7 Monthly streamflowchange under different RCPscenarios

Season	Month	Near-term			Mid-term	Mid-term			
		RCP8.5	RCP4.5	RCP2.6	RCP8.5	RCP4.5	RCP2.6		
Belg	Feb	- 53	-35	-23	-72	-52	-36		
	Mar	-68	-43	-44	- 84	-46	-37		
	Apr	-66	-36	-46	-91	-74	-29		
	May	-45	-22	-46	-73	- 58	-16		
Kiremt	Jun	13	20	37	23	34	29		
	Jul	25	34	44	24	38	48		
	Aug	29	46	44	27	42	52		
	Sep	11	23	26	10	20	32		
Bega	Oct	-29	-27	-15	-43	-20	-3		
-	Nov	-28	-16	-8	-36	-14	-5		
	Dec	-33	-25	-21	-42	-33	-11		
	Jan	-41	-36	-22	-60	- 30	-20		

Table 8MK test results for theseasonal flow under differentRCP scenarios

Scenarios	RCP8.5			RCP4.5			RCP2.6		
Season	Belg	Bega	Kiremt	Belg	Bega	Kiremt	Belg	Bega	Kiremt
Kendall's coefficient	-0.5	-0.2	-0.2	-0.1	0.1	-0.01	-0.1	0.04	-0.02
S	- 898	-296	-377	-236	- 890	-11	-236	71	-41
P value	0.0001*	0.053*	0.01*	0.12**	0.0001*	0.9**	0.12**	0.6**	0.79**

* and ** indicate significant and non-significant change point, respectively

Seasonal change of streamflow in the near and mid-term periods

Kiremt (main rainy) season The streamflow under RCP2.6 and RCP4.5 scenarios may increase over the Kiremt season. The projected streamflow tends to increase under RCP8.5 scenario between 27 and 29% in the near-term and midterm periods. The flow under the RCP4.5 scenario may also increase between 46 and 38% in the 2020s (2020–2049) and 2050s (2050–2079), respectively. However, the increase in predicted streamflow under RCP2.6 scenario for mid-term (55%) is slightly larger than that for the near-term (44%) (Table 7). These results are in agreement with studies reported in Taye et al. (2015) for the Upper Blue Nile basin.

Belg (small rainy) season During the Belg season, the river flow was found to be most likely to decrease under RCP8.5 than RCP4.5 and RCP2.6 scenarios. Under these scenarios, the flow may be decreased between 66% and 91% in the near-term and mid-term, respectively. However, the seasonal streamflow may change between -43% and -74% for RCP4.5 and from -46 to -37% under RCP2.6 scenarios (Table 7). The maximum reduction of flow can be anticipated in the Belg season as compared to the other seasons. This may be attributed to the increase in average temperature and ET_o. The projected precipitation under RCP4.5 and RCP8.5 scenarios shows that precipitation may significantly decrease in the near-term and mid-term periods, respectively. This decline of streamflow may cause an acute shortage of irrigation water owing to increasing demands for fresh water in the future periods.

Bega (dry) season The simulated streamflow in the Bega season may be decreased in all RCP scenarios in the near and mid-term period (Table 7). In the 2020s and 2050s, the flow may be changed between -41 and -60% under the RCP8.5 scenario, respectively. Streamflow under RCP4.5 and RCP2.6 may also be decreased from 35 to 33% and 22–20% in the near-term and mid-term periods, respectively (Table 7). Generally, it can be concluded that there is a simple relationship between the changes in temperature, ET_o, precipitation and river flow. Irrespective of precipitation, ET_o changes were found to have a strong linear relationship with temperature changes (Table 4). The increasing ET_o and decreasing rainfall and flow can be increased the seasonal and annual CWD of maize crop in the coming 60 years.

Seasonal streamflow trends and change point detection

The trends and shift in the seasonal and annual streamflow under RCP scenarios were computed using the MK and Pettitt tests (Table 8, Figs. S2, S3). Both significant and insignificant trends were observed during the Kiremt, Belg and Table 9Summarized resultsof change point detection forstreamflow using Pettit test

Scenarios	RCP8.5			RCP4.5			Relative change (%)		
Day	P value	After	Before	P value	After	Before	RCP8.5	RCP4.5	
$\overline{Q_{\min}}$ flow (n	n ³ /s)								
1	0.0001	1.42	0.81	0.001	4.84	5.34	-42.96	-9.20	
7	0.0001	1.41	0.801	0.001	4.96	4.243	-43.19	-14.32	
30	0.0001	1.4	0.8	0.00	4.90	4.167	-42.86	- 14.96	
90	0.0001	0.98	0.55	0.015	4.91	4.1	-44.18	- 16.50	
$Q_{\rm max}$ (m ³ /s)									
1	0.039	230	450	-	-	-	-48.88	-	
7	0.023	220	330	-	-	-	-33.33	-	
90	_	_	_	0.026	140	170	_	-17.65	

Bega seasons at 5% significance level (Table 8). Streamflow significantly decreases under RCP4.5 scenario during the Bega season. Similarly, the trend analyses of flow under RCP8.5 scenario indicate statistically decreasing trend during the Belg, Kiremt and Bega seasons. An abrupt downward change in streamflow can occur in all seasons under RCP8.5 in the early 2050s (Fig. S3). However, under the RCP4.5 scenario, the change point in the downward direction can be expected around 2045s, 2060s and 2030s during Belg, Bega and Kiremt seasons, respectively. However, a significant change point was not found for flow under an RCP2.6 scenario in all seasons indicating a linear insignificant decreasing trend.

Trend analyses and change point detection

Using IHA, flow was separated into 1 day, 7 days, 30 days and 90 days minimum flow and a statistically significant downward shift were found under RCP8.5 scenario (Fig. S4). The change point may occur in 2055s, and 1 day minimum annual streamflow before and after the change point was 1.42 and 0.81 m³/s, respectively (Fig. S4). The average annual streamflow may be decreased after 2055, and the magnitude of the decrease might be 42.96% (Table 9). Similarly, for 7 days, 30 days, and 90 days minimum flows, a significant downward shift may be anticipated in 2055 and after this, the minimum flow may decrease by 43.19%, 42.86% and 44.18%, respectively (Table 9) under the RCP8.5 scenario. The statistically significant downward shift for 1 day, 7 days, 30 days and 90 days annual minimum flow was also detected under RCP4.5 scenario around the year 2035. The relative change point before and after the shift years is expected to decrease by 9.20%, 14.32% for 1 day, 7 days, and 14.96%, 16.50% in 30 days and 90 days time steps, respectively. However, minimum flow under RCP2.6 is not expected to show any shift for 1 day, 7 days, and 30 days and 90 days (Fig. S4).

Similarly, the maximum flow for 1 day and 7 days exhibit a statistically significant downward shift under RCP8.5 in the year 2060s and the annual streamflow may decrease after 2060. The magnitude of the decrease may be anticipated to 48.88% and 33.33% for 1 day and 7 days flow, respectively. However, no significant change point was found for 30 days and 90 days flows. Similarly, for 1 day, 7 days, and 30 days annual maximum flows, a significant change point was not detected under the RCP4.5 scenario. Conversely, for 90 days maximum flow, the significant downward shift was detected in the year 2030s under the RCP4.5 scenario and it is expected to decrease by 17.65% (Table 9). However, a shift in 1 day, 7 days, 30 days and 90 days annual maximum flows was not detected for the coming 60 years under RCP2.6 scenarios. For the coming six decades, surface water availability in Birr watershed may be strongly affected by climate change in RCP8.5 and RCP4.5 scenarios. Especially, minimum flow during Belg and Bega seasons may decrease significantly. The irrigation water demand on maize crop could be increased under climate change scenarios. Generally, the increase of temperature may shift the time of peak irrigation water demand and this may lead to yield reductions (Sean et al. 2015). Therefore, the competition for fresh water in general and agricultural water demand, in particular, will be tense in the coming six decades.

Conclusions

This study investigated the impacts of climate change on surface water availability and crop water demand in the Birr watershed, Ethiopia. The streamflow trends and variability were assessed using the MK test under different climate change scenarios. Some of the important conclusions drawn from this study are stated as follows:

 The average temperature and evapotranspiration are likely to show an increasing trend in all the stations during the baseline and future scenarios including near and midterm periods. There is no statistically significant trend found in precipitation during the period 1989–2015. The areal average precipitation may be decreased in Belg and Bega season under all RCP scenarios. However, mean monthly and seasonal precipitation may increase in future during the Kiremt season. At the same time, the average annual precipitation may be expected to decrease except for RCP4.5 at Dembecha station at 5% level of significance. Under RCP8.5 scenario, magnitude of change in all climatic variables was found to be more significant as compared to RCP2.6 and RCP4.5 scenarios for the future periods (i.e., 2020–2049 and 2050–2079).

- 2. The rise in IWR and CWD for maize crop was found in all future scenarios. The maximum incremental CWD and IWR are expected during the developmental growth stage. Although CWD may slightly decrease in the near and mid-term periods during late and initial stage as compared to other growth stages, it could significantly increase in the development and mid-stage growth periods. This increment in future CWD and IWR of maize crops may be attributed due to increase in average temperature and evapotranspiration. Evidently, more water can be required for supplementary irrigation. Otherwise, maize crop may suffer from dry spells at sensitive growth stages (flowering and mid-stages) and this may expose a region for food insecurity. The well-maintained terraces and rainwater harvesting systems in the watershed can serve for water supply through the farm ponds for supplementary irrigation during the dry period (Bitew et al. 2015). However, these are not enough and need more measures for additional supplementary irrigation including storage schemes.
- 3) The HBV model results indicate the satisfactory performance of streamflow simulation during calibration (NSE = 0.89) and validation (NSE = 0.85). The model results point that there is a decline of streamflow in the 2020s (2020–2049) and 2050s (2050–2079) for all RCP scenarios in Birr watershed. It is expected that there may be a significant decrease in flow volume during Belg and Bega seasons in the future.
- 4. The minimum flow for the 1, 7, 30 and 90 days has shown a downward shift in the years 2035 and 2055 under RCP4.5 and RCP8.5 scenarios, respectively. Similarly, maximum flow (only 90 days) indicated a downward shift in the year 2030 under the RCP4.5 scenario, while the maximum flow for the 1 and 7 days under the RCP8.5 scenario also showed a significant downward shift during the years 2030 and 2060, respectively. This could be attributed to the increment of average temperature and evapotranspiration in the future. The decrease in both minimum and maximum flow will impose tension on the side of irrigation water demand in the future. Therefore, storage schemes may be helpful to combat water shortage during the Bega and Belg seasons.
- 5. Therefore, this study could provide important insight into the climate change impact on the hydrological variables.

The study points to an upcoming water resource problems so that mitigation and adaptation strategies can be made ahead. The study will also assist policy makers in decision making on irrigation development in the watershed.

6. The present study is focused on surface water availability and crop water demand assessment in changing climate conditions. Given the results of this study, the authors further recommend a comparative assessment of the different GCMs outputs with multiple RCP scenarios and uncertainties associated with them for the studied region in future. Future studies are also recommended to consider CWD for multiple crops and the varying crop calendars considering climate change.

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